Doctoral Dissertation | Politecnico di Torino

Influence of Occupant's Behaviour on Indoor Environmental Quality and Energy Consumptions

- A Roadmap to predict the unpredictable energy-related occupant behaviour

Valentina Fabi

Politecnico di Torino, Torino, Italy
Denmark Technical university, Copenhagen, Denmark

May, 2013

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ROADMAP

TO PREDICT THE UNPREDICTABLE ENERGY-RELATED OCCUPANT BEHAVIOUR

"Isn't it sad that you can tell people that the ozone layer is being depleted, the forests are being cut down, the deserts are advancing steadily, that the greenhouse effect will raise the sea level 200 feet, that overpopulation is choking us, that pollution is killing us, that nuclear war may destroy us - and they yawn and settle back for a comfortable nap. But tell them that the Martians are landing, and they scream and run."

Isaac Asimov, The Secret of the Universe

TABLE OF CONTENTS

PREDICTING THE UNPREDICTABLE HUMAN BEHAVIOUR

CHARTING THE JOURNEY

REACHING MILESTONES

SCALE IT UP

ON THE HORIZON

I. PREFACE

This research project is based on the work, I have done with the collaboration of both Polytechnic of Turin and Technical University Denmark at Copenhagen. As it is always the case with such a work, I would not have been able to finish it without the help and support of numerous colleagues and friends. I felt privileged to know some of the best scientists in the world in field of the sustainability and indoor climate research.

I would like to give a special thank Professor Stefano Corgnati. for his precious help and suggestions and his constant supervision in the research. Thanks to his constant guidance, advices and stimulating discussions all over the PhD, this research period has been for me a period of deep professional, personal and cultural enrichment. I could and can always rely on your judgements and suggestions.

I am sincerely grateful to Rune Andersen. It is impossible to account here for all your support and advices without which this work would not have been completed as it is. I can only highlight a few here and keeping the others in my memory Starting with listen to the studies I have been doing, over the support and advice for developing papers up to the continuous support during and probably beyond the work of this dissertation.

Further thanks are devoted to Professor Marco Filippi. I really appreciate the help I have received from him, who has pointed me in the right direction and supported my decisions all the way.

I would also like to express my sincere gratitude to Professor Bjarne W. Olesen, who was always able to find time in his busy schedule for constructive discussions of how to proceed.

I would also like to thank Daniela and all my colleagues from TEBE Group and Indoor and Environment Energy Management Competence Centre, not only for becoming my friends during these 3 years and turning IEEM into more than 'just a workplace'. I enjoyed working among you.

And many thanks to my colleagues at the International Centre for Indoor Environment and Energy for their warm welcome and their hospitality during my staying in Copenhagen. I have always enjoyed the special international atmosphere at the centre.

I would like to dedicate this work to my family, for supporting me all over these years, even when the situation was not easy. They gave me the time and opportunities to pursue my ambitions and goals, even though it sometimes resulted in sacrifices in our family.

To Paolo, for always being present with his love, for believing in me and in my choices and for giving me the serenity to face each difficulties. Thank you for bringing so much happiness into my life.

II. EXECUTIVE SUMMARY

Buildings are dynamic, and the interactions of operators, occupants, and designers all influence the way in which buildings will perform. At the core of this research is the belief that technical solutions alone are not sufficient to face great challenges of saving energy while still maintaining or even improving current comfort levels. Buildings are engineered using tested components and generally reliable systems whereas people can be unreliable, variable, and perhaps even irrational. The studies in literature also reveal the gap between how designers expect occupants to use a building, and how they will actually operate it. Actually, there is often a significant discrepancy between the designed and the real total energy use in buildings. The reasons of this gap are generally poorly understood and largely have more to do with the role of human behaviour than the building design. Knowledge of user's interactions within building is crucial to better understanding and a more valid predictions of building performance (energy use, indoor climate) and effective operation of building systems.

The present work undertakes a theoretical and empirical study of the uncertainty of energy consumption assessment related to occupants' behaviour in residential buildings. The main purpose of this research is to propose a methodology to model the user behaviour in the context of real energy use and applied it to a case study. The methodology, based on a medium/long-term monitoring, is aimed at shifting towards a probabilistic modelling the occupant behaviour related to the control of indoor environment with respect to the energy-related issues. The goal is to determine users' behavioural patterns describing user's interaction with the building controls. The procedure is applied first at modelling occupants' interactions with windows (opening and closing behaviour) and then at modelling the heating set-point preferences.

This research is based on the assumption that only switching from a deterministic approach in building energy simulation to a probabilistic one it will be feasible to obtain energy consumption prediction closer to reality. This probability is related to variability and unpredictability during the whole building operation. In this way, it become crucial to take into account the occupants' presence and interactions with the building and systems. Actually, building energy simulation tools often reproduce building dynamics using numerical approximations of equations modelling only deterministic (fully predictable and repeatable) behaviours. In such a way, "occupant behaviour simulation" could refer to a computer simulation generating "fixed occupant schedules", representing a fictional behaviour of a building occupant over the course of a single day. This is an important limitation of energy simulation tools for modelling occupant's interactions with buildings, and highlights that the results are essentially unrealistic.

The whole dissertation consists of four parts. In the first part the development of a theoretical model of the occupant behaviour is described based on a comprehensive literature review. With respect to the complexity of this issue, a specific literature survey is addressed to derive the most dominating driving forces useful for a more accurate description of occupant behaviour related to the habits of opening and closing the windows. Existing studies on the topic of window opening behaviour are highlighted and a theoretical framework to deal with occupants' interactions with building controls, aimed at improving or maintaining the preferred indoor environmental conditions, is elaborated. The analysis of the literature highlights how a shared approach on identifying the driving forces for occupants' window opening and closing behaviour has not yet been reached.

In the second part of this dissertation, a method for defining occupant behaviour in simulation programs based on measurements is proposed. The proposed approach is based on measurements of both indoor and outdoor environmental parameters and the behavioural actions of the building occupants (window opening, TRV's set point adjustments, occupancy sensors, etc..). From the collected data, different suitable user behavioural patterns (models) were defined by means of statistical analysis (logistic regression, Markov chain, etc..) and implemented in a building energy simulation tool. Moreover, a probabilistic distribution instead that a single value is preferred as a representation of energy consumptions. The proposed procedure was applied for modelling the human behaviour related to the window opening and closing and the change in thermostatic radiator valves (TRVs), and its implementation in the simulation tool IDA ICE so that the results obtained are probabilistic in nature.

The third part of the dissertation deals with the validation of the obtained models to ensure the effectiveness of the models. In this section, the validation procedure is carried out using other data coming from an analogue dataset of dwellings where the same indoor and outdoor parameters are measured. These data will be used to validate the models of window opening behaviour. The validation is performed by comparing the probabilities of window opening and closing with the actual measured state of the windows in the dwellings. In literature, a variety of logistic models expressing the probability with which actions will be performed on windows, as a function of indoor temperature, outdoor temperature or both. Previously published models are then also compared using this validation procedure.

The fourth part of the thesis represents a sightseeing of the future application of this field of research, focusing on the understanding of how technology and building design can improve energy efficiency exploiting the goal of making users more aware and hence careful on energy consumption.

Overall, this dissertation highlights the importance of researching the individual's behaviour in order to understand the differences in real building energy usage. Besides being limited to the cases of window opening and closing for most of the analyses, the methodology presented can also be applied to other types of behaviours.

III. SOMMARIO

Gli edifici hanno un comportamento dinamico, e le interazioni degli operatori, occupanti, e designer influenzano la prestazione energetica degli edifici. Al centro di questa ricerca risiede la convinzione che le soluzioni tecniche da sole non sono sufficienti per far fronte alle grandi sfide del risparmio energetico mantenendo o addirittura migliorando i livelli di comfort attuali. Gli edifici sono progettati con componenti collaudati e sistemi in genere affidabili, ma le persone che li vivranno possono essere imprevedibili e irrazionali. Gli studi in letteratura rivelano inoltre che esiste un notevole divario tra il modo con cui i progettisti si aspettano che gli occupanti utilizzino un edificio, e il modo in cui effettivamente lo faranno funzionare. Effettivamente, vi è spesso una discrepanza significativa tra l'uso di energia degli edifici previsto e quello reale. Le ragioni di questo divario sono in genere poco conosciute e in gran parte hanno più a che fare con il comportamento umano piuttosto che con la progettazione degli edifici. La conoscenza delle interazioni dell'utente all'interno dell'edificio è dunque un aspetto fondamentale per una migliore comprensione e di conseguenza una previsione più valida delle prestazioni dell'edificio (in termini di consumo di energia e di qualità climatica dell'ambiente interno) e il funzionamento efficace dei sistemi.

Il presente lavoro rappresenta uno studio teorico ed empirico sull'incertezza della valutazione del consumo energetico considerando il comportamento degli occupanti in edifici residenziali. Lo scopo principale di questa ricerca è quello di proporre una metodologia per modellare il comportamento dell'utente con riferimento ai consumi energetici reali e applicata ad un caso di studio. La metodologia si delinea con uno spostamento verso una modellazione probabilistica del comportamento degli occupanti relativo al controllo dell'ambiente interno: l'obiettivo è quello di determinare modelli di comportamento degli utenti capaci di descrivere l'interazione con l'edificio e i sistemi. La procedura proposta viene quindi applicata ad un caso di studio: in particolare vengono definiti sia dei modelli di uso delle finestre ("window opening behaviour") sia modelli di preferenze di set-point di riscaldamento in ambito residenziale.
Questa ricerca, dunque, si basa sul presupposto che attraverso solo il passaggio della simulazione energetica dinamica da un approccio deterministico ad una probabilistico sarà possibile ottenere una previsione dei consumi energetici più vicina alla realtà. Questo approccio probabilistico è legato alla variabilità e alla imprevedibilità del comportamento dell'occupante durante l'intero ciclo di vita dell'edificio: cruciale diviene quindi tenere conto della presenza degli occupanti e delle loro interazioni con l'edificio e sistemi. In realtà, allo stato attuale, gli strumenti di simulazione energetica degli edifici riproducono spesso le dinamiche degli edifici usando equazioni numeriche che modellano comportamenti solo deterministici (completamente prevedibili e ripetibili). In tal modo, con il termine "simulazione del comportamento degli occupanti" si fa riferimento a una simulazione numerica che prevede la generazione di "schedules" fisse relative sia all'occupazione che al comportamento degli utenti. Queste schedules dunque rappresentano un comportamento immaginario di un occupante dell'edificio nel corso di una giornata tipica. Effettivamente, questa è una limitazione importante degli strumenti di simulazione energetica delle prestazioni energetiche degli edifici, mettendo in evidenza che i risultati ottenuti sono essenzialmente non realistici.

La tesi si compone di quattro parti. Nella prima parte è descritto lo sviluppo teorico della modellazione del comportamento degli occupanti degli edifici sulla base di una indagine bibliografica. Vista la complessità del tema, è stata effettuata una revisione specifica degli studi presenti al fine di definire le variabili dominanti ("drivers") che spingono l'utente ad interagire con l'edificio e i sistemi. In particolare, sono stati investigati con uno sguardo critico gli studi legati alle abitudini di apertura e chiusura delle finestre. A partire da questa visione generale del tema viene dunque elaborato il quadro teorico entro cui risiede la logica delle interazioni occupanti-edificio-sistemi volte a migliorare o mantenere le desiderate condizioni ambientali interne. L'analisi degli studi di letteratura evidenzia come un approccio comune sull'identificazione dei parametri guida, i "drivers", non è stato ancora raggiunto.

Nella parte seconda viene proposto un metodo per la modellazione del comportamento degli occupanti di tipo probabilistico. L'approccio si definisce a partire da un monitoraggio a medio/lungo termine di parametri ambientali interni ed esterni e delle azioni comportamentali degli utenti (apertura della finestra, regolazione del set point di riscaldamento, ecc.). In questo approccio di modellazione di tipo probabilistico, a partire dai dati raccolti, è possibile definire diversi modelli di comportamento degli utenti mediante analisi statistiche (regressione logistica, catene di Markov, etc..). Questi modelli statistici di comportamento quindi vengono implementati negli strumenti di simulazione energetica degli edifici. Inoltre, una distribuzione probabilistica dei consumi al posto di un singolo valore è da preferirsi come una più realistica rappresentazione delle prestazioni energetiche degli edifici. La procedura proposta è stata applicata ad un caso studio sull'uso delle finestre e sulle preferenze del set-point di temperatura in ambito residenziale, tramite la definizione di modelli stocastici di comportamento dell'utente implementati e poi simulati nello strumento di simulazione energetica degli edifici IDA Ice.

La parte terza della dissertazione è legata alla validazione dei modelli statistici definiti per garantire la loro efficacia. In questa parte della ricerca, i dati di un campione analogo di abitazioni dove gli stessi parametri interni ed esterni sono stati raccolti, vengono utilizzati per validare i modelli di comportamento. La validazione viene eseguita confrontando le previsioni di apertura e chiusura delle finestre con lo stato attuale delle finestre registrato nelle abitazioni. Dal momento in cui in letteratura sono presenti alcuni modelli logistici legati all'uso delle finestre, in funzione della temperatura interna, temperatura esterna o entrambe, anche questi modelli vengono verificati con questa procedura di validazione.

La parte quarta della tesi si rivolge alle possibili future applicazioni di questa ricerca. In questa sezione, il focus è sulla comprensione di come la tecnologia e la progettazione siano in grado di migliorare l'efficienza energetica con l'obiettivo di rendere gli utenti più consapevoli e attenti ai consumi di energia.

Nel complesso, questa tesi sottolinea l'importanza di descrivere il comportamento dell'individuo legato all'interazione con edifici e sistemi in modo più accurato e realistico, al fine di comprendere le differenze nei consumi di energia reali degli edifici. Inoltre, nonostante l'applicazione descritta in questa tesi sia limitata per la maggior parte delle analisi all'uso delle finestre, il metodo presentato può essere applicato anche ad altri tipi di azioni comportamentali.

IV. LIST OF PAPERS

PAPER I

Fabi V., Andersen RV., Corgnati SP., Olesen BW. *"Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and model."* , Building and Environment (2012), pp. 188-198 DOI information: 10.1016/j.buildenv.2012.07.009.

PAPER II

Andersen, R., Fabi, V., Corgnati, S.P., Toftum, J., Olesen, B.W. "*Window opening behaviour modelled from measurements in Danish dwellings*". Submitted to Building and Environment Journal on January,10th 2013.

PAPER III

Fabi V., Andersen RV., Corgnati SP., Olesen BW*. "A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings*." Building Simulation Journal, 2013, DOI information: 10.1007/s12273-013-0119-6.

PAPER IV

Fabi, V., Andersen RV., Corgnati SP. "*Influence of Occupant's Heating set-point preferences on Indoor Environmental Quality and Heating Demand in Residential Buildings*", HVAC&R Research Journal DOI information:10.1080/10789669.2013.789372.

PAPER V

Fabi V., Andersen RV., Corgnati SP "*Validation of models of users' window opening behaviour in residential buildings*", accepted to IBPSA 2013 Conference, August 25th – 28th 2013, Chambery, France.

OTHERS

V. Fabi, S. D'Oca , R.V .Andersen, S.P. Corgnati. "*Influence of window opening/closing behaviour and heating set-point adjustments on heat consumption in dwellings*". Accepted to Clima 2013 Conference, 16th-19th August 2012, Prague, Czech Republic.

Fabi V., Andersen RV., Corgnati SP., Venezia F." *Influence of User Behaviour on Indoor Environmental Quality and Heating Energy Consumptions in Danish Dwellings*". Proceedings of 2nd International Conference on Building Energy and Environment, 1st-4th August 2012, Boulder, Colorado, US.

Fabi V., Andersen RV., Corgnati SP., Venezia F." *Main physical environmental drivers of occupant behaviour with regard to space heating energy demand*". Proceedings of 10th International Conference Healthy Buildings, 8th-12th July 2012, Brisbane, Australia.

Fabi V., Andersen RV., Corgnati SP., "*Main physical environmental variables driving occupant behaviour with regard to natural ventilation*." Proceedings of 5th International Building Physics Conference, 28th-31th May 2012, Kyoto, Japan.

Fabi V., Andersen RV., Corgnati SP. ,Filippi M., Olesen BW., "*Description of occupant behaviour in building energy simulation: state-of-art and concepts for their improvement*." Proceedings of Building Simulation Conference 2011, 14th -16th November, Sydney, Australia.

Fabi V., Andersen RV., Corgnati SP. ,Filippi M., Olesen BW., "*Effect of occupant behaviour related influencing factors on final energy end uses in buildings*". Proceedings of Climamed11 Conference, 2nd -3rd June 2011, Madrid.

Corgnati SP., Fabi V., Filippi M., Talà N., "*Statistical analysis methods to investigate energy use in buildings*". Proceedings of PALENC 2010, 29th September – 1st October, Rodhes Island, Greece.

PREDICTING THE UNPREDICTABLE HUMAN BEHAVIOUR

Introductory chapters

"All human actions have one or more of these seven causes:
chance, nature, compulsion, habit, reason, passion and desire.
The origin of action is choice, and that of choice is desire and reasoning."

Aristotle (384-322 BC)

INTRODUCTION

One of the most important attributes of a building, after ensuring that it stays standing, is that it provides a thermally safe haven for its occupants in the climate and environment where it is built. As buildings evolved over millennia the requirement for providing shelter merged into the desire for comfort. Actually, people rarely think about their environment unless it demands their attention. As long as they were comfortable, they have rarely concerned their selves with the indoor environment in which they spend so much of their time. Actually, a high percentage of human activity is related to the aim of a comfortable life within the built environment. Thus, in the recent years, the topic of the level of the indoor environmental quality in buildings has become more and more important, due to its direct correlation with operating energy consumption in buildings [Fabrizio et al. 2010].

Actually, buildings account for more than 40% of the primary energy consumption in the EU member states, and households are responsible for the consumption of more than 26% [EC, European Union Energy and Transport in Figures]. More than 66% of that consumption is used for heating, ventilation, air conditioning and lighting. This implies that the reduction of the energy consumed to make the indoor environment comfortable is crucial to the efforts of reducing the global CO_2 emissions.

Actually, when dealing with energy performance of buildings and their environmental impact, various factors play an important role in determining it, starting from building geometry and its physical properties, to the equipment installed for its functioning (the heating, ventilation, air conditioning systems, etc..),to the boundary conditions like the outdoor environment and finally the behaviour of its occupants.

Although it is common knowledge that control actions can significantly affect the indoor climate, the impact of people on building performances is hardly considered, even though just the presence of occupants has an influence. This fact results in the significant discrepancy between the designed and the real total energy use in buildings. Several studies (Branco et al. 2004, Nordford et al. 1994, Marchio et al., 1991) have highlighted that the differences between real and predicted energy use depends on both the final realisation of the construction, and the technical installations, and the real use of the built systems operated by occupants. Differences in users' attitudes, preferences in thermal comfort and reactions to the indoor environment determine great variations in energy consumptions. However, relatively few longitudinal studies have investigated the interactions of the occupants in real indoor environment in detail. In most buildings, occupants operate control devices such as windows, shades, radiators and fans to bring about desired indoor environmental conditions.

Knowledge of such user actions is crucial towards understanding and both an accurate prediction of building performance (energy use, indoor climate) and effective operation of building systems. The added value of this knowledge relies on the possibility to bring about a better awareness of the nature, logic, types and frequency of control-oriented occupant behaviour in buildings and thus, support the development of reliable, empirically-based, behavioural models of occupants-systems interactions in buildings. By consequence an improvement in the accuracy of building energy simulation tools by implementations of the developed occupant behaviour models could arise.

Actually, nowadays, building energy simulation tools cannot precisely replicate the actual performance of buildings because the simulations are based on a number of basic assumptions that affect the results. Occupant behaviour is usually introduced to simulation tools in the form of input variables like internal heat gains, hourly ventilation rate, usage pattern of heater or air conditioner, etc.. It is clear that the definition of occupant behaviour in building energy simulation tools would significantly influence the validity of the outcome of the simulation. Moreover, occupant behaviour is also found to be an important and sensitive variable when applying simulation tools to assessment of building thermal performance. The variation in occupant behaviour will result in large variations in requirements of building design. Consequently, if occupant behaviour is not well represented in simulation model as it is, the simulation results will be significantly different from the actual building performances.

Because of the very close link between occupant behaviour and building energy consumption as well as the assessment of building thermal performances, there is an increasing need to understand the characteristics of occupant behaviour, especially in residential buildings where indoor environment is usually controlled by occupants on their own individual requests.

Aim of the study

The main purpose of the study described in this thesis is to propose a methodology to model the occupants' interactions with building controls in the context of real energy use including both the identifications of the variables with influence on occupants' behaviour and the determination of the impact of the behaviour on the energy performances of buildings. This was addressed first with the definition of different suitable user behavioural patterns (models) and secondly with their implementation in a building energy simulation tool.

To achieve these goals the work is divided into three main research questions defined for this study.

Which are the main influencing factors for a performed behaviour?

The first research question aims at determining factors, both external and individual influencing the behaviour of the building occupants aimed at improving or maintaining the comfort conditions. This research step is addressed by a critical analysis and identification of the general process leading from occupant's behaviour driving forces to energy consumption. Occupants' behaviour models can be used in energy calculations and simulation programmes to deliver more accurate energy predictions.

How to integrate a behaviour model into the building energy performance simulation tools?

In the second step, the purpose is to address current limitation in building energy simulation when dealing with the occupant's interaction with the built environment and to consider how the developed occupants behaviour models could be applied in energy simulations. This is done by switching from a deterministic approach of building energy simulation toward a probabilistic one that takes the occupants' interactions with the building controls into account. A probabilistic approach is proposed and applied to simulate occupant behaviour realistically.

How much the occupant's behaviour weights on the building energy performance?

The third step is to assess the impact of different occupant behaviour models on the energy performance of a building. Fixing all the parameters related to the energy performance of the building (i.e. climate, building envelope, building equipment), the building energy simulations are aimed at verifying the influence of the characterized occupants behaviour on energy consumptions. A further step is represented by the application of occupants' behaviour models into building energy simulation tools to verify the "robustness" of the building design respect the users.

The extra-goal of the research on energy-related occupant behaviour cannot be reached within the 3-years period of this PhD study: the steps to be completed within this dissertation are the evaluation and the quantification of the impact of a single action, in particular the window opening behaviour, future field study should include other aspects of occupants control on building systems in order to enhance a more accurate representations of reality.

The added knowledge respect to the state of the art could be listed as follows:

- Identification of the complexity and multidisciplinary of the topic, and a proposal of common work between technical engineering and social sciences

- A comprehensive understanding of the nature, logic, types and frequency of energy-related occupant behaviour
- Development of a methodology to investigate and to model the energy-related occupant behaviour

Actually, this kind of knowledge could help architects and building designers to find better and more "robust" design, to improve the performance of building management and automation systems via integration of occupant-responsive control algorithms and methods as well as to support the initiation of occupants information campaigns to educate and inform occupants regarding the implication of their control actions concerning indoor environment and energy performances of buildings. Facility managers could also be supported in their communication and interaction with building occupants. Moreover, this dissertation would help on providing ideas and suggestions toward the improvement of design, operation and user's interfaces of buildings' environmental control systems.

CHARTING THE JOURNEY

The energy-related occupant behaviour

"All these primary impulses, not easily to describe
in words, are the springs of man's actions"

Albert Einstein

1. The energy-related occupant behaviour

Energy use in residential buildings is influenced by the behaviour of occupants in various ways. Energy-related occupant behaviour is related to building control actions (in order to control the indoor environmental quality) as well as household or other activities. These actions and activities may be driven by various factors. In the first part of this chapter, the general framework underneath the energy-related occupant behaviour is presented. In the following, a diagram is proposed that relates personal, environmental and contextual factors to energy use. This diagram is instrumental in relating variables that determine energy use in dwellings and offices. In the last part, these determinants of households' and employers' energy use are discussed.

1.1. Adaptive opportunities and models

The principle which underlies the adaptive approach to human thermal comfort indicates that "If a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort" [Humphreys M.A. and Nicol J.F., 1998]. This principle implies that if people are uncomfortable they will take actions which they think will improve their comfort. If the action is successful they will reduce or avoid discomfort.

These actions can be divided into changes that alter the environment to make it more comfortable and into changes that adapt the occupant to the prevailing environment. The first might be to adjust the heating set-point, to open/close a window, to turn lights on or off or to adjust the solar shading, while adjusting clothing, adjusting body posture and consuming hot or cold drinks fall into the latter category. In this research the focus is mainly on the first category of actions because they affect energy consumption directly, but since thermal comfort is thought to be one of the main drivers of many of the adaptive actions that affect the consumption of energy directly, studies regarding clothing behaviour have also been investigated.

The adaptive model of thermal comfort proposed by de Dear et al. (1998) and included in recent versions of ASHRAE standard 55 and EN 15251 is a regression equation that relates the acceptable minimum and maximum indoor temperature to the monthly average outdoor temperature. It is based on the notion that the occupants' level of adaptation and expectation is strongly related to outdoor climatic conditions. At the base of adaptive model of comfort is the belief that the subjects consciously or unconsciously, play an active role in realizing thermal conditions and that they prefer to reach more easily satisfaction in relation to the microclimate, implementing a process of adaptation, meant as the gradual reduction of individual reactions to environmental stimuli. In general, research has demonstrated that occupants are more comfortable when they have increased freedom of choice to adapt their conditions in a clear and intuitive way (Wagner et al. 2007). Furthermore it has been demonstrated that small adaptive changes (for instance clothing or posture) can lead to dramatic differences in physiological comfort (Baker and Standeven, 1996).

It's important to note that to choose the adaptive approach for a building at the design stage implies by consequence to provide building occupants with rich opportunities of interacting with controls. In such cases it is even more important to consider the behaviour of the occupants in the design stages.

Hoes et al. (2009) conducted a simulation study on the effects of occupant behaviour on the simulated energy performance of buildings and concluded that the simple approach used nowadays for design assessments applying numerical tools are inadequate for buildings that have close interactions with the occupants. When using the adaptive model in the design of a building, occupants are expected to adapt to the environment or adapt the environment to their needs. This means that in such buildings occupants are expected to closely interact with the available building controls. As a consequence, the behaviour of the occupants becomes increasingly important in the determination of the indoor environment and in the energy performance of the building.

In temperate climates the window is possibly the most common thermal control device in any building. If people feel hot and want to feel cooler indoors, they often open the window to cool the indoor environment: if they are too cool and the window is open they will close it. This window opening behaviour is not only useful for energy saving in summer, by reducing the need for mechanical cooling or heating, but also provides for a beneficial interaction between the indoor and the outdoor environments [CISBE/SLL, 2005].

1.2. Occupant behaviour: a complex system

When it comes to interaction between buildings and human beings, a variety of disciplines is occupied in research on energy-related comfort parameters such as room temperature and indoor air quality. So it is worthwhile to explain how behaviour is defined within the topic of this dissertation.

First, it is worth to highlight that occupants' interactions with building control systems are only one aspect of human behaviour. Human behaviour can be expressed throughout the results of a continuous combination of many factors crossing different disciplines, from the social to natural sciences.

Concerning the building science area, occupant behaviour related to building control systems has traditionally been connected above all to indoor and outdoor thermal conditions. In early studies, the outdoor air temperature accounts for most of the variations in the interaction of the occupants with the elements of the built environment (e.g. windows or radiators) [Brundrett, 1977; Dick and Thomas, 1951]. These parameters can be named as "external factors" as proposed by Schweiker, [Schweiker, 2010] and the number of studies concerning them have increased in the last years [Andersen et al., 2009; Haldi and Robinson, 2009; Nicol, 2001; Nicol and Humphreys, 2004; Schweiker and Shukuya, 2009].

In the field of social sciences, human behaviour is set in relation with causes which could be called "internal or individual factors" [Schweiker, 2010], such as preference, attitudes, cultural background and so on. In addition to external factors, they influence the occupant behaviour with a range of cognitions and actions in a very complex way. Research on the individual factors leading to one action rather than another has been conducted in the field of behavioural psychology [Ajzen et al. 2004; Ajzen and Fishbein, 2005; Goven and langer, 2009; Refsgaard et al., 2009].

With respect to the energy-related issues of this research, the term 'behaviour' is predominantly meant the following: observable actions or reactions of a person in response to external or internal stimuli, or respectively actions or reactions of a person to adapt to ambient environmental conditions such as temperature, indoor air quality or sunlight. In this definition of behaviour attitudes and motives of an individual which lead to a specific action are not included. Data concerning behaviour often stem from sensors (e.g. for window opening) in terms of indicators for observed behaviour. Another approach is asking the occupants to rate their degree of satisfaction with the ambient environment or to ask them to give information on their behaviour, e.g. how often a person opens the window or for how long a person closes the sun shading during a given time period. Both methodological approaches – technically measured data as well as self-reported information from the occupants - are helpful for a better understanding of energy-related behaviour. Both approaches have their advantages and their margin of error.

The mutual influences in between humans - building - environment cannot be described in a simple way, but require a basic methodological approach able to describe and reproduce the intricate network that gives rise to the phenomenon.

1.3. Steps of Behaviour – from drivers to energy use

In this section a methodological approach is proposed to deepen the knowledge about the process explaining the occupant interactions with the building control systems. This interaction could be caused by a combination of both "external" and "internal" factors [Schweiker ,2010] as explained in the previous section. On the basis of several studies, some items referring to the occupant behaviour related to the building control can be defined and the general process leading to energy consumptions can be identified as proposed in Figure 1.

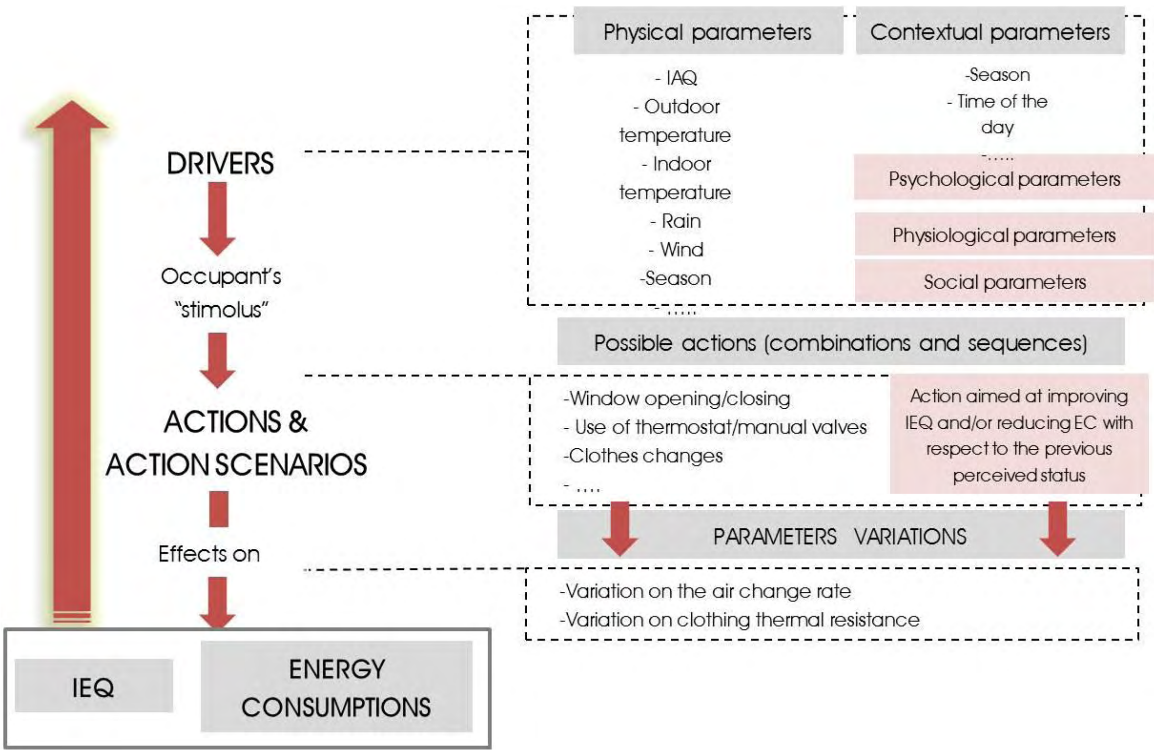

Figure 1. Flux diagram: from drivers to energy consumption and indoor environment.

Occupant behaviour influencing factors, both external and internal, that we could name with the general term "Drivers", are the reasons leading to a reaction in the building occupant and suggesting him or her to operate an action (they "drive" the occupant to an action). These drivers include physical environmental factors, psychological factors, physiological factors, social factors and contextual factors. Indoor or outdoor temperature are examples of the physical environmental factors, while preferences or attitudes are psychological factors, age and gender are physiological factors. Contextual factors, for instance, are the typology of the office (single or open plan) or the position of the window.

The central operator that could lead to a minor or major energy consumption is the occupant itself, that represents the second crucial point in the flux diagram defined and proposed by the authors in Figure 1.

With reference to indoor environmental quality, the occupant reacts consciously or unconsciously to an external or internal stimulus ("Occupant Stimulus" in the flux diagram proposed in Figure 1) in order to improve, restore or maintain the comfort conditions (thermal, lighting, acoustics, indoor air quality, …). In this way, the occupant becomes the central operator with control of the energy consumption.

The third crucial point in the flux diagram is represented by the action scenarios. With this term we indicated the occupant reactions stimulated by a driver or a combination of them. Window opening or closing, set-point changes, clothing changes are all examples of this kind of actions. In general, behavioural actions cannot be regarded singular, because they continuously interact with each other and the borders cannot be distinguished in every case. The reactions could be determined both by some "action logics" operated by the occupants their self and by the system and equipment control and partly by the building behaviour itself. In this way, it could be more correct to name them "action scenarios".

The control related actions performed by the occupants can be divided into changes that alter the environment to make it more comfortable, into changes that adapt the occupant to the prevailing environment and finally into actions that have an effect on the indoor environment indirectly. The first might be, for example, to adjust the heating set-point or to open/close a window; while adjusting clothing or body posture and consuming hot or cold drinks fall into the second category. The third category include actions related to the chance of internal heat gains/ energy use, for example the use of appliances or equipment (use of TV, refrigerator, etc.).

All the operations aimed by the occupants to improve or maintain the indoor environmental quality have a consequence on the indoor environment. A variation in air change rates or room air temperature are examples of the "parameter variation" due to the window opening. Different action scenario outcomes could have a direct influence on both indoor environmental quality and on the energy consumption.

Indoor environmental quality and energy consumption are the "process output": their variability range could be very wide, as shown before, and depending on many variables.

It is significant to observe how this whole process is not a closed system, i.e. the changes brought by the effects of the action scenarios on energy use and indoor environmental quality are themselves an element of influence on "the drivers". Pushed to the desire to emphasize this continuity that is an inherent part of the process, it is more accurate to argue for a cycle of processes that influence user behaviour. In this way the energy consumption becomes a driver that affects the behaviour along with the environmental quality. The energy output could be minimum if actions scenarios are managed in a prudent way or maximum if the users follow actions logics scenarios maximizing the energy wasting. In this way, it is possible to identify different users' behaviour typologies depending on the way the actions sequences are performed. From an energy perspective occupants could be named "energy saving users" or "energy wasting users". From an indoor environmental perspective, occupants could be divided into air quality users or thermal comfort users or both.

1.4. Drivers

The comfort or discomfort of an occupant is predominantly determined by four main environmental factors: air quality, thermal comfort, acoustical ambience, and visual comfort. The interaction effects of these variables on comfort are not well established and are usually based on only a few reports.

The relationship between occupants' behaviour and the building control and its effects on the indoor environment and energy consumption, is dealt with by several authors. In particular, there are three main topics investigated in the existing researches: energy use for space heating, use of artificial lighting and the habits of shading windows, ventilation and the habits of opening/closing the window. Building typologies aims of investigations are different moving from a research topic to another: heating energy use is especially investigated in dwellings, lighting energy use is studied only in office building. Window opening/closing behaviour investigations are dealt with both in dwellings and office building. In the following sections drivers for window opening behaviour, heating set-point adjustments and window blind adjustments are discussed analysing the main parameters of drivers. These drivers has been divided into five groups: physical environmental factors, contextual factors, psychological factors, physiological factors and social factors.

- *Physical environmental:*

Examples of physical environment aspects that drive occupant behaviour with an effect on energy consumption are temperature, humidity, air velocity, noise, illumination, and odour.

- *Contextual:*

Contextual drivers are factors that have an indirect influence on the human being. They are determined by the context. The insulation of buildings, orientation of fa□ades, heating system type, thermostat type (e.g. manual or programmable), etc. are examples of contextual drivers.

- *Psychological:*

Occupants tend to satisfy their needs concerning thermal comfort, visual comfort, acoustical comfort, health, safety, etc. Furthermore, occupants have certain expectations of e.g. the indoor environmental quality (temperature, etc.). Other examples of psychological driving forces are awareness (e.g. financial concern, environmental concern), cognitive resources (e.g. knowledge), habit, lifestyle and perception.

- *Physiological:*

Examples of physiological driving forces are age, gender, health situation, clothing, activity level, and intake of food and beverages. These factors together determine the physiological condition of the occupant.

- *Social:*

Social driving forces refer to the interaction between occupants. For residential buildings this depends of the household composition (e.g. which household member determines the thermostat set point or the opening/closing of windows).

According to the analysis of drivers resulting from the reviewed studies, it is possible to define which drivers have the greatest influence leading the occupant to make an action (Figure 2). These "preeminent" drivers are crossing the five categories, highlighting the complexity of the research regarding occupants. The 'physical environmental' category presents the higher number of parameters, moreover they are found to be drivers for both office and residential buildings. On the other hand, in conducted studies, prevalent contextual parameters resulted to be drivers only for the residential buildings.

The following prevalent drivers result from the analysis of each singular end-use. In particular, in Figure 2 it is highlighted that several factors are in common between the analysed end uses. Moreover, there are some parameters establishing a relationship between only two end uses.

Window opening behaviour – heating set-point adjustments – window blind adjustments.

Physical environmental drivers. The main physical environmental parameter stimulating the occupant to make an action is related to temperature, both indoor and outdoor.

Outdoor temperature: higher outdoor temperatures are related to lower use of heating and higher use of open windows and vice versa. Moreover the higher the outdoor temperature the more is the use of window blind systems.

Indoor temperature: Indoor temperature is strongly related with outdoor temperature, but also to thermal comfort. Indoor climate preference in terms of temperature is one key driver for the behaviour of the occupants, both for window opening behaviour and for heating set-point and window blind adjustments; but indoor temperature is strongly connected to the occupant's perception of comfort.

Solar radiation: the probability of closing windows and the thermostatic radiator valves are inversely correlated with solar radiation. Solar radiation is the main driver for the use of window blind system.

Physiological drivers.

User's age: the behaviour of elderly people was found to be significantly different from that of younger people. Older occupants ventilated less and kept radiators on for longer periods than younger occupants did are more sensitive to a visual discomfort.

Social drivers.

User's presence: the continuous presence of people at home increases energy use for heating and the length of time windows are kept open and blind system used.

Window opening behaviour – heating set-point adjustments

Physical environmental drivers.

Wind speed: window opening decreases with wind velocity and was found to be an important variable in the determination of positioning of thermostatic radiator valves.

Contextual drivers.

Type of dwelling: single houses are associated with highest chosen temperature and more hours with radiators on. But, as compared to apartments, with shorter periods of windows open.

Type of room: kitchens are related with a decrease of energy consumption for heating and an increase of window opening correlated with cooking periods, as obviously expected.

Psychological drivers.

User's expectation: user's attitudes and preferences about indoor climate in terms of indoor temperature.

<u>Window opening behaviour – window blind adjustments</u>

Contextual drivers.

Time of the day. Occupants open or close windows and adjust the window blind system when they arrive or leave the workplace.

Orientation of the window. Different behavioural patterns are recognized in the different orientation of the facade, with the most interaction of the occupant with windows (opening/closing and blind adjustments) in the south facade.

In Figure 2 occupant behaviour drivers analysed are categorized for window opening behaviour, heating set point adjustments and window blind adjustments. The intersection of the three circles shows the common drivers for the interactions of the user with the building control system, highlighting the strong relationship linking natural ventilation with heating and lighting behaviour.

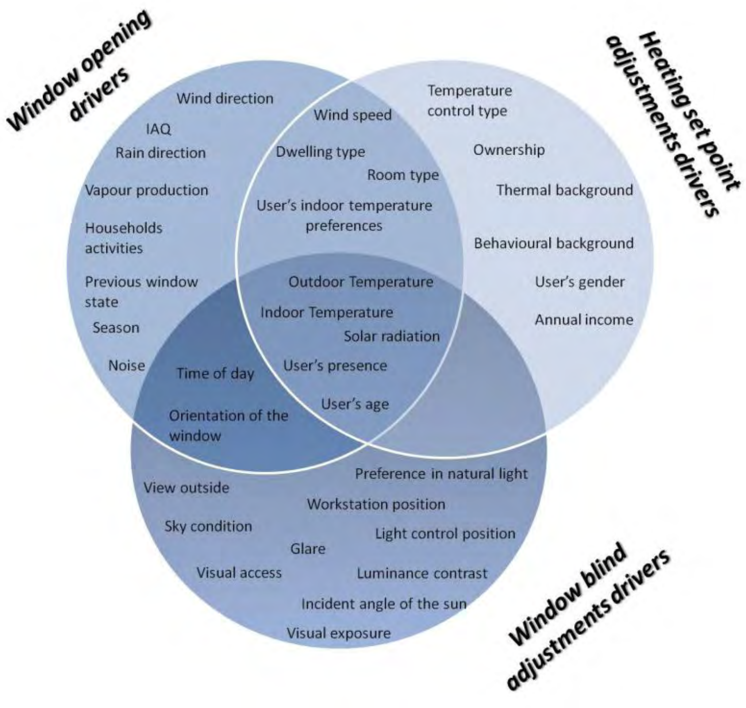

Figure 2. Predominant occupant behaviour drivers for window opening, heating set-point and window blind adjustments.

1.5. Action scenarios

As discussed in literature (Papakostas and Sotiropoulos, 1997), the complex of occupant behaviour can be split up into two distinct operations in terms of influence on indoor environment. The first is the operation by the occupants involving the development of internal heat gains in the residence space and associated with the presence of occupants at home and use of lighting and households appliances. The second is the operation by the occupants aiming at the control of indoor environmental conditions (thermal, air quality, light, noise), including window opening behaviour, usage patterns of thermostat or air conditioning and so on. The generation of internal heat gains is not the scope of this research.

As presented in the flux diagram in Figure 1, the action scenarios represent the occupant's reactions stimulated by a driver or a combination of them in order to improve or maintain the comfort conditions. These reactions could be determined both by some "action logics" operated by the occupants their self and by the system and equipment control and partly by the building behaviour itself. In this way, it could be more correct to name them "action scenarios".

There are several possibilities for the occupants to control the indoor environment:

1- First of all, the occupant can operate directly aiming at controlling the indoor environment, listed as follows. These kinds of operations involve the use of set-point and the ventilation system, the habits of opening or closing window and the habits of shading windows. For example, regarding the frequency of opening/closing or shading windows occupants can be defined as active or passive users (Haldi and Robinson, 2008).

2- Concurrently, occupants can make operations having an effect on indoor environment indirectly. These actions could be related to the chance of internal heat gains/ energy use: operations of this second kind are the use of appliances and equipment (use of TV, refrigerator, etc.), lighting, use of hot water (taking bath or shower), cooking.

3- A third typology of actions (affecting indirectly indoor environment) that building users can perform in order to restore comfort are represented by the adjustments of the occupants themselves to the existing environmental conditions. These operations include the change of place (actions related to the active movement within the room, the building or between building and outside, for example leaving room), active body adaptation (change body posture and the amount of clothes worn), and the thermo-regulation or passive body adaptation (describing the processes occurring within the human body in order to keep the core temperature stable within small limits).

1.6. The influence of occupant behaviour on indoor environmental quality and energy consumption

The energy efficiency of buildings is significantly affected by the presence, actions and attitudes of building occupants. Unoccupied houses require little or no energy, however a great deal of energy is used to ensure the environmental conditions in the home (temperature, lighting, ventilation, etc.) are 'comfortable' for the occupants. Thus, the way the occupants behave and interact with the building can have a massive impact on the energy used and the comfort levels achieved. With the overall decrease in building-related energy consumption, occupant related energy consumption is becoming all the more important [Haas et al., 1998; Linden et al., 2006; Branco et al., 2004]. The fact that occupant behaviour may vary by up to a factor of two in similar buildings even when systems are identical suggests that energy consumption in buildings is dependent on more than just the characteristics of the building and that occupant behaviour might have a deep impact on energy efficiency. The interaction between the occupant and the building (i.e. the control of the heating and ventilation systems) is thought to have a strong influence on energy consumption (de Dear, 2004; Lenzuni, 2008; Karjalalainen, 2007; Lan, 2008; Moujalled, 2008; Ye, 2006). Thus, it is essential to assess the influence of occupant behaviour on energy performance as it may be a key factor in the realisation of energy improvements. Insight into the determinants of behaviour will also help in attempts to discern the effect of building regulations on energy consumption. Whereas building regulations might determine the type of building amenities on the one hand, the effect of occupant behaviour on energy consumption might be largely determined by interaction between the occupant and these amenities on the other. Indoor conditions are largely dependent on building characteristics. However, comfort preferences can vary across people and even across people in the same household. The control of indoor conditions (ventilation, draft, temperature) could conceivably have a strong effect on the interaction between people and the building. Variations in preferences for comfort and indoor conditions have also been shown to depend on individuals. An investigation of energy consumption for heating in 290 similar houses revealed that there was considerable variation between houses: since the houses were "identical" (apart from orientation) the variation was largely due to the way the houses were used.

According to some authors (Haas et al. 1998, Filipp'h et al. 2005), occupant behaviour affects energy use to the same extent as mechanical parameters, such as equipment and appliances: in an experimental study conducted over 3 years in multifamily buildings in Switzerland, Branco et al. (2004) noted that the real energy use was 50% higher than the estimated energy use (246 MJ/m^2 as opposed to 160 MJ/m^2). The differences between the two results were due to the real conditions of utilisation, the real performance of the technical system and the real weather conditions. Knowledge of such user actions is crucial for better understanding and for more valid predictions of building performance (energy use, indoor climate) and effective operation of building systems.

Various studies of occupants' behaviour toward building systems for environmental control in buildings have been carried out. They investigate the existence of patterns of opening/closing windows, switching on/off the heating system and AC unit, opening/closing shades, and their relationship with internal/external climatic conditions. The main purpose is to achieve better understanding of people's control behaviour in terms of patterns and energetic consequences, to be able to predict more accurately the performance of building systems as well as to improve user satisfaction. Therefore studies have been performed in real or tests spaces where information is gathered on occupancy, status of systems frequency of control actions for switching thermostats, operating shades and opening/closing windows, indoor environment (temperature relative humidity, illuminance, etc..) and the outdoor environment /temperature, relative humidity, solar radiation, wind, etc..), other factors like orientation, sun position etc..are also taken into account.

In the revised literature, different energy end-uses which are determined both by technical and architectural characteristics and by the behaviour of the occupants have been studied. As presented in Figure 3, that refers to the references in the investigated papers, there are three main topics of reserach: energy use for space heating, use of artificial lighting and the habits of shading windows, ventilation and the habits of opening/closing the window.

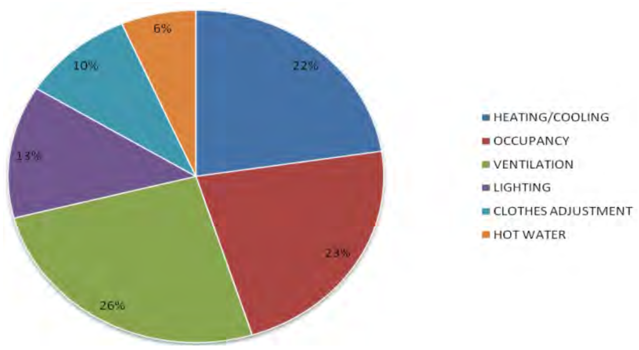

Figure 3. Major issues related to the occupant behaviour investigated in investigated papers in literature

In particular, this dissertation takes into the account two specific building typologies: residential and office buildings. Figure 4 represents the main investigations in literature considering two building typologies of interest (residential and office buildings): heating and cooling set point changes operated by the occupants are investigated more often in the residential building (71%), while the lighting-related topic in the office building (100%). Natural ventilation and window opening behaviour researches focused the attention both on office (75%) and residential building (25%), but with different aims that will be dealt with later.

A further sector of the research concentrates on the occupation profiles within the office building (71%), also analysing the intermediate activities and the space utilisation by the occupants, to provide more accurate behaviour models for building energy simulation tools.

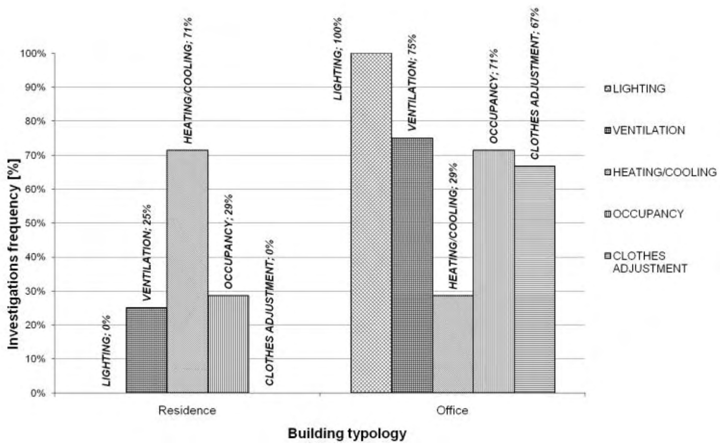

Figure 4. Building typology of the end-energy use investigations in the performed survey of literature.

1.7. FOCUS ON PAPER I:

WINDOW OPENING BEHAVIOUR

As a matter of fact, window opening behaviour, usage pattern of thermostat or air conditioner are adaptive actions to thermal environment according to the adaptive approach (Humphreys and Nicol 1998). Among these actions, window opening behaviour is the easiest and the most common way for occupants to control thermal environment and to restore their comfort. Occupants usually open the windows to cool the environment when they fell hot indoors, but they will close the window if the indoor thermal environment is too cool and the windows is still open. The analysis of main drivers emerging from the literature (PAPER I) clearly indicated that the interactions of the users with the building control (windows or heating set-point) is not only influenced by perceived thermal conditions but also as a response to perceived indoor air quality (IAQ), draughts, rain, outdoor noise levels, the desire to conserve energy, etc. However, reliable values of key drivers, such as rain or psychological variables, are difficult to obtain, while others, such as draught levels, are subject to great uncertainty. In particular, the topic of occupant behaviour with regard to control of the indoor environment has mainly been studied with two aims: investigating the window opening and ventilation behaviour to find if occupants are provided with adequate fresh air, and energy related investigations of occupant behaviour. The former category of studies has usually been carried out in dwellings and has had a health or a comfort perspective, while the latter category has focused on studied in offices with a comfort, and energy performance perspective. In the following Table 1 and Table 2, the major parameters found in literature driving the occupant behaviour aimed at controlling the indoor environment in relation to natural ventilation are split into five categories of influencing factors for residential and office buildings.

Table 1. Driving forces for energy-related behaviour with respect to ventilation / window operation in residential buildings

Physiological	Psychological	Social	Physical environmental	Contextual
Age	Perceived illumination	Smoking behaviour	Outdoor temperature	Dwelling type
Gender	Preference in terms of temperature	Presence at home	Indoor temperature	Room type
			Solar radiation	Room orientation
			Wind speed	Ventilation type
			CO_2 concentrations	Heating system
				Season
				Time of day

Table 2. Driving forces for energy-related behaviour with respect to ventilation / window operation in office buildings.

Physiological	Psychological	Social	Physical environmental	Contextual
		Shared offices	Outdoor temperature	Window type
			Indoor temperature	Season
			Solar radiation	Time of day
			Wind speed	
			Rain	

Several field studies have been conducted in different climates, to find out correlations of window opening behaviour with physical environmental parameters.

Wind and rain are drivers for the closing windows behaviour: occupants are likely to close windows if the sensation of draft in the office is producing a predominant discomfort. Generally, it depends on wind direction and wind speed but results [Herkel et al., 2008; Roetzel et al., 2009] show an inverse linear correlation between wind velocity and window opening. Window opening is highest at low wind velocity, independent of the type of room. Above wind velocity of about 8 m/s, nearly all windows are found closed [Roetzel et al., 2009]. The occurrence of rain is another cause for occupants closing windows, but this aspect is linked to the window type, opening percentage, and wind direction. Several studies [Roetzel et al., 2009, Andersen et al. 2009] have shown solar radiation as an important variable related to the window opening behaviour: the investigations show that windows were opened more often and for long periods in sunny weather and indicate that the probability of closing a window is negatively correlated with solar radiation. Temperature, both outdoor and indoor, is a main influencing factor for the opening/closing behaviour in residential but also in office building. The higher the outdoor temperature is, the more windows are open. Most of the investigations [Dubrul, 1988, Rijal et al., 2007, Herkel et al., 2008, Haldi et al., 2008, Andersen et al., 2009, Roetzel et al., 2009] have shown that, in temperature range -10°C to +25°C, a direct linear correlation between outdoor temperature and the probability of an open window.

Since the effectiveness of natural ventilation is strongly dependent on characteristics of ventilation openings and their controllability (aspects closely related to the type of windows and its size/placement within façade), the window opening/closing behaviour in residential building are more linked to the building characteristics than in office building. Type of dwelling (single houses or apartment), the orientation and type of the room (bedroom, living room or kitchen) are found to be drivers for the window opening behaviour only in residential buildings. Type of dwelling influences the length of time windows are open and has an effect also on how wide window are left open. However, the direction of the effect depends on the type of room being considered. According to the studies presented in [Dubrul, 1988] the main ventilation zones are bedrooms, while the greatest percentages of windows which are never opened are in living rooms. Similar percentages are found for kitchens and bathrooms even though these are subjected to vapour production. In houses, as compared to apartments, window in living rooms and kitchens were found to be open for shorter periods, whereas windows in bedrooms were open for longer.

Some factors have been found to characterize occupant behaviour in relation to natural ventilation both in residential and in office building [Dubrul, 1988, Rijal et al., 2007, Herkel et al., 2008, Haldi et al. 2009, Roetzel et al., 2009]. In particular, time of the day is investigated more often in office building: several studies [Rijal et al., 2007, Herkel et al., 2008, Haldi et al. 2008, Roetzel et al., 2009] demonstrated that occupants open or close windows when they arrive or leave the workplace. Intermediate window switching during the day is relatively low, so windows are usually left in the same position for long periods of time, till discomfort occurs. There's a relation between time of day and occupant behaviour in residential building too [Dubrul, 1988]: early morning (when the inhabitants wake up) or early afternoon (when the inhabitants are cooking) are the moments of the day in which occupants tend to open the windows more often. In office buildings, the results generally showed a strong correlation of window opening behaviour with the season [Dubrul, 1988, Herkel et al., 2008]: the percentages of open windows are lowest in winter, highest in summer and intermediate in autumn and spring. Regarding seasonal variations, the open question is if it is the "season" itself or the changes in outdoor conditions that drive the occupant behaviour. Most recent studies have been limited to the investigation of thermal stimuli [Rijal et al., 2007, Herkel et al., 2008, Haldi et al. 2008, Stemeers et al., 2008] although other studies have found that other drivers such as indoor air quality, noise, rain etc. also play an important role in determining the window opening behaviour [Warren and Parkins, 1995, Nicol, 2004]. Referring to office buildings only, previous state is an important parameter in the context of night ventilation [Dubrul, 1988].

Indoor temperature is strongly related with outdoor temperature, but also to the thermal comfort. Studies demonstrated that indoor climate preferences in terms of temperature are one key driver for the behaviour of the occupants, but this driver is strongly connected to the occupant's perception of the comfort [Dubrul, 1988, Rijal et al., 2007, Haldi et al., 2008, Roetzel et al., 2009]. Age of the occupants (children or elderly people) is mostly investigated in residential buildings [Dubrul, 1988, Iwashita et al., 1997, Guerra Santin et al., 2009].The behaviour of elderly people was found to be significantly different from that of younger people: older people tend to ventilate less than the young.Lifestyle (presence at home or smoking behaviour) as well as households activities (for example cooking or sleeping) are the main social drivers investigated in several researches [Guerra Santin et al., 2009, Dubrul, 1988]. Presence of occupants and the use of windows were related: the longer the dwelling is occupied the more the windows (especially in bedrooms) are kept open. Also the smoking behaviour is an important driver: where occupants smoke rooms are ventilated on average for twice as long as in non-smoking households.

From the analysed studies it is clear that there is not a shared approach to the identification of driving forces for occupants' window opening and closing behaviour. In particular, it emerges how there is still a disagreement as to whether indoor or outdoor temperature or both are best predictors when simulating the actions on windows. Moreover, some parameters are not considered in any of the surveyed studies. There is a lack of understanding in the relationship between indoor air quality and the window opening behaviour of occupants. Most studies focus on determining the most important drivers and put little emphasis on the variables that do not show up as drivers. However, highlighting variables found to have little or no impact on the occupants' window opening behaviour reveal contradictions between the studies and may help directing future research. Behind the parameters that are found to have an impact on occupant behaviour, Table 3 shows the variables that were included in the surveys, but found not to be drivers.

Table 3. List of variables that have been found not to drive window opening behaviour. The column 'Presence in "drivers tables"' indicates if the variable has also been found to be a driver in other papers.

Parameter	Building Type	Driver Type	Presence in "drivers tables"
Wind speed	Residential	Physical Environmental	Yes
Wind direction	Office, Residential	Physical Environmental	No
Solar Radiation	Office, Residential	Physical Environmental	Yes
Rainfall	Office, Residential	Physical Environmental	No
Age	Residential	Physiological	Yes
Income	Residential	Social	No
Thermal sensation	Residential	Psychological	No
Day of week	Residential	Time	No
Wood burning stove	Residential	Building properties	No

From the table it appears clear that there are parameters that distinctly are not drivers, like wind direction or income, but there are other investigated variables which appear to have an impact on the window opening behaviour (Table

1 and Table 2) as well, indicating that the they cannot be applied to models for any building, since they cannot be generalised. Unfortunately, the table is far from being exhaustive because many papers only report the variables that have an impact on the occupant behaviour. Moreover, the aim of most existing studies is the window state instead of on the action of opening and closing the windows (transition from one state to another). This is an important distinction, since the window state influences the indoor environment. If the indoor environmental variables are used to infer models of window state, the predictive variables are influenced by the state that they are trying to predict. In a cold climate low indoor temperatures would occur when the windows are open and not when they are closed. In such a case the result of the analysis would be that the inferred probability of a window being open increases with decreasing indoor temperature, with the illogical implication that the probability of opening a window would increase with decreasing indoor temperatures.

Influence of window opening behaviour on air change rate

One parameter having a high influence both on the energy consumption and on indoor environmental quality is the air change rate. Since the thermal load for ventilation is related to the air change rate, a close examination of this indicator is important to consider when investigating the effects of the occupant behaviour.

The air change rate is affected by the occupants' behaviour, indoor environment and weather, but how dependent is the air change rate on the behaviour of the occupants?

The studies mentioned in Table 4 show that air change rates vary significantly from home to home and the window opening behaviour of the occupants has a considerable effect on the air change rate. We have not been able to find studies investigating the direct connection between air change rate and energy consumption, but since the air change rate has a big impact on the energy consumption it is evident that different behaviour patterns will result in differences in energy consumption. One aspect that affects the air change rate is how often and for how long the windows are opened but also the degree of opening will have an impact.

Table 4. Major findings in literature about variation of air change rate due to the occupants.

Paper	Number and type of dwellings	Measurement method	Average air change rate [h^{-1}]	Percentage of measurements lower than 0.4 h^{-1}
Bedford et al. (1943)	358 observations in 6 properties	Decay of Hydrogen	0.8	11%
Wallace et al. (2002)	1 single family house	One year (SF6 as tracer gas)	0.65	-
Offerman et al. (2008)	73 new naturally ventilated single family houses	24 Hours (PFT tracer gas)	Not stated (median: 0.25)	75% lower than 0.35 h^{-1}
Price and Sherman (2006)	1515 new single family houses	Questionnaire survey	-	between 50 % and 90% lower than 0.35 ACH
Kvistgaard et al. (1985)	16 single family houses	205 days (N2O and SF6 as tracer gas)	0.68	20 %
Bek□et al. (2010)	3-5 days of measurements in 500 bedrooms	build-up of CO_2 emitted by occupants	0.46	-

Further details related to this focus could be found in the PAPER I at the end of this dissertation.

REACHING MILESTONES

Modelling and simulation of occupant's behaviour

" If you want to understand people, don't listen to their words, look at their behaviour"

Albert Einstein

2. The modelling and the simulation of occupant behaviour

On the most general level, two purposes of modelling occupant behaviour can be distinguished:

- modelling occupant behaviour in order to understand the driving forces for the behaviour itself
- modelling the occupant behaviour in order to reveal its relationship to energy demand and usage and the driving forces for variations.

Within the framework of this research, the second is the major concern, while the first may be necessary to gain deeper insights into the factors leading to variations in the relationship.

Models are always a reduction of complexity and abstraction, at the same time it has to be guaranteed that all relevant parameters are considered, namely objective physical (environmental) parameters, personal variables, and the interaction between these two sides. The models are translated into computer simulation as a connection of theory and experiment. This includes mathematical logic processing, by which there may be the risk of overestimating the degree of precision, respectively the explanatory power of the results.

Computer simulation in the field of occupant behaviour and energy use can serve as an approach to circumstances and practical solutions by visualizing the processes in different energy-related settings. The models can be used as basis for calculation of expected energy consumptions as well as verification of theoretical assumptions about driving factors for energy-related behaviour.

Beyond the calculation of energy consumption, the models could show the potential to face practical implications such as

- the fit between building operation and occupant behaviour (match or mismatch),
- behaviour as basis for building optimization (under which conditions behaviour turns into counterproductive behaviour?),
- behaviour as a basis for interventions (e.g. information about the building concept, handling of controls, as well as training for energy-related behaviour).

The choice of model depends strongly on the objective of the simulation, but also on the software chosen or available.

Deterministic models are using predefined typologies of schedules, which give deterministic input values for computer simulations.

Probabilistic models are defining parameters or equations to evaluate the probability of an action or state.

Besides of these approaches, there are in literature other methodologies used for modelling the energy-related occupant behaviour.

Psychological models of occupant behaviour can be grouped into those explaining the behaviour itself and those related to the energy use in buildings.

Average value models are defining the important parameters for occupant behaviour which influences the total energy use of a building for a selected period (e.g. daily, weekly, or monthly basis).

Agent based models are modelling occupants as individuals with autonomous decisions based on rules and experiences (e.g. memory, self-learning).

Action based models are defining "occupant behaviours" as actions—movement and control action—that change the state of objects (movement is the change of occupant location, control actions are the operation state change of windows, lights, air-conditioners, etc.), proposing a uniform description for occupant movement and control actions respectively, and classifying each action by several typical patterns that can be easily investigated and applied to evaluate the impact of occupant behaviours on building systems.

Average and deterministic models are often based on assumptions, not on data, but could be based on data as well. At best, they are representing average, minimum, maximum, … behaviours related to energy demand, ventilation rate, … Implementing them into simulation algorithms, the outcome is a single value for each assumed/ derived type of behaviour. In order to show variety (of behaviours, types of occupants, …) various simulations have to be run once each for each model.

Probabilistic models could be based on assumptions as well, but in practice, they are mainly based on data. They are representing probabilities of a behaviour. Various types of occupants can be represented either by different models or by variables related to the aspects modelled within one model. The outcome is a distribution of behaviours/ energy demands and the variety is shown by results of different models or the distribution of one model.

Agent-based simulation models are being used to quantitatively study multi-agent systems in which agents are autonomous, and interact with each other and their environments. The agents may be very different objects varying from individual human beings to components of energy networks. The agents are in a specific state at a specific time during the simulation. Due to interactions with other agents the state may change over time. An agent-based model for simulating domestic user behaviour can be used in a co-simulation with, e.g. a building model.

Action based models provide a new approach for building occupancy simulation. Compared to the "fixed schedule" method, this model considers the randomness that result in the uneven and non-synchronous change of occupancy in space and time. Compared to other random process methods, this model keeps the time and space relevance of occupancy and is more practical due to the great reduction of inputs.

In this dissertation the probabilistic approach will be described both to model (statistically) and to simulate the occupant's behaviour. Then, an application of this two-steps probabilistic methodology will be applied to case studies. The method developed in this research was based on the assumption that only switching from a determinist approach to a probabilistic one, a better measure of the impact of occupant's behaviour on the performance indicators will be provided. This probabilistic approach is related to variability and unpredictability during the whole building operation.

This approach consists of two different steps of modelling the behaviour (Figure 1): using a database of indoor/outdoor environment variables and behaviour it was possible to infer models of occupant's interactions with the building envelope and systems. These models can be used to provide probabilistic input for the simulation software (in this case, heating set-points). The statistical models were implemented into the building energy simulation software used to run several simulations providing probabilistic outputs.

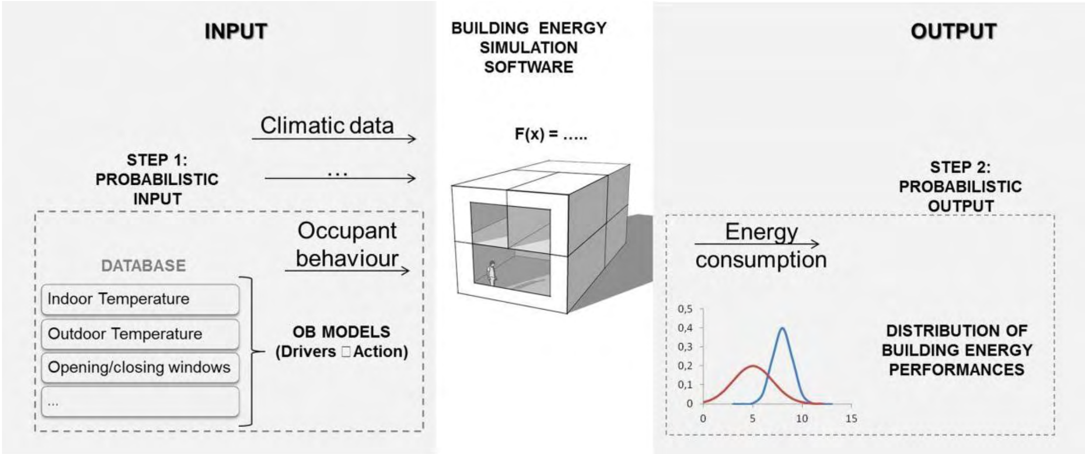

Figure 1. The two steps of the probabilistic modelling

From a practical point of view, the proposed approach means to start with continuous measurements of both indoor environmental parameters and external climate conditions along with the behaviour of the building occupants (such as window opening, TRV set point temperatures, occupancy sensors, etc.), performed in a sufficient number of areas and rooms representing different interaction zones in the building. The monitoring period may be different lengths, ranging from medium (i.e. one week – or better if repeated for different seasons) to long-term time spans (i.e. a yearly basis).

The simple measurement of physical quantity time profiles (such as relative humidity, temperature, pollutant concentrations, luminance, etc.) generates huge amounts of information which are difficult to "translate" into behaviour.

In order to overcome these barriers, different suitable user behavioural patterns (models) were defined by means of statistical analysis (logistic regression, Markov chain, etc.) and can now be implemented in many of the actual simulation tools (such as Esp-r, IDA Ice).

When in the probabilistic approach, models of user behaviour are implemented, the energy simulations show improved accuracy and validity of the results. Moreover, a probabilistic distribution instead of a single value is preferred as a representation of energy consumptions.

Drivers collection

A complete database should include all the parameters regarding the possible occupant behaviour driving forces. In particular, as explained in the first section of this dissertation, both external parameters (physical environmental and contextual variables) and internal parameters (social, psychological and physiological variables) should be collected.

Typically, the data to assess the behaviour of the building occupants can be obtained by setting up a measurement campaign in building typology with characteristics analogue to the object of application along with questionnaires given to and answered by the occupants. In this way, the data could be generalized for similar application studies.

Occupant's behaviour model development

All the data collected by means of both objective procedure and subjective procedure, should be analysed in a statistical way. As a result of the monitoring data analyses by means of the statistical analysis, the probability of doing a certain action (opening or closing the window, turning up/down the heating system) is inferred for a defined behavioural models. Users control actions are deduced by mean of logistic regression with interaction between variables or Markov chain or other typologies of statistical analysis. The results are "occupant behaviour descriptors" to integrate within a building energy simulation software. The number of occupant behaviour descriptors are relative to the aim of the analysis and the collected database.

Software implementation

Most of simulation programs are deterministic in nature, so there is the need to translate the probability control of building indoor environment (calculated in the simulation software on the basis of the equations previously used to describe statistically the behaviour) to a deterministic signal.

Simulations

A probabilistic distribution of energy consumptions depending on user type is obtained by running several simulations. Fixing all the parameters related to the energy performance of the building (i.e. climate, building envelope, building equipment), the simulations are aimed at verifying the influence of the characterized users behaviour on energy consumptions. Running a high number of simulations it is possible to have a curve of energy performance of the building in different situations and for different occupant typologies. In this way, it's preferable to have a probabilistic distribution (a "probabilistic output") instead of a single value as a representation of energy consumptions.

3. Statistical modelling the energy-related occupant behaviour

The traditional approaches look at human behaviour as if they would behave in a fully deterministic way: that is to say in a fully repeatable manner. Moreover, in a design stage some "design conditions" are simulated, meaning that when the building is realized, the occupants' interactions with the indoor environment will exactly coincide with the design values during the entire operational time.

However, if we analyse more carefully what happens in the real world, it is easy to discover that actually, many parameters influencing environmental conditions and human behaviour vary significantly and unpredictably during the entire building life. This implies that, for smaller or larger amounts of time, not all the interactions of the building occupants to control the indoor environmental parameters would satisfy the assumed requirements in all rooms.

In order to set up such an evaluation procedure for the modelling the occupants' interactions with the indoor environment, some concepts which have been long used in mechanical engineering may be adopted. In particular, a technique which seems to be suitable to this task is the so-called "reliability-based design procedure" of mechanical components.

The philosophy behind this method accounts for stochastic factors, and the result of the design process will be no more a "single value" for the system performance, but a probability to fulfil a certain performance over the time. The human actions should then be characterized by a certain reliability and useful information. In this way, the evaluation of the occupant behaviour will be not only based on fixed action typologies (e.g. opening windows if indoor temperature exceeds of a certain limit), but also on coupling these repeatable interactions with the building control systems with a probability of performing an action.

From a practical point of view, the proposed approach means to start with continuous measurements of both indoor environmental parameters and external climate conditions along with the behaviour of the building occupants (such as window opening, TRV set point temperatures, occupancy sensors, etc.), performed in a sufficient number of areas and rooms representing different interaction zones in the building. The monitoring period may be different lengths, ranging from medium (i.e. one week – or better if repeated for different seasons) to long-term time spans (i.e. a yearly basis).

The simple measurement of physical quantity time profiles (such as relative humidity, temperature, pollutant concentrations, luminance, etc.) generates huge amounts of information which are difficult to "translate" into behaviour.

In order to overcome these barriers, different suitable occupant behavioural patterns (models) were defined by means of statistical analysis (logistic regression, Markov chain, etc.) and could be implemented in many of the actual simulation tools (such as Esp-r, IDA Ice).

3.1. Database characteristics

Typically, the data to assess the behaviour of the building occupants can be obtained by setting up a measurement campaign along with questionnaires given to and answered by the occupants.

The measurement campaign can be addressed to evaluate the external factors and could be applied only to one parameter (for example, room operative temperature), but may include measurements of many other quantities (related to the thermal and IAQ environment).

Monitoring indoor and outdoor climate variables and occupants' control actions is to be conducted preferably on a yearly basis (offices or dwellings) with identical or similar characteristics to limit the variability due to different envelope typologies or installed plant systems. A series of variables concerning indoor environmental conditions (temperature, relative humidity, CO2 concentrations, etc.) are to be monitored and meteorological data (wind velocity, global solar radiation, rainfall precipitations, etc.) should be obtained from national meteorological stations in the building's proximity. Occupants interactions with controls, as heating set-points temperatures or window positions, should be gathered by measurements of the most representative zones and rooms of the building, for example one TRV in the bedroom and one in the living room of each dwelling.

Internal driving forces should be collected by means of surveys and questionnaires, aimed at investigating the factors strictly connected to individual and subjective data. In particular, users' preferences, thermal backgrounds, behavioural backgrounds, attitudes, lifestyle, activity, age and gender should be included in the database.

Moreover, as explained in the previous section, there are some specific "drivers" having the greatest influence on the occupant to make an action. These "preeminent" drivers are crossing a different field of study, highlighting the complexity of the research regarding occupants, but they should be gathered in order to characterize as much as possible the behaviour of the building occupants.

Even if the majority of the existing studies mainly focused on monitoring activities through measurements, it is important to point out again that surveys and questionnaires addressed to occupants are also an important tool to properly characterize users' behaviour. Both objective and subjective evaluations are always sought.

All the data collected by means of both objective and subjective procedures should be analysed in a statistical way.

As a result of the monitoring data analyses by means of the statistical analysis, the probability of doing a certain action (such as opening or closing the window, turning up/down the heating system) was inferred for defined behavioural models. User control actions are deduced by means of logistic regression with interaction between variables, Markov chains, or other typologies of statistical analysis. The results are "occupant behaviour descriptors" used as "probabilistic inputs" to integrate within building energy simulation software.

In general, the existing probabilistic models of are expressing the probability with which actions will be performed on windows, valves, lights, etc. There are several statistical approaches applicable for the development of such models. The logistic regression models will be here introduced.

3.2. Theory of logistic models

When modelling human actions, it is of interest to predict whether an action has taken place, given a set of independent variables. Formally, this implies the inferring of a relationship between a dichotomous outcome variable Y and a set of p independent predictors (covariates) $x = (x_1, \ldots, x_n)$. In our case we will set $Y = 1$ if a window is open and x may potentially include all driving variables available. Classical least squares regression theory used for linear models is inappropriate for binary outcome variables, because of the violation of the crucial assumption that errors are normally distributed. Indeed for binary data, it is straightforward to show that the residuals $\varepsilon = y - y_{\text{fitted}}$ are distributed according to the binomial distribution.

In order to overcome the above limitation, the class of generalised linear models (GLM) was developed.

In our case of a binary outcome variable Y, the analysis is performed using the binomial family of GLMs. The quantity of interest is the mean value of the outcome variable (in other words the probability that the outcome binary variable Y will be one), given the values of a set of independent variables $x = (x_1, \ldots, x_n)$.. This quantity is called the conditional mean $E(Y|x)$ and we will set $p(x) = E(Y|x)$ to simplify the notation. In classical linear models we would assume that $p(x) = \beta_0 + \beta_1 * x_1 + \cdots + \beta_n * x_n$ but it would then be possible for p to take values outside the interval [0, 1]. It is thus necessary to use a suitable transformation g of p(x). A classical choice is the canonical logit transformation

$g(x) = \log(\frac{p(x)}{1-p(x)})$ which defines the class of logistic regression models. In this case the probability distribution is called the logit distribution, defined as:

$$p(x_1, \ldots, x_n) = \frac{\exp(\beta_0 + \beta_1 * x_1 + \cdots + \beta_n * x_n)}{1 + \exp(\beta_0 + \beta_1 * x_1 + \cdots + \beta_n * x_n)} \quad (1)$$

where $\beta = (\beta_0, \ldots, \beta_p)$ are constants estimated by regression through maximum likelihood estimation.

The parameter β_0 as the intercept and $\beta_i (i \neq 0)$as the slope associated with the variable x_i.

For the advanced models more complex models need to be set up, through retaining simplicity. The statistical tests used for logistic regression will be here briefly introduced.

As decision criterion during the selection process, Akaiake Information Criterion (AIC) is used to determine whether the alternative model is better than the current model. The AIC gives a relative measure of the information lost when a given model is used to describe reality. It is calculated by

$$AIC = 2K - 2\ln(L) \quad (2)$$

Where K is the number of the parameters and L the maximized likelihood value of the estimated model (Akaiake, 1973). The AIC is then calculated considering the fit between the model and the data together with the variables used in the model. The lowest AIC-value is supposed to be calculated for the model, which best describes the measured data with the minimum number of variables necessary.

Correlations between explanatory variables may result in inflation of the estimated variance of the inferred coefficient, which in turn will result in too wide confidence intervals. To estimate the size of the inflation due to correlations between all explanatory variables (multicollinearity), generalized variance inflation factors (GVIF) were calculated for coefficients of all continuous explanatory variables. The GVIF estimates the inflation of the variance, due to multicollinearity as compared to as it would be if there were no multicollinearity. Since the GVIF is an estimate of the inflation of the variance, the GVIF^(1/(2·DF)) is an estimate of the factor by which the standard error and confidence interval is inflated due to multicollinearity between explanatory variables.

Finally, when using logistic regression, it is required that all variables are independent of each other.

A limitation of using a single probability distribution is that it does not predict a formal time-evolving probability for an action to be performed, based on a set of given environmental conditions. Its purpose is to predict, based on the included variables, the probability for the outcome variable Y to take the value one (or the system of interest to be found in this state), rather than for the transition of this variable between states. Such a distribution thus does not explicitly provide any probability of direct action and therefore does not describe the real dynamic processes of the system to be modelled.

3.3. FOCUS ON PAPER II:

STATISTICAL MODELS FOR PREDICTING OCCUPANTS' WINDOW OPERATION

This application describes the development of models of occupants interactions with windows and for their possible implementation in a building energy simulation tool.

The probability of opening and closing a window (change form one state to another) is inferred separately. In this way the most dominating drivers for each action on windows (opening and closing) was derived and the problem of feedback on indoor environment from window state, overcome. The present contribution extends the knowledge about the windows control in dwellings and underlines the importance of appropriate occupant behaviour models for a better prediction of energy consumptions in buildings.

The final goal of this study is to develop models of occupant's behaviour related to the interactions with windows deriving the most dominating driving forces useful for a more accurate description of occupant behaviour related to the habits of opening and closing the windows.

Data collection

Simultaneous measurement of occupant behavioural actions (window opening and closing), indoor and outdoor environment was carried out in residential buildings during the period from January to August 2008 in Copenhagen, Denmark. Since the number of dwellings is restricted to a 15 dwellings, the main purposes is to apply the proposed procedure to a case study in order to get all the required information of occupants interactions with controls.

The probability of opening and closing the windows was then inferred by logistic regression. Moreover, a linear model gave the measure of the degree of opening. Four different user behavioural patterns were defined according to their ventilation principle and ownership since this has been shown to influence the occupants' window opening behaviour.

Measuring method

Measurements were carried out in 10 rented apartments and 5 private owned single family houses. Half of the apartments were naturally ventilated while the other half were equipped with constantly running exhaust ventilation in the kitchen and bathroom. Three single family houses were naturally ventilated while the other two were equipped with exhaust ventilation. When sending invitations to participate in the monitoring program, the aim was to find occupants who spent most of their time in their dwellings.

The objective of the measurements was to define reference occupant behaviour patterns, suited for simulation purposes. The following variables were measured continuously in all 15 dwellings.

<u>Indoor environment factors measured every 10 minutes</u>

- Temperature in °C
- Relative humidity (RH) in %
- Illuminance in Lux
- CO_2 Concentration in ppm

Outdoor environment acquired from meteorological measuring stations in 10 minute intervals

- Air temperature in °C
- RH in %
- Wind speed in m/s
- Global Solar radiation in W/m²
- Number of hours with sunshine (daily values)

Behavioural actions

Window position (open/closed)*

*In three of the cases the actual opening angle of the window was also measured

Figure 2. Pictures of the instruments used to measure the indoor environmental variables and window opening behaviour. Top left: CO2 monitor connected to a data-logger with built in temperature, relative humidity and illumination sensors. Top right: Window state sensor (open/closed). Bottom: window state sensor (open/closed) and window position sensor.

Occupant behaviour model development

Multivariate logistic regression with interactions between selected variables was used to infer the probability of a window opening and closing event. The statistical analyses were conducted using the statistical software "R" and the models were inferred using the 'step' function in R.

The method relies on the probability function described in the following formula:

$$log\left(\frac{p}{1-p}\right) = a + b_1 \cdot x_1 + b_2 \cdot x_2 + \cdots + b_n \cdot x_n + c_{12} \cdot x_1 \cdot x_2 + c_{13} \cdot x_1 \cdot x_3 + \cdots \quad (3)$$

Equation 3 deals with interactions between variables by adding interaction terms to the model. It was used to infer the probability of windows being opened or closed. The Akaike information criterion (AIC) was applied as a basis for forward and backward selection of variables in the regression models [Schweiker and Shukuya, 2009]. The final models included variables and interaction terms that resulted in the lowest AIC. To limit the complexity of the model, only interaction terms between continuous and nominal variables, e.g. indoor temperature and day of week were included in the analyses.

In the interpretation of the coefficients, the sign, the size and the scale of the corresponding variable have to be taken into account. E.g. a coefficient for solar hours of 0.057 might seem to impact the probability more than an outdoor relative humidity coefficient of 0.029 (group 4, opening model). However, when the scales of the two variables (solar hours: 0 to 16.1, outdoor RH: 28% to 100%) are taken into account the picture changes: 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. In the example described above the magnitude of the impact was 0.057 • (16.1-0) = 0.91 and 0.029 • (100-28) = 2.08 for the solar hours and the Outdoor relative humidity respectively, revealing that the Outdoor RH had a higher impact on the probability than the solar hours.

When using logistic regression, it is required that all variables are independent of each other. Since the data was obtained in 15 dwellings with different physical properties and different inhabitants, all variables could not be assumed a priori to be independent of the dwelling it was obtained from. The variables independence from the dwellings, were tested by assigning a number to each of the dwellings and using this as a factor in the analyses. If an interaction term between a variable and the dwelling number was retained in the model, it was taken as an indication of dependence and the variable was removed from the model.

Finally, to estimate the size of the inflation due to correlations between all explanatory variables (multicollinearity), generalized variance inflation factors (GVIF) were calculated for coefficients of all continuous explanatory variables.

Statistical models of window opening behaviour

When analysing the window opening data the database was divided depending on the state of the window (open/closed) to infer the probability of opening and closing the window (change from one state to another) separately. The 15 dwellings were divided into four groups on the basis of the ownership (owner-occupied or rental) and the ventilation type (natural ventilation or mechanical ventilation) (**Table 1**).

Table 1. Description of groups investigated related to the ownership and ventilation type.

Group	Ownership	Ventilation type
1	Owner-occupied	Natural
2	Owner-occupied	Mechanical
3	Rental	Natural
4	Rental	Mechanical

Generally the occupants' window opening and closing behaviour was governed by different variables indicating that the occupants could be driven by different factors when open/close windows had different reasons for opening and closing windows.

From the four opening and closing investigated models it appears that some common patterns of behaviour exist. In all four groups of dwellings, the CO_2 concentration had an impact on the window opening probability while the outdoor temperature affected the closing probability.
Interestingly, wind speed was not found a variable influencing behaviour in any model of the four groups.

The results from the analysis with a limited number of interaction terms provide a possibility of defining behaviour patterns for simulation purposes.

provide a method for calculating the probability that the window will be opened or closed during the next 10 minutes. To estimate the effect of the control on windows by different user behaviour patterns, the probability equations determined in R could be implemented in a building energy simulation tool. A comparison with a random number can determine if the window is opened/closed or not.

Reliability of the analysis

Since the occupancy into the dwellings was not measured, it was determined using the monitored CO_2 concentration. This method may lead to uncertainties since short changes in the occupancy may have passed unnoticed. Since most of the periods without occupancy were removed, any correlations between behaviour and CO_2 concentration indicate relationships between air quality and behaviour.

We chose to use the Akaike information criterion (AIC) as a basis of variable selection in the inference of the models. Another option would be to use Wald tests to test the significance of each term and use this as a selection criterion. We chose to use the AIC, since selecting variables based on their significance does not take the risk of over fitting into account. This risk increases with the number of observations. The AIC includes a penalty that increases with the number of estimated variables in the model, which discourages over fitting.

Since the measurements were made during the winter, spring and summer the results in this paper are only valid for these seasons. When implementing the models into simulation programs, the models without seasonal effects) can be used for the entire year. In models including seasonal effects the spring season can be used as a representation in autumn.

Indoor relative humidity turned out to have an influence on the opening/closing, even though it was in the range 30% to 70 %, where humans are insensitive to relative humidity. On the other hand, the relative humidity does affect the thermal sensation and this might be why it affected the opening/closing probability.

Further details on field measurements and data analysis results of this case study could be found in PAPER II, in the end of this dissertation.

4. Simulating the energy-related occupant behaviour

The development process of software for building energy calculations (Clarke, 2001) started from a first (and second) generation, named "simplified methods", where the implemented mathematical formulations were very thin and characterized by many simplified assumptions (e.g. steady state calculation). The first developed software (first generation software) arose from the implementation of handbook type procedures, typically characterized by simplified schemes and operating in steady state condition, therefore providing only indicative results. Then, models were introduced that take partly into account the building dynamics for the energy performance evaluation (second generation software). Third generation software (the current generation of software) are associated with the name of "dynamic methods" (Hand, 1998), because thanks to development of computational technologies, they can model heat flows, electrical, lighting, sound simultaneously. Although these software present easier and more intuitive graphical interface and various functions have been introduced to help the process of data entry, they require modelling considerable experience for the user (Swan, 2009). Currently, a wide variety of simulation programs are available (ESP-r, TRNSYS, DOE-2, BLAST, Energy Plus, IDA ICE, Virtual Environment, etc.). Their complexity levels range from steady-state calculation to very sophisticate programs, including CFD simulation.

Assuming that the simulation is a theoretical representation of the status and operation of a building, it cannot perfectly replicate the real dynamics that govern the energy use: for example, the actual climate can vary from the meteorological data available, the systems may not work exactly as expected from the curves of load operation; performance may also vary with the age of the plant and the actual number of worked hours and the maintenance scheduled activity. Above all, the energy performance can be affected by the actual behaviour of the building occupants. Every building design is based on assumptions about how the building will be used, but when the building is realized, it may be used differently than its designer assumed or planned, affecting results validity. Occupant behaviour may empathize between expectations and reality. For example, to face this topic, different assumptions to model the occupants' window-opening behaviour are made in literature: assumptions are the defined schedule window opening based on occupancy or the expectation that window opening to be controlled by temperatures, humidity, wind, rain or to produce an established airflow rate, supposing the occupants use the windows to achieve the design ventilation rates (Rijal et al., 2007). These assumptions do not necessarily represent the occupants' actual behaviour and for this reason, it is necessary to use algorithms for users interactions with the building control systems based on field investigations in real buildings. Actually, some algorithms have already been integrated in simulation software in order to explain with more accuracy some punctual aspects of the building energy use (e.g. Lightswitch models by Reinhart, 2004). Although a platform for the integration of occupant models (Bourgeois et al. 2006) into one software package exists, there is no complete and interlinked set of models considering all aspects of occupant behaviour.

4.1. Energy-related occupant's behaviour and building energy simulation

If an occupant is exposed to the exact same conditions a number of times, (s)he will not react in the exact same manner every time. As a consequence, the behaviour of occupants will by nature include elements of randomness. Actually, building energy simulation tools are based on heat transfer and thermodynamic equations, which are deterministic. Typically human actions (operation of lights, blinds, and windows) are modelled based on predefined fixed schedules or predefined rules (e.g. the window is always open if the indoor temperature exceeds a certain limit). These tools often reproduce building dynamics using numerical approximations of equations modelling only deterministic (fully predictable and repeatable) behaviours. In such a way, an "occupant behaviour simulation" could refer to a computer simulation generating "fixed occupant schedules", representing a fictional behaviour of a building occupant over the course of a single day [Glicksman and Taub, 1997]. Often, the occupant behaviour is not specifically addressed in the simulation programs, but only modelled by means of its effect. e.g. the infiltration rate may be modelled as a fixed value that does not vary over time, with the assumption that occupants will manipulate windows in order to reach this infiltration rate.

On the other hand, models of human behaviour are based on statistical algorithms that predict the probability of an action or event. For example, the existing empirical models of window operation tend to be based on statistical algorithms that predict the probability that an event occurs or has occurred (e.g. opening a window) at certain environmental conditions. They are based on observations of real windows in real buildings that allow statistical correlation between "window state" (open, partially open, closed, etc.) and outdoor temperature, time of day, season, indoor environmental conditions, etc. In other words, they consider window operation as a stochastic process where the probabilities of control events are based on environmental (indoor and outdoor) factors. Moreover, buildings have multiple occupants, those occupants interact with one another and the behaviour of one occupant may differ from that of another. On this topic, J.A. Clarke (2006) proposed a probabilistic model of the discomfort and a second probabilistic model of actions taken in response to that discomfort to model stochastic occupant behaviour in buildings. Most building simulation tools integrate the effects of occupant presence within their calculations in a very simplified way, usually considering all occupants to be present according to a fixed schedule and multiplying the number of occupants by fixed values of metabolic heat gain. Other profiles, relating to small power or lighting gains, may also be entered on a similar basis. Occupants' interactions with window openings tend either to be defined by fixed schedules or by deterministic responses to physical stimuli. Window open behaviour has been shown to be poorly represented in commonly used building simulation tools (Dutton 2009): building energy simulation software, such as EnergyPlus and ESPr, combine the ventilation modelling of a network flow model with thermal energy simulation. As thermal effects influence the performance of natural ventilation systems, and ventilation performance impacts building energy performance, the combination can provide both more realistic building thermal performance and improved ventilation prediction.

A widely used technique in energy simulation is to model the influence of occupants through diversity factors ("diversity profiles" for various categories of internal gains and types of buildings) to estimate the impact of internal heat gains (from people, office equipment and lighting) on energy and cooling load calculations (Abushakra et al. 2001). The profiles depend on the type of building (typical categories being "residential" and "commercial") and sometimes on the type of occupants (for example size and composition of a household).

ESP-r already offers some integrated behavioural models such as the Hunt model (Hunt 1979) for the switching of office lighting, the Lightswitch 2002 algorithm developed by Reinhart (2004) on the basis of Newsham et al.'s (1995) model to predict dynamic personal response and control of lights and blinds. Lightswitch is a sophisticated model for the interaction of occupants with blinds and lighting systems; using a simplified stochastic model of occupant arrival and departure. Bourgeois (2005) attempted to bridge the gap between energy simulation and empirically based information on occupant behaviour via a self-contained simulation module called SHOCC (Sub-Hourly Occupancy Control) to enable sub-hourly occupancy modelling and coupling of behavioural algorithms such as Lightswitch 2002 across many ESP-r domains. Page et al. (2008) hypothesized that the probability of occupancy at a given time step depends only on the state of occupancy at the previous time step. As suggested by Fritsch et al. (1990) in relation to window operation, Page et al. (2008) explored the use of Markov chains toward occupancy prediction. Page introduced a single influencing "factor"; specifically, the time of day. With this method, the simulation is calibrated using real schedules of presence and absence. If the real schedules tend to include a lunch break around noon, then the time of day factor allows that pattern of behaviour to be reproduced. Dealing with occupant activity simulation, in Tabak's User Simulation of Space Utilisation (USSU) System, there are many different tasks and occupants can interact via shared activities such as meetings and presentations. Unlike Page's method, USSU is not schedule calibrated, but questionnaire results are used to calibrate his model. In the recent years, the number of studies regarding occupants interactions with buildings' environmental control systems is increased, aiming at establishing a link between user control actions (or the state of user-controlled devices) and indoor or outdoor environmental parameter. On the other hand, even if most studies regarding occupant behaviour are conducted for individual building systems (lighting, shading, etc.), there are significant differences between the studies in terms of building size and type, relevant control devices (thermo-static radiator valves, shades, windows, etc.), duration of observation, measured environmental factors, and measurements' precision. However, these studies have provided a number of valuable insights into the circumstances and potential triggers of occupancy control actions in buildings. On the other hand, given the complexity of domain, additional long-term and (geographically and culturally) broader studies are necessary to arrive at more realistic models of control oriented user actions in buildings.

4.2. Development of simulation procedure

The proposed procedure to simulate the human behaviour realistically is based on a probabilistic approach for the evaluation of both input parameters and output parameters. This probabilistic approach is related to variability and unpredictability during the whole building operation.

Figure 3 shows the two different steps representing the proposed approach and described in the following sections. The philosophy behind this method accounts for stochastic factors, and the result of the design process will not be a "single value" for the system performance, but a probability to fulfil a certain performance over the time (Corgnati et al., 2006).

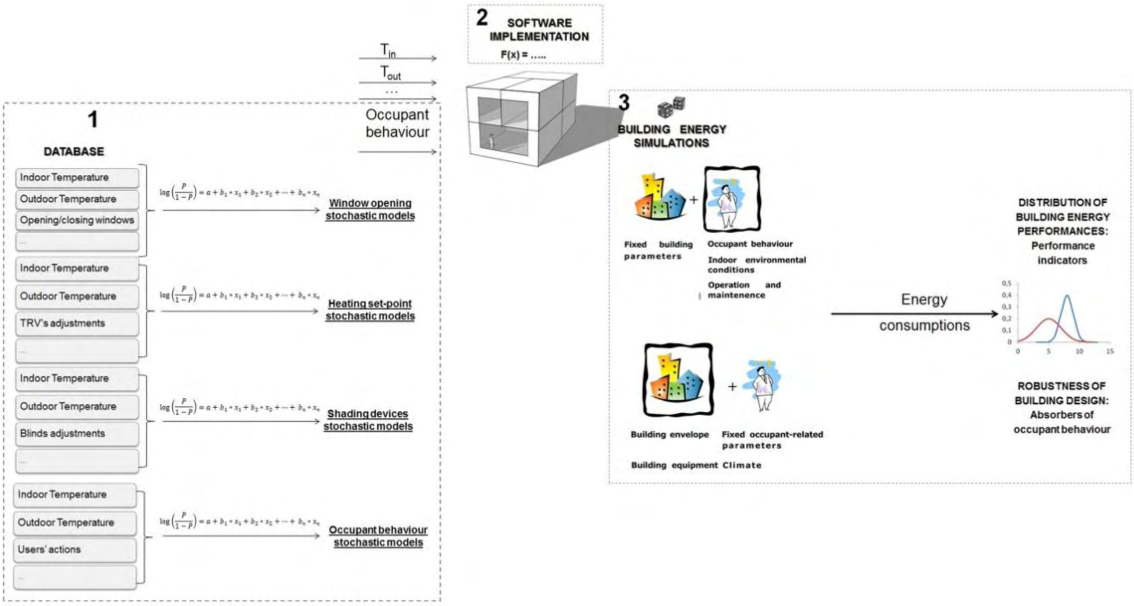

Figure 3. The probabilistic approach to simulate energy-related occupant behaviour

As a result of the monitoring data analyses by means of the statistical analysis, the probability of doing a certain action (opening or closing the window, turning up/down the heating system) was inferred for a defined behavioural models. The results are "occupant behaviour descriptors" to integrate within a building energy simulation software.

Software implementation

One of the main objectives in developing models for occupant behaviour is the implementation in computer simulation programs. With probabilistic models, this task demands either dynamic simulation programs suitable to handle probabilistic functions or the consideration of a group of people in a steady state calculation. For the latter, e.g. a group of 100 occupants is considered, and the probability of the state of an open window is translated into the ratio of people having the window open and closed based on the probabilistic model under certain conditions. This rather simplified implementation was applied e.g. by Schweiker and Shukuya (2010). Relations for energy-related behaviour (e.g. thermostat set point, window opening) found by any type of regression analysis can be applied in building simulation software to predict energy-use and indoor climate. The idea is to change from a deterministic approach of building energy simulation toward a probabilistic one taking into account the occupants' presence and interactions with the building and systems. Results of the statistical analysis show the possibility of defining occupants' behavioural models building uses and buildings systems to control the indoor environment to be implemented in simulation tools for building energy analyses.

In order to investigate the effect of occupant behaviours both on energy consumption and indoor environmental quality, simulations should be run in thermal zones maintaining location, weather file, and building construction of the monitored buildings. In the occupancy schedule, the occupant could be still considered as always present, but the control of a building's indoor environment is now probabilistic in nature; it does not follow predefined controllers or fixed rules. The probability of adjusting the temperature set-point or opening a window is calculated in the simulation software on the basis of the equations previously used to describe the behaviour statistically. Most simulation programs are deterministic in nature, so there is a need to translate the probability of an event into a deterministic signal. One way of doing this is to compare the probability to a random number to determine if the event takes place. As the given probability is the probability of doing a certain action in a certain time period, the comparison is to be made with a random number that changes with the same interval. The action occurs when comparing the random number with the calculated probability; the former was smaller than the latter. In this way it is possible to calculate the energy performance through a performance indicator. An example of the algorithm implementation in simulation software is represented in Figure 4.

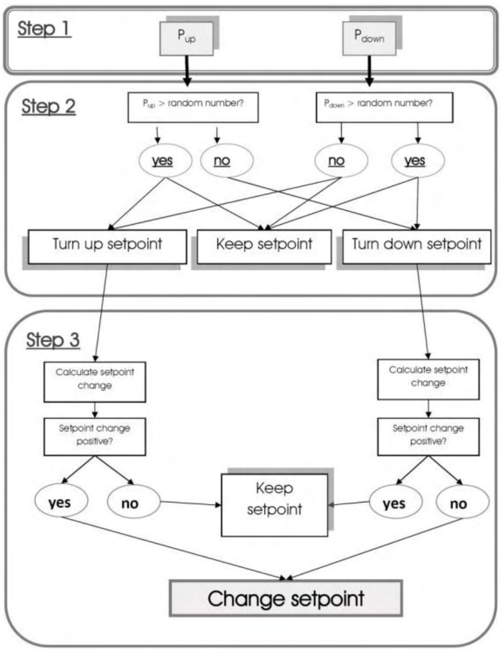

Figure 4. Example of algorithm for the software implementation

A probabilistic model of the output parameters: simulation results

A probabilistic distribution of energy consumptions depending on user type is obtained by running several simulations. Fixing all the parameters related to the energy performance of the building (i.e. climate, building envelope, building equipment), the simulations are aimed at verifying the influence of the characterized users behaviour on energy consumptions. Running a high number of simulations it is possible to have a curve of energy performance of the building in different situations and for different occupant typologies. In this way, it's preferable to have a probabilistic distribution (a "probabilistic output") instead of a single value as a representation of energy consumptions.

Indeed this approach aims to represent a procedure that could be extended to all the users' interactions with the indoor environmental controls systems, like window operations, heating set point adjustments, solar shading operations.

A further step is represented by the application of user models into simulation programs to verify the "robustness" of the building with respect the users. Once the user behaviour has been characterized by a model and its impact on energy performance is verified with a number of simulation, it is interesting to check what happens changing the building properties and equipment with the same user behavioural pattern.

Based on Ferguson et al. (2007), Hoes et al. 2011 defined the performance robustness as the ability of a building to handle changes (or disturbances) in the building's environment and maintain the required performance. Therefore, it is important to take performance robustness into account during the design process (Leyten and Kurvers, 2006).

Nevertheless factors involved in the energy programs implementations can be extended to thermal mass, facade percentage of transparency, shading devices or window opening with the aim to understand which of these have the most influence in energy use and so, constitute recommendations for improved buildings design with regard to energy reduction. This allows the designers (engineers, architects or technicians) to select the most robust solution for the building design.

4.3. CASE STUDY I (PAPER III)

WINDOW OPENING BEHAVIOUR IN RESIDENTIAL BUILDINGS

The proposed procedure was applied for modelling the occupant behaviour related to window opening and closing, and its implementation in the simulation tool IDA ICE so that the results obtained are probabilistic in nature.

This application study is based on the developed models of window opening behaviour described in paper II. Actually, the defined four different users' behavioural patterns could be implemented in many existing simulation tools. In this application study, IDA ICE (Indoor Climate and Energy) simulation tool was used and the equation describing the probability of user interfering with the control of the indoor environmental quality and the event taking place integrated in the program using the algorithm represented in Figure 5. IDA Ice (Indoor Climate and Energy) is a dynamic multi zone simulation software application for accurate study of thermal indoor climate and energy consumption of the entire building, developed by EQUA. This open source program allows modellers to manage occupant behavioural patterns, by implementing statistical equations.

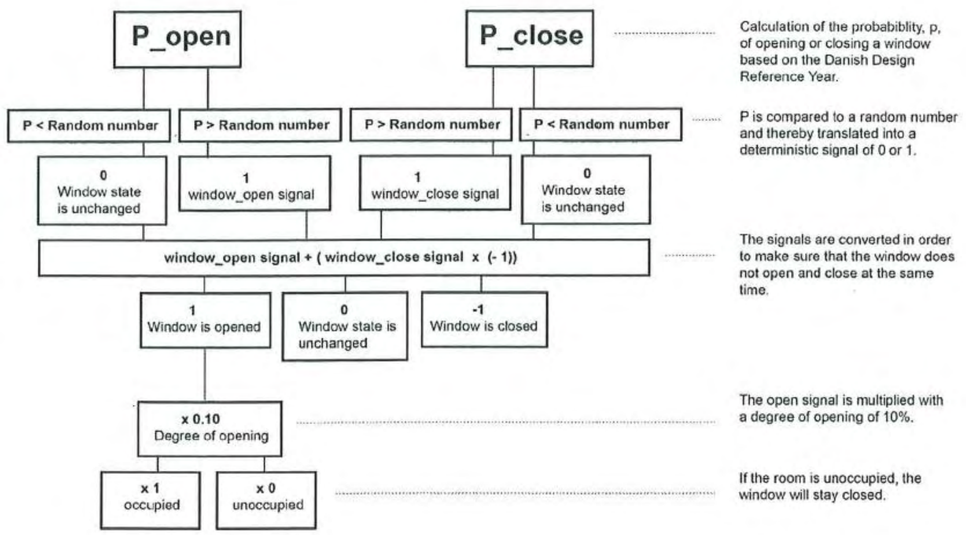

Figure 5. Algorithm for the prediction of window opening and closing in IDA Ice

The simulated building

A typical room located in Copenhagen was adopted for both living room and bedroom to evaluate the influence of windows control related occupant behaviour on total energy use. European Standard EN 15265/2005 "Thermal performance of buildings – Calculation of energy use for space heating and cooling- General criteria and validation procedures" provided a test room suitable for the simulations. Both bedroom and living room are provided of a water bone radiator with a constant heating set-point of 21℃ from September to June. None of the room had the cooling system. As internal source, one person was considered present in each of the rooms with a house living schedule (from 0:00 to 8:00 and from 17:00 to 24:00) at a metabolic activity of 1.2 met. The equipment and lighting schedule follow the house living schedule. The light in the room, with an emitted heat per unit equal to 50W, is automatically switching on if the minimum work plane illuminance is lower than 100 Lux based on the study of the Lightswitch-2002

(Reinhart, 2004); and switchiing off at an illuminance level of 500 Lux. According to the mechanical ventilation type of the database dwellings, two models are set differing only for the ventilation type: one model was realized for the natural ventilated buildings and another one for the mechanical ventilated building (exhaust ventilation).

The deterministic "standard reference model"

To get an indication of the performance of the four models and their ability to predict window opening behaviour, simulations were run for each model using the simulation reference model. The results were compared to the corresponding models where a standard window control (on/off temperature control + schedule) is used. The standard schedule plans that the windows will open if the indoor temperature exceeds a certain value (25°C ±2°C) and the outdoor temperature is lower than the indoor temperature.

The implemented probabilistic model.

In the occupancy schedule the occupant was considered always present, but control on windows was probabilistic in nature, it doesn't follow maximum and/or minimum set-point controller. The probability of opening and closing the windows was calculated basing on the logistic regression previously described and following the algorithm of Figure 5. Specifically, two behavioural patterns were simulated: groups with natural ventilation (I and III) and groups with mechanical (exhaust) ventilation (II and IV) according to the behavioural models previously defined (see PAPER II).

A probabilistic model of the output parameters: simulation results

Results are given in the form of primary energy, accordingly with the European Standard EN 15603 that establish the conversion factors as fpfuel= 1.36 for heating and as fpelectricity mix UECPTE= 3.14 for other electric systems and appliances. The air change rate was used as a first indicator of the size of the change in performance caused by a shift in window opening behaviour. Fluctuations on air change rate were signs of a shift in the window opening behaviour governed by a change in the indoor climate large enough to influence the window opening behavioural models. In the following tables (table 6, table 7) it is highlighted the comparison between the building simulated with a control of windows based on fixed rules of temperature (On/off + temperature) and the buildings modelled with a probabilistic approach.

Table 2. Air change rates, ventilation losses, space heating energy demand and primary energy for natural ventilated buidings

User types	Air change rate ($m^3/(s\cdot m^2)$)		Ventilation losses (kWh/m^2)		Heating, EP (kWh/m^2)	Total Energy, EP (kWh/m^2)
	Bedroom	Living room	Bedroom	Living room		
I	0,58	0.65	70	72	266	393
III	0.58	0.64	71	70	266	392
Standard NV	0.87	0.86	77	76	281	407

Table 3. Air change rates, ventilation losses, space heating energy demand and primary energy for mechanical ventilated buidings.

User types	Air change rate ($m^3/(s\cdot m^2)$)		Ventilation losses (kWh/m^2)		Heating, EP (kWh/m^2)	Total Energy, EP (kWh/m^2)
	Bedroom	Living room	Bedroom	Living room		
II	0.91	0.59	140	96	349	479
IV	0.73	1,00	112	80	321	451
Standard MV	0.81	0.78	90	87	299	429

From the tables it emerges that the probabilistic approach used for the simulations of the four users types provides significant discrepancies compared with the deterministic approach. Actually, for the natural ventilated buildings (groups I and III, Table 2) it appears that the predefined-fixed control of windows produce higher results than the probabilistic control: the air change rate is up to 33.8% more in the bedrooms, while the ventilation losses arrive to be 9.9% less in the buildings where the probabilistic approach is used. Obviously, in the space heating energy demand and in the total primary energy the differences are less visible, but still present as it results a 5% of discrepancy between the values referred to the heating demand and a 4% if we refers to the primary energy.

Table 3 is related to the groups with the exhaust mechanical ventilation. It appears clear that in this case the predefined schedule for the window control underestimate the opening and closing events: in the buildings modelled with the probabilistic approach, the air change rates rise up to 33.6% more (bedroom, group IV), the ventilation losses up to 54.8% more (bedroom, group II): this result perfectly fits with the existing studies on the topic, where bedrooms are the rooms were windows are most frequently opened. By consequence, space heating energy demand is underestimated, and it results that the buildings where the windows are controlled with a probabilistic function consume up to a 58% more energy than a building where the control on windows is regulated by a fixed schedule related to the temperature.

A probabilistic distribution of energy consumption depending on user types was obtained by running 20 simulations of the same model. The probabilistic distribution curve in Figure 6 showed that the air change rate for group IV (with mechanical exhaust ventilation) ranged from 0.87h-1 to 1.14 h-1 in the bedroom (variation equal to 24%). In the case of space heating demand, this shift in air change rate was reflected in a range of 10 kWh/m2year (ranging from 313 to 323 kWh/m2year). This range of results represents the variety in window opening behaviour often found between dwellings and therefore formed a good basis to improving the analysis of actual building energy performance.

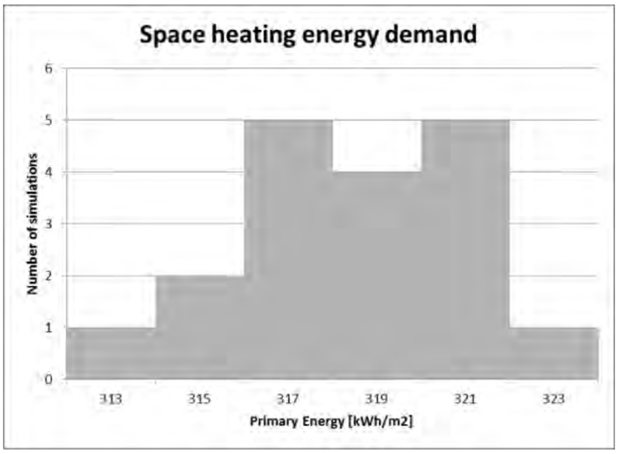

Figure 6. Distribution of space heating energy demand for Group IV occupant types

Further details on case study's characteristics and simulation results could be found in PAPER III, in the end of this dissertation.

4.4. CASE STUDY II (PAPER IV)

HEATING BEHAVIOUR IN RESIDENTIAL BUILDINGS

The approach proposed in this section is also used for the application for heating/cooling set points, but actually it could be extended to cover use of solar shading and other actions that occupants take with an influence on indoor environment and energy consumption.

MODELS OF OCCUPANT'S HEATING BEHAVIOUR

Database

The database is constituted by the data gathered during the monitoring campaign of indoor and outdoor climate variables and occupant's control actions was conducted in the same dwellings of the first analysis on window opening. (15 Danish dwellings in the period from March to August 2008 in Copenhagen). In this case, occupants' adjustments of heating set-points temperatures were monitored by measurement of the setting of one TRV in the bedroom and one in the living room of each dwelling. The dwellings were divided into three groups selected by inhabitants' frequency of TRVs manipulation: the three groups were named active, medium and passive users.

Occupant behaviour model development

In the analyses the probability of turning up/down the heating was inferred for the three user types. Set-point dependency on indoor and outdoor environment and users control actions was deduced by mean of logistic regression with interaction between selected variables. The results were models that predict probabilities of turning up and down the set-point. A model that predicts the size of the set-point change was inferred using linear regression.
The variables that had a statistically significant impact on heating set-point adjustment are indoor relative humidity, outdoor temperature, solar radiation, wind speed and time of the day. The statistical analysis revealed that for active users the most important variables in determining the probability of turning up the set-point were indoor relative humidity, time of the day and outdoor temperature. For medium users outdoor temperature and wind speed were negatively correlated with the TRV set-point indicating that the heating set point was increased when these variables decrease while the time of the day was the most influential variable in the determination of turning down the heating. The model for passive users showed no significant variable influencing the probability of increasing the heating set-point whereas wind speed was positively correlated with the probability of turning down the heat, indicating that an increase of wind speed increased the probability of turning down the heating

BUILDING ENERGY SIMULATION IMPLEMENTATION

The defined behavioural models of thermostatic radiator valves usage by the occupants can now be implemented in simulation tool for energy simulations. This passage is done in the same way already done for the window opening behaviour models (see PAPER III).

The simulated building

The window was considered as not operable and a water radiator was supporting the HVAC plant in providing the required thermal comfort. The meteorological data used in the simulations refers to the Danish Design Reference Year. As internal heat gain, one person was considered always present at an activity level of i.e. 1.2 met (70W/m^2). Lighting schedule was connected to the people presence and based on the study of the Lightswitch-2002 (Reinhart, 2004), the light (50W per unit) was switched on if the minimum work plane illuminance was lower than 100 Lux. It was switched off at an illuminance level of 500 Lux. A building equipped with a mechanical Air Handling Unit (AHU) was chosen to avoid the influence of occupants' window opening behaviour. The AHU was equipped with a heat exchanger for heat recovery. The air supply temperature was constantly 16°C.

The deterministic "standard reference model"

Energy consumptions were calculated accordingly to the comfort levels recommended in the EN 15251 (2007). These simulations were run in the deterministic way on the base of schedules assumptions decided a priori describing occupancy, lighting and equipment load. For example, set-point for categories I-II-III have been set respectively on 18-20-21°C accordingly to operative temperature of EN15251 for energy calculations.

The implemented probabilistic model.

In the occupancy schedule the occupant was considered always present, but control on heating set-point is probabilistic in nature, it doesn't follow maximum and/or minimum set-point controller.

A probabilistic model of the output parameters: simulation results

Results are given in the form of primary energy, accordingly with the European Standard EN 15603 that establish the conversion factors as fpfuel= 1.36 for heating and as fpelectricity mix UECPTE= 3.14 for other electric systems and appliances.

When using implement behavioural patterns, a significant difference was appreciated on energy demands for the three different cases. Energy consumption did not linearly increase accordingly to occupants' frequency of interaction with set-point controller. Active users did not always represent the most energy wasting user type. Generally, deterministic energy consumptions were lower than probabilistic users' consumptions as summarized in Table 4. Set-point temperatures in the implemented probabilistic simulation ranged around 23 °C, definitively higher than the values recommended by EN 15251. Influence of users' types on final energy demand could be evaluated by a factor (ratio between the higher energy consumption and the deterministic one) ranging from 1.10 to 1.30 (Table 4).

Table 4. Results for simulation I –II for primary energy consumptions [kWh/m2year].

	STANDARD	ACTIVE	MEDIUM	PASSIVE	factor
Category I	84	93	93	86	1.10
Category II	73	83	83	77.0	1.14
Category III	60	74	77	74	1.30

The probabilistic distribution curve reported in Figure 7 and Figure 8 show that the probability of primary energy consumption for active users in comfort category II range from 82 kWh/m^2 to 85 kWh/m^2. This could be attributed to the frequency in manipulating thermostatic radiator valves but also to indoor temperature preferences or even to saving measures.

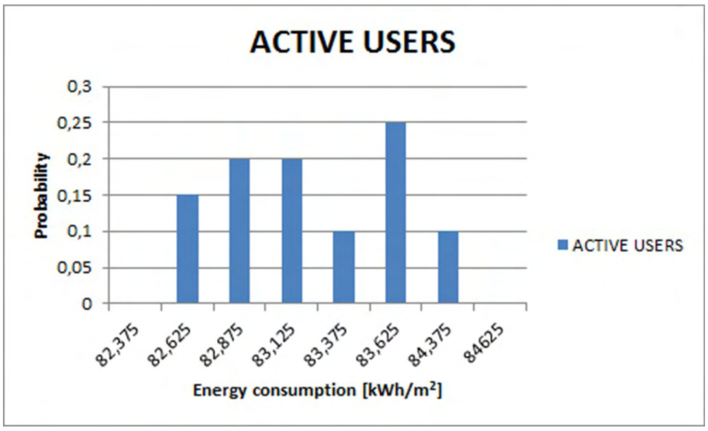

Figure 7. Distribution of primary energy consumptions for active user type.

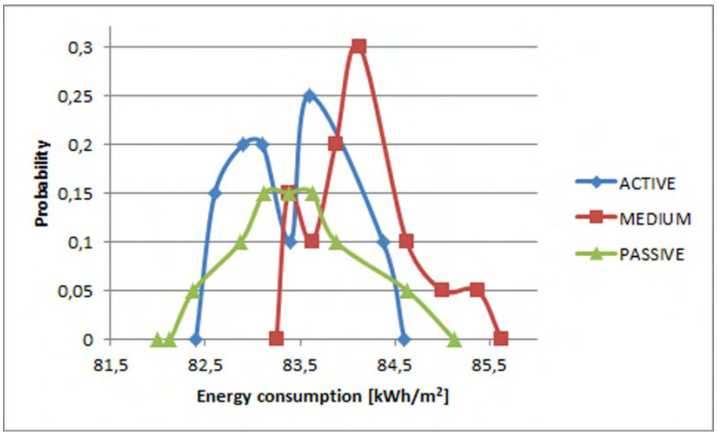

Figure 8. Distributions of primary energy consumptions for different user types.

Further details on case study's characteristics, data analysis and simulation results could be found in PAPER IV, in the end of this dissertation.

SCALE IT UP

Ensure the effectiveness of the models

"The combination of some data and an aching desire for an answer does not ensure that a reasonable answer can be extracted from a given body of data.

John W. Tukey

5. Validation of behavioural models

Validation of occupant's behavioral models, such as those used to represent the interaction of the occupants' with the built environment in building energy simulations, is an issue that is gaining importance,

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

Generally the published statistical models of occupant's behaviour are not validated. Actually, so far, only two papers about the validation of behavioural models are published in literature, regarding respectively the office buildings and residential buildings. In 2009 Haldi and Robinson have proposed a cross-validation procedure to perform the evaluation of the predictive power of window opening behaviour models developed for office buildings. Appling the suggested validation criteria, in 2011, Schweiker et al. (2011) 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) there is still remaining a considerable space for further research work.

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 experimental observations.

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 a set of data not used in estimation. The main idea behind the validation is to have two sample, one used as "training sample", to generate the algorithm, and the other sample, the "validation sample", is used for estimating the accuracy of the algorithm.

In this dissertation, models for the prediction of occupants' actions previously developed (see PAPER II) have been validate to ensure their effectiveness. This involves predicting the values of a second dataset (the validation set) using a model based on data from the first dataset (the training set). A comparison between observed and simulated window opening proportions for several indoor and outdoor temperatures ranges is provided as validation. This allows for a direct unbiased assessment of the predictive power of the developed models.

5.1. Validation procedure

The aspects used by Haldi and Robison (2009) and by Schweiker et a. (2011) to assess the predictive power of the models are used for assessing the effectiveness of the developed window opening behaviour models (PAPER II) .

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 of the models to reproduce well the list of the observed criteria, by comparing the observed window states and the predicted window states.

Defining positive the open state of the window and negative the closed one, on the basis of the measured state of the window, 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.

Connected to this criteria is the evaluation of the overall prediction by defining if the models predicts a consistent overall opening ration throughout the simulation period,

Since the developed models predict the probability of an action (opening or closing) occurring using a logistic regression (equation 3), 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.

Finally, the evaluation goes through the aggregated results looking at the predicted total number of open window sis consistent with observations.

Based on these criteria the best performing model will be retained.

5.2. FOCUS ON PAPER V:

VALIDATION OF WINDOW OPENING MODELS

The effectiveness of the developed window opening behaviour models is verified with the validation procedure previously explained.

A general validation procedure should involve comparing each model's ability to directly reproduce observed window states. Then results should be classified in four groups:

- A predicted open window is: truly open (TP) or Falsely open (FP)
- A predicted closed window is : truly closed (TN) or falsely closed (FN).

Based on definition provided in this chapter, these results could be aggregated to define the overall True Positive Rate (TPR), the False Positive Rate (FPR) and the Accuracy which gives the proportion of correct predictions. The accuracy is defined as ACC= (TP+TN) /(P+N).

For this validation works 10 simulations were repeated using a 10-min time step for the whole period with available measurements data obtained in 10 measured dwellings in Copenhagen with characteristics analogue to the first dataset. The same indoor and outdoor variables are monitored in the second monitoring campaign as well as the behavioural actions on windows. Further details about dataset and models could be found in PAPERV.

The validation analysis have produced 10 x 10 = 100 sets of simulated window states, to be compared with the 15 sets of observed data of windows. Based on the ten repeated simulations these indicators are displayed in Table 1.

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 the Figure 1 the model represents quite accurately the real opening actions in the living room, in particular in case of dwelling 1 and dwelling 2 the prediction is significant.

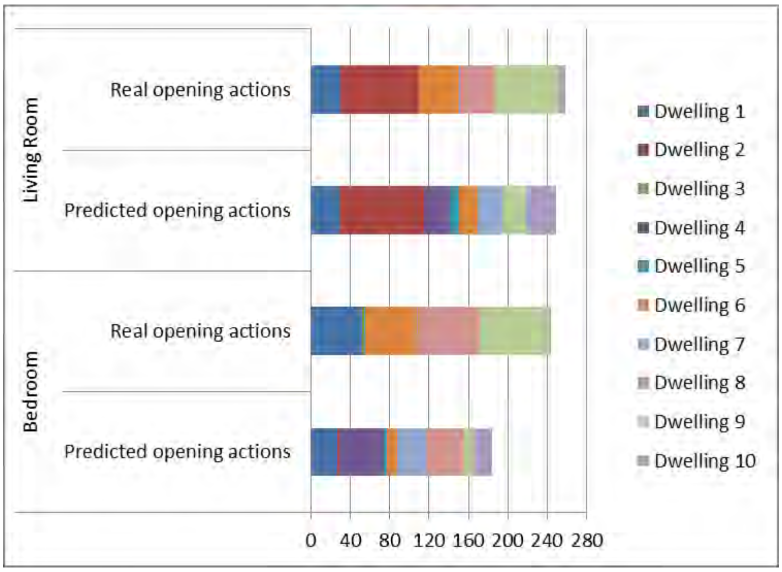

Figure 1. Comparison between predicted and observed number of actions on windows for each dwelling tested with the G2 model

Since by merging the dwellings in groups, inner dynamics of a single dwelling are lost and the specific behaviour is flattened in the groups, further analysis were carried out by validating each single dwelling model. The validation of the singular dwelling model is done in two successive step. First, the dwellings of both dataset are 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 first dataset (7 models) were tested in active users' dwellings of the validation dataset, and in the same way passive users' models (5 resulting models) were performed in passive users' dwelling. The resulting average accuracy of the models is not high, since the TPR and the FPR values are not significantly different from each other, with the exception of the active models tested in the living room, where TPR values are quite different from FPR values.

Since the aim of the validation process is to scale up the effectiveness of the window opening behaviour models for simulation purposes, it is important to find a model that is performing well without defining a priori the type of the occupant. For this reason, further analysis 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 is 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 computed simulations are given in Table 2.

Table 2. 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 2 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 CO_2 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.

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 CO_2 concentration and illumination values (Group 2 and d16 models) and a negative correlation with sun hours and illumination level for closing windows.

Further details on case studies, used statistical models and analysis results could be found in PAPER V, in the end of this dissertation.

5.3. Validation of window opening models existing in literature

The validation procedure regarded also models of window opening behaviour already developed in literature. In particular, the models proposed for residential buildings by Haldi and Robinson (Schweker et al.,2011) (Neuch□tel database) and Schweiker (Schweker et al.,2011) (Tokyo database) were tested. The models and the regression coefficients of the tested models are displayed in Table 3.

Table 3.Regression parameters of the tested literature models.

Models and variables	Haldi and Robinson Neuchatel database	Schweiker Tokyo database
P_{open}		
a	-1.51	-6.528
T_{out}	0.1389	
T_{in}	-0.245	0.0549
P_{close}		
a	-0.15	-2.367
T_{out}	-0.1725	-0.0543
T_{in}	-0.071	-0.071

For the Swiss dataset, the forward selection procedure retains outdoor temperature as the most influential variable, followed by the addition of indoor temperature. Using a similar procedure, outdoor and indoor temperature were both found to be significant, however, when developing a multivariate logistic model outdoor temperature was not found to be significant for opening probabilities. (Schweiker et al., 2011).

These models were both tested using the validation dataset already used in the previous analysis and the same criteria were retained for assessing the predictive performance. As in the previous tests, 10 statistical simulation were run for each model in the 10 measured dwellings of the validation dataset.

The results of the computed simulations are given in Table 4.

Table 4. Validation parameters for the literature's 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
Haldi&Robinson Neuch□tel database	3%	3%	2%	2%	82%	91%	136	148
Schweiker Tokyo database	5%	9%	12%	12%	76%	82%	286	283

As displayed in Table 4, the overall performance of the models is not high, even if the number of predicted action on windows of Japanese models are pretty close to the real number of actions on both bedroom and living room.

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

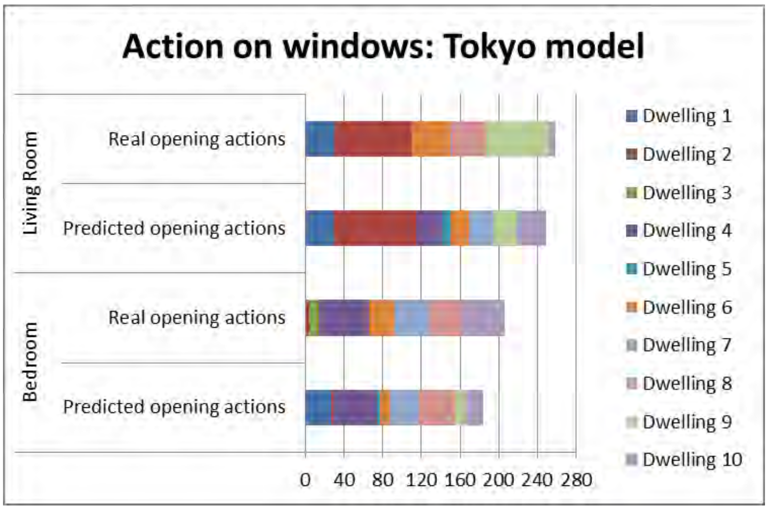

Figure 2. Comparison between predicted and observed number of actions on windows for each dwelling tested with the Tokyo model.

ON THE HORIZON

Future projections

"*As a general rule … people ask for device only in order not to follow it; or if they follow it; in order to have someone to blame for giving it*"

Alexandre Dumas

6. Information feedback and occupants' energy behaviour

Energy information systems comprise software, data acquisition hardware, and communication systems that are intended to provide energy information to building energy and facilities managers, financial managers, and utilities. This technology has been commercially available for over a decade, however recent advances in Internet and other information technology, and analytical features have expanded the number of product options that are available. For example, features such as greenhouse gas tracking, configurable energy analyses and enhanced interoperability are becoming increasingly common.

Energy information systems are used in a variety of buildings operations and environments, and can be characterized in a number of ways. Basic elements of these systems include web-based energy monitoring, web-based energy management linked to controls, demand response, and enterprise energy management applications.

A number of industry experts have pushed for the adoption of building information systems that can provide facility managers and occupants with meaningful and actionable information. Wyon (1996) proposed a "3-i principle of user empowerment." Wyon believes that through insight, information, and influence we can enable managers and occupants to positively affect building performance and resource consumption. Although Wyon's 3-i principle was proposed several years ago, today's Internet-enabled technologies provide a platform for making these goals possible.

Using information feedback to educate and influence building managers and occupants

A handful of nimble technology development firms are stepping up to fill the need for effective data visualization in buildings. These firms are developing a new generation of information displays—dashboards—with features and interfaces tailored to the needs of building owners, operators, and occupants. Distinct from conventional Energy Management and Control Systems (EMCSs), these information dashboards typically do not provide detailed system operation. Instead they are designed to visually display trends and anomalies, and to educate a broad range of building stakeholders about the ecological implications of building performance and occupant behaviour. Many of these products include real time information displays, and allow users to view data using a number of different metrics, such as energy nits, utility costs, or carbon emission equivalents. Several studies have examined how information feedback can help occupants to reduce energy, though the majority of these have focused on homes. On average, these studies found that real-time energy feedback resulted in overall energy savings of 10-15%.

Since the 1970s, many researchers from various fields have studied how feedback on energy use impacts residential consumer understanding and behaviour. Studies involving informative billing and periodic feedback have realized energy savings between 10 and 20%. It is assumed, based on theory and field research, that if residential consumers had more detailed and/or frequent information about their consumption, they would both better understand their energy use patterns and be able to change them effectively (Darby 2000; Van Raaij & Verhallen 1983).

Continuous energy feedback was first tested by McClelland & Cook (1979). They found that homes with continuous electricity use feedback had, on average, a 12% lower electricity use than their neighbours without monitors. Hutton et al. (1986) installed the "Energy Cost Indicator" (ECI) in 25 households in three cities. Over 75% of subjects in each of the ECI treatments indicated that the feedback provided by the monitor was somewhat useful in helping them to conserve energy. California, where residents had the lowest level of energy use understanding, showed the most support of the ECI, and was willing to pay more for the monitor. Sexton, Johnson & Konankayama (1987) installed a real-time monitor in 68 homes after these households had spent one year adjusting to time-of-use electricity pricing. This monitor had to be turned on by the user; the screen displayed price and electricity use over the hour, day and month, and had a blinking light feature if the budgeted bill was exceeded. Monitoring in this study did not stimulate overall conservation, but residents did switch from peak to off-peak use. Interestingly, for all households except those with a 9:1 peak : off-peak rate, monitoring actually increased total consumption, especially of air conditioning. Van Raaij & Van Houwelingen (1989) conducted a study with a similar monitor for one year, absent time-of-use pricing; they found that the average reduction in electricity use for households with the monitor was twice as much as those given other types of feedback. The monitor was used mainly as a permanent check on the effects of energy conservation efforts; the majority of participants felt that they needed the monitor present to help them conserve. Indeed, after the experiment was over, consumption in the monitor group rose again to be equal to that of the other feedback and control groups. In a more recent study.

Matsukawa (2004) gave a computer monitor to 113 Japanese households for three months. These consumers could see graphs and tables of their energy use on an hourly basis, as well as a graphic comparison to their historical performance. Matsukawa was able to monitor the frequency with which households interacted with the monitor. The elasticity of electricity demand with respect to monitor use was significant, but quite small (-.015). Price elasticity for households who used the monitor frequently (more than three times per month) was only .04 higher than that for households who used the monitor once a month.

Matsukawa postulates that the modest impact of the monitor-provided information on electricity use may imply that monitor-provided information in the experiment was not as helpful as the households may have expected, and that there was a time cost to users in terms of information processing, even when the monitor was free to them (Matsukawa 2004, 16). Ueno et al. (2005) conducted a micro-level study of nine Japanese households. Residents had access to a graphical display of their energy use, broken into different end-uses. The computer display also included energy prices and historic energy use and past bills. Installation of the monitoring system led to a 9% reduction in power consumption. An increased knowledge about energy-saving behaviours caused decreased consumption of both appliances displayed on the monitor and other appliances in the houses. Residents were far more interested in the daily load curve than the summarized ten-day curves; this is a surprising result, given the preference for less frequent information found by Van Raaij & Verhallen (1989) and Matsukawa (2004).

Two main conclusions can be drawn from this broad group of studies.

First, real-time feedback has not been shown to stimulate more energy conservation than monthly or weekly feedback. Indeed, Sexton, Johnson & Konankayama (1987) saw an increase in energy use. What is new is the discussion of increased "awareness" as a major result of feedback. It seems that awareness, not behavioural change or financial savings, is the major impact of maximizing feedback frequency.

The second point is that an increase in sophistication of real-time feedback technology has not corresponded with an increase in measured energy savings. In fact, Ueno's end-use study yielded less energy conservation than McClelland & Cook's basic electricity monitor, 30 years before. It seems that it is the presence of the information itself - not its presentation in a more salient, graphical format - that is causing the behaviour change.

As a consequence of the unclear economic advantage of real-time usage feedback over other forms of energy feedback information, the main applications of real-time feedback have been in either commercial settings for facilities managers, or in schools and universities as an educational tool and technological experiment. Electric monitoring companies like Heliotronics (www.heliotronics.com) and Fat Spaniel (www.fatspaniel.com) advertise to schools, companies and homeowners interested in learning about the quantity of energy they use (or produce, in the case of photovoltaic systems) and its environmental effects. There is no price information displayed in either of these systems; energy costs are calculated in environmental terms. These products are clearly being developed by and marketed to people who are already deeply interested in the environmental performance of buildings. Both company systems are rife with colorful graphics, but they are oriented toward homeowners with residential photovoltaic systems, rather than toward the general energy consumer market.

Petersen et al. (2005) conducted a study testing whether quantity-based, educational realtime feedback stimulated energy conservation in dorm residents. It was found that in the context of a "dorm energy competition," the dorms with real time feedback did conserve more energy than other dorms on campus. However, more research must be done to determine whether residents will respond similarly to non-price signals absent the competitive context.

One study completed in 2007 looked at the energy use for 200 families in the Canadian province of Newfoundland and Labrador using PowerCost Monitor devices manufactured by Blueline Innovations. The devices consist of an external meter reader that attaches to the glass cover of standard electricity meters, and a receiver located inside the home that displays energy use, cost, time, and outside temperature. The study found that families with the devices reduced energy consumption 18% on average. In the Newfoundland study, homeowners may have been motivated to save money by reducing utility bills. Other research shows that feedback alone is not sufficient to change behaviour. For example, a study conducted at the Eindhoven University of Technology (Netherlands) published in the Journal of Economic Psychology showed that a group of test subjects with energy feedback, but no energy saving goals, used the same energy as a control group given no feedback. Test subjects given feedback and energy saving goals saved on average approximately 20%. The findings indicate sufficient motivational factors must be present in addition to effective feedback information. Ideally, future energy feedback systems will be integrated with smart building controls. Researchers at UC Berkeley tested a prototype for a thermostat and home-energy manager as part of a program to develop demand response enabling technologies. The prototype interface, dubbed DREAM for the Demand Response Electrical Appliance Manager, was conceived as a device that would receive dynamic utility price signals as well as information on electrical use from sensors throughout the home. The DREAM device might allow future homeowners to see immediately how energy decisions impact comfort, cost, and energy use.

Peffer (2011) tested the usability of the DREAM interface at the as part of her PhD dissertation. Peffer evaluated the test subjects' energy choices and preferred interface features. The interface elements with high specificity, such as an energy display of a single appliance, were considered by users to be the most valuable. However, the subjects varied considerably in their preferences, and the research showed that there is no "one-size-fits-all" solution. In order for feedback systems to be adopted by users, they will require flexible interfaces that can be adapted to meet users' needs. For example, technically savvy users might want a detailed 24-hour display of data, while other users prefer more simplified presentations of information.

Other research has been conducted to learn whether new and innovative feedback systems can motivate people to make smart ecological choices. Researchers at Carnegie Mellon University created a virtual polar bear living on an ice floe that grows or shrinks based on test subjects' actions. When the subjects lowered energy use by changing their thermostat or taking shorter showers, the ice floe grew and the virtual bear thrived. Poor energy choices caused the ice floe to shrink, making the polar bear's habitat more precarious. The study found that people who formed an emotional attachment to the cartoon bear were more likely to take ecologically preferable actions.

Using a similar approach, designers of dashboards for Ford and Honda hybrids are experimenting with novel features such as a tree icon that grows leaves when drivers conserve gas, losing leaves when drivers get poor mileage. Nissan in Japan offers a service that allows drivers to compare their mileage and annual gas use with that of other drivers, using drivers' competitive instincts to help them get better mileage. These feedback systems remind drivers that their driving habits have an impact on the environment, doing so in a game-like and non-judgmental manner.

In Italy, Energy@home project details a system that can provide users with information on household consumption directly on the display of the appliance itself, on the smart phone or on their computer. The Energy@home project is a further step towards the development of the so-called "smart grid", that, in the near future, will allow continuous real-time bidirectional information exchange between utilities and appliances in the houses to enable each customer to "self-manage" his/her energy behaviour depending on both power supply availability and price.

In terms of specificity and frequency, there are unanswered questions in the literature to date:

- Is there a point at which specificity and frequency of energy feedback information ceases to lead to increased energy use awareness and/or behavioural change?
- Should feedback frequency be daily, hourly, or continuous?
- Should the information presented include only utility prices, or should non-price information be included as well?
- Would residents pay more attention to per unit or cumulative price?

These are critical questions when one is considering the costs and benefits of feedback strategies. It may be that after a certain level of feedback frequency and specificity has been reached, consumers will no longer respond to additional feedback by changing their energy use behaviour. It is even possible that continuous feedback might be less effective than monthly or periodic feedback, since consumers respond more strongly to large cumulative energy use numbers than smaller numbers representing short time increments, even though these numbers are more informative about specific energy-use behaviour (Bittle, Valesano & Thaler 1979-80).

7. Robustness of building design with respect to occupants' behaviour

A particular field of application of this research is to minimize the difference between the predicted building energy demand and its actual energy consumption by evaluating the building envelope design's potential in reducing the impact of occupants' behaviour on energy performances.

Once the occupant's behaviour has been characterized by a model and it is verified its impact on energy performance with a number of simulations, it is interesting to check what happens changing the building properties and equipment with the same occupant behavioural pattern.

"Robustness" is defined by Hoes et al. (2009) as "the sensitivity of identified performance indicators of a building design for errors in the design assumptions". The quoted "sensitivity" is expressed by different probabilistic distributions of outputs obtained by testing different building designs. In fact, as displayed in **Figure 1**, even if different building features can provide the same average value for the performance indicator, individual values from which the average is derived may appear with a different frequency, being more or less centred respect to the mean value. The closer single results to the average are (i.e. with a mathematical definition, the smaller the standard deviation is), the more robust the design.

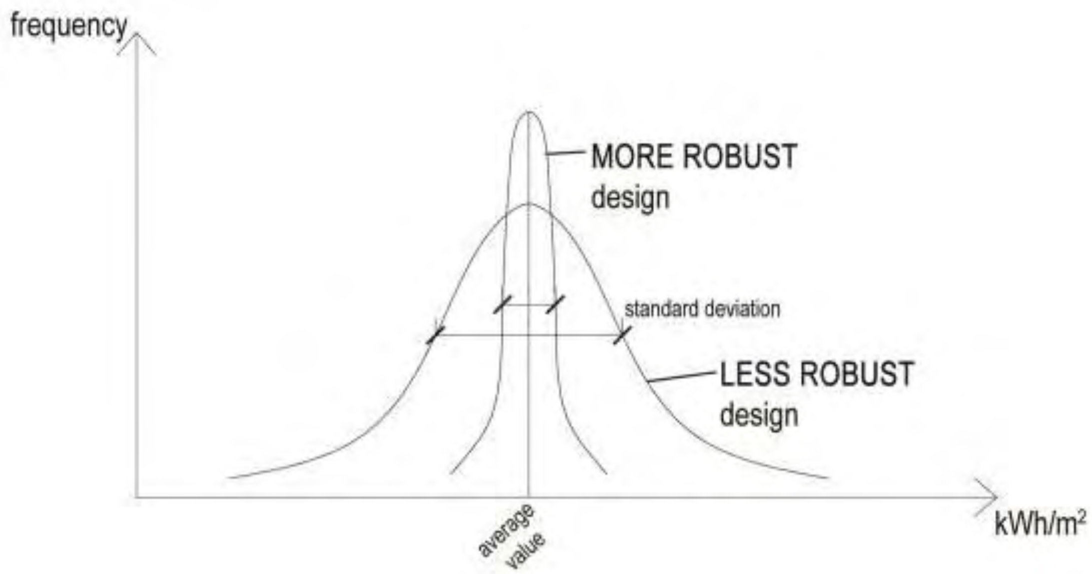

Figure 1. Explanation of robustness design

As stated in the previous paragraphs, among the most erroneous design assumptions occupants' behaviour has a major role, therefore the main question arising when dealing with the building's robustness is:

How different buildings respond to differences in occupants' behaviour?

Rijal et al. (2007) tried to answer to this question while implementing on ESP-r the Humphreys algorithm, a model dealing with the occupants' actual interactions with windows in offices. First, they developed an office model to be analysed implementing in ESP-r the algorithm and run simulations in order to compare

simulations' results using the Humphreys algorithm compared to averaged ventilation rates. After, they investigated the influence of office building design on behaviour and energy use adding solar shading and solar shading combined with higher thermal mass. They discovered that in the model with thermal mass and shading, these features affected window opening frequency.

Hoes et al. (2009) further investigate building sensitivity for the user behaviour, defining five variants to a reference model, previously simulated in ESP-r using a modelling method that combines Sub-Hourly Occupancy Control (SHOCC) and User Simulation of Space Utilization (USSU). The first model (SHOCC), developed by Bourgeois (2006), deals with the use of lighting, sun-shading, windows' opening and use of equipment in offices and includes a stochastic presence predictor suitable for cellular offices; the latter (USSU) has been developed by Tabak et al. (2006) and it has been implemented in this research because of its ability in formulating more complex occupant presence predictions.

The five analysed design parameters – U-glass factor, G-value, Transparency, thermal mass and R values –

have been varied to define 5 cases study: average values of design parameters, Low mass and closed fa□ade, low mass and open façade, heavy mass and closed façade, heavy mass and open façade. Cases' results are assessed through the Relative Standard Deviation (RSD), calculated from average value and standard deviation for a number of performance indicators. RSD is then used to compare the robustness of different design options, a small RSD indicating a performance indicator less sensitive to user behaviour.

Results show the low mass and closed model as the more robust, but with the worst indoor environment conditions and therefore point out the importance of occupant behaviour accurate predictions in more massive and less glazed offices.

Following Hoes' study, a master thesis recently discussed at DTU by Sørensen (2011), investigate how thermal mass, thermal resistance, transparency, glass type and solar shading influence window opening behaviour. This research was carried on developing a reference model on IDA ICE, in which logistic regression equations for users' behaviour were implemented, based on observation of real occupants in fifteen Danish dwellings performed by Andersen (2009). In this model the listed building features were combined and analysed, varying for each parameter the user's model twenty times to represent occupants' variability. Performance indicators sensitivity to building design is again evaluated using Relative Standard Deviation, whose graphs show that all design proposals were almost equally robust toward changes in occupant behaviour, despite dramatic alterations of building envelope design.

The above overview indicates that developments are on-going to allow a better understanding of which devices have the most influence in energy use and users' behaviour. The final outcomes will constitute recommendations for improved buildings design with regard to energy reduction. This will allow the designer (engineers, architects or technicians) to select the most robust solution for the building design.

In order to illustrate the impact of the design parameters on occupants' behaviour and on energy use in the building, Buso's master thesis defined several versions of the basic model of the Office Reference Building with alternative design features. To widen the research, five thermal zones, characterized by different design and orientation, are simulated in three weather climates – Stockholm, Frankfurt and Athens – with the aim to investigate how the different building design's options affect the building's performances and robustness when location and orientation are varied. First, the highest predictive power of probabilistic models respect to the classical deterministic approach is proved, then the envelope features are varied to investigate how they can affect building energy consumption and occupants'' behaviour.

Analysing results, it has been proved that having a massive envelope, a closed fa□ade and fixed shadings provides both the lowest heating and cooling energy consumption and the lowest results' fluctuation when switching the occupants' type. Therefore these building's features are the most robust ones being able to centre the simulations' set results respect the average values,. This observation is particularly true in Frankfurt and Stockholm in building zones with one external wall, since the design significantly influences the building's robustness respect to occupants' behaviour. In Athens the same conclusion can be drawn, but the building envelope's variations have a lower impact on occupants' interactions with windows. In building zones with two external walls, instead, no common trends are defined when matching different climates, meaning that in zones with a higher external surface/floor ratio the climate has a deeper impact on occupants' behaviour than the building design. Dealing with the influence of weather climate, its contribution in modifying the robustness' degree of the same scenario comes out clearly: in Athens all the investigated scenarios in all zones have lower results' variation than the corresponding models in Frankfurt and Stockholm.

Thus, thesis' results demonstrate that when low and certain energy performances are required, designers should include in the building's design massive envelope, a closed façade and fixed shadings, especially in the coldest climate.

Beside the numerical results, this robustness study shows how dynamic simulation software can be used as tools during the design phase: detailed occupants' behaviour's description will allow better defining the building features' robustness' degree when different design options are compared, in order to obtain the most suitable solution.

V. GENERAL DISCUSSION

About the proposed methodology

The results of the research conducted in the current project lead to a definition of a methodology for the identification of energy-related occupant behaviour patterns that can be used for predicting more accurate building energy performances.

Average and deterministic models are often based on assumptions, not on data, but could be based on data as well. At best, they represent e.g. the average for window opening frequency. Implementing such values into simulation algorithms, the outcome is a single value for each assumed/ derived type of behaviour. In order to show variety (of behaviours, types of occupants, …) various simulations have to be run once each for each model.

Probabilistic models could be based on assumptions as well, but in practice, they are mainly based on data. They are representing probabilities of a behaviour. Various types of occupants can be represented either by different models or by variables related to the aspects modelled within one model. The outcome is a distribution of behaviours/ energy demands and the variety is shown by results of different models or the distribution of one model.

About driving forces

The adaptive principle relies on the notion that discomfort is the driver for adaptive actions and as such for occupant behaviour. As it was raised in the description of the theoretical model and the following analysis with regard to the purpose of behaviour, human occupant behaviour is affected by several factors. The performed literature review (PAPER I) highlights that what seems to be a simple task, as to open or close windows, is in reality a task that is influenced by many factors, which interact in complex ways. It has been highlighted how a shared approach on identifying the driving forces for occupants' window opening and closing behaviour has not yet been reached. Generally, most studies focus on determining the most important drivers and put little emphasis on the variables that do not show up as drivers. However, the reporting of variables found not to be drivers may reveal contradictions in the obtained results and may be a significant tool to help direct future research.

The various types of energy-related occupant behaviour are not isolated phenomena, but rather a combination that should be investigated in relation to each other. Information in the literature on the relationships between different types of energy-related occupant behaviour is however limited; more research is needed for a better understanding of the relationships. The description of the dynamics regulating the relationship between occupant behaviour and energy consumption is still an unresolved problem. In this sense, it is fundamental to apply approaches in the interpretation of the phenomena shared as much as possible.

About statistical modelling

Statistical analyses were used to determine the factors that influence energy consumption. The analyses carried out in this research were exploratory in nature. The objective was to deliver relationships between different variables (occupant behaviour, household characteristics and building characteristics) which would then deepen the understanding of the relative influence and interaction between the variables and pave the way for energy-consumption predictions for certain groups.

Using logistic regression to infer the probability of a window opening or closing event, we have assumed that the probability function looks like in the formula and that all observations were independent of each other. Essentially the assumption would hold true if all inhabitants of the dwellings reacted similarly to the conditions they were subjected to. In any other case the observations in each dwelling will be influenced by the habits of the inhabitants of the individual dwelling and as a result they would not be independent from each other. We have dealt with this problem by using the number of the individual dwelling as a factor in the first attempts to infer models. Interactions between variables and dwelling number were taken as signs of dependence and the variables were removed from the final models. In doing so, we may have removed variables that had an influence on the opening/closing probabilities.

It was chosen to use the Akaike information criterion (AIC) as a basis of variable selection in the inference of the models. Another option would be to use Wald tests to test the significance of each term and use this as a selection criterion. We chose to use the AIC, since selecting variables based on their significance does not take the risk of over fitting into account. This risk increases with the number of observations. The AIC includes a penalty that increases with the number of estimated variables in the model, which discourages over fitting.

About simulation

The models used in the analysis were based on actual measured interaction of building occupants with the within the indoor environment. The probabilistic distribution curve obtained as output results reported in paper III (Figure 1) shows an unexpected narrow range of variability, and could be attributed to the degree of opening of the windows that was sometimes very small causing a small variability on the air change rate. The degree of opening was calculated with a linear regression based on the measures coming from only three windows.

Only a singular interaction with the built environment was simulated (either window opening nor heating set-point adjustments) with the probabilistic approach, while the other user interactions with building (i.e. artificial lighting, blind adjustments, occupancy profiles) were simulated with the standard approach. This could have contributed to the unexpectedly narrow range of variability. Moreover, by merging the dwellings in groups inner dynamics of a single dwelling are lost and the specific behaviour is flattened in the groups as well. Further research to deepen this topic are required and they should analyse in a statistical way the single behaviour of each dwelling in order to obtain a specific model of user behaviour and randomly simulate these different behaviours in order to better represent users' variability.

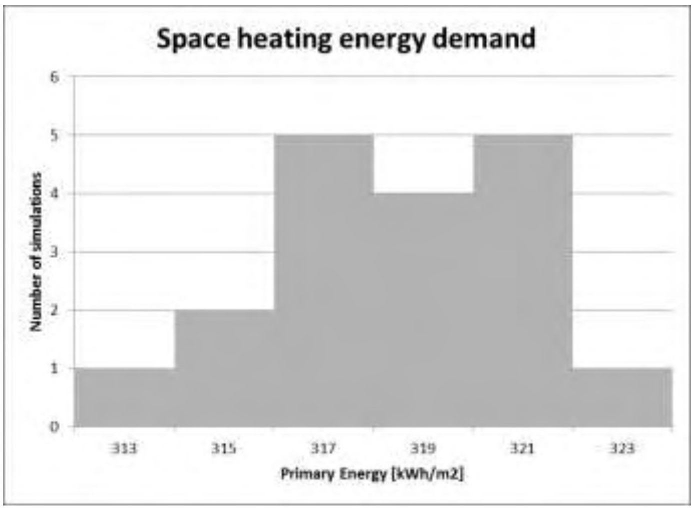

Figure 1. Distribution of space heating energy demand for Group IV occupant types (PAPER III)

The approach proposed here can be extended to cover heating/cooling set points, use of solar shading and other actions that occupants take with an influence on indoor environment and energy consumption. The approach can be used to study variations in thermal mass, facade percentage of transparency or shading devices with the aim of constituting recommendations for improved buildings design with regard to energy reduction.

About validation

The model will not predict the behaviour of the occupants 100% accurately. Occupant behaviour is highly individual and to some extent random. As a consequence, no model will be able to predict perfectly the behaviour of one particular occupant, and in this sense we cannot say of much is 20% accuracy. Moreover, the cross-validation method here proposed is just a way to validate the models. Another way to do it consists of taking the energy consumption of n similar houses and see by simulation if the curve of obtained energy consumption is close at the real energy consumption curve.

Suggestions for future work

Whole building simulation model outputs are currently often singular values, often leading to false confidence that estimated building energy consumption will match simulated results. A range of estimated energy consumptions integrating high, typical, and low energy consuming behaviours can be determined by integrating the results of various two-step models such as average, agent-based, or action-based models in order to represent occupant behaviour in greater detail in building energy simulations. The range of values can be applied to provide various building energy use scenarios such as those needed for energy certificates, large scale energy models, or long-term energy predictions. When used for the energy certificates for individual buildings, the energy use scenarios may be used to predict the impact of their own energy use decisions to the home and building owners and building occupants.

Building users adapt their energy-related behaviour to changes in their local environment including changes in building technologies. Based on collected field data from longitudinal studies, energy use models can be built representing the adaptation of occupants at different stages to changes in building services and building quality resulting from thermal renovations. This behaviour may also be referred to as "learning behaviour".

Current energy use models mainly concentrate on "business as usual" scenarios. Dynamic occupant behaviour models may also be applied in energy use estimations for unstable energy supplies or energy disruptions caused by natural disasters to predict the range and impact of individual conservation measures over short and long time periods.

The introduction of new construction methodologies and building technologies may incur a higher probability of error in the design, construction, and commissioning phases of a building than following traditional building practices until the technologies become common practice. Errors in the phases prior to occupancy can potentially affect the overall thermal comfort in the buildings and effectiveness of occupants to modify their surroundings to meet their comfort criteria while meeting a building's energy use targets. Thus, risk assessments may be conducted considering various scenarios of construction and installation defects and the relative remedial, maintenance, and operation costs in conjunction with the range of occupant responses to meet both comfort and energy criteria.

Although studies have been conducted for occupant satisfaction/dissatisfaction and occupant behaviour in residential settings, further research into the combined impact of design decisions, commissioning settings, and operation/maintenance decisions on thermal comfort and occupants' wellbeing may provide further insight into the actions occupants take to adapt to their surroundings.

VI. CONCLUSIVE SUMMARY

In this dissertation energy-related occupant behaviour was studied by means of literature review, measurements and simulation in order to elaborate a general methodology to take into account this uncertainty in the energy consumption.

The main purposes of this methodology regard:

- The identification of those factors having a major influence on the occupant behaviour
- The implementation of probabilistic models into a dynamic building energy simulation software
- The evaluation of the building energy consumption in relation to the differences in occupant behaviour related to window opening and closing the preferences of the heating set-point.

The investigations are standing on three pillars:

- A comprehensive literature review not only including publications within the field of built environment research, but also in the social science area
- A field measurements conducted in residential buildings gathering quantitative physical and behavioural data of 15 dwellings
- Implementation on building energy simulation software and verification of the obtained statistical occupant behaviour models for assessing their impact on building energy consumption and their predictive power.

Contribution of the proposed probabilistic methodology

The probabilistic methodology for occupant's behaviour open new perspectives for building energy simulation software. The following issues currently ignored by deterministic approaches are of particular interest and can be tested in the near future:

Increased accuracy. The integration of occupant behaviour will improve the realism of building simulation results enabling the energy and comfort implications of building design and controls to be more reliably assessed at the design stage.

Improved basis for low energy design. In the particular case of passive and low energy buildings, where the behaviour of occupants has a particular crucial impact, this method has a special interest.

Energy consumption variability study. The probabilistic output proposed in this methodology, which yields to a distribution of results rather a fixed value, could be used for assessing the variability of energy demand and indoor conditions.

Robust Design solution. The design of buildings which are robust to a wide range of behavioural types is made possible and verifiable, by directly testing the impact of specific action probabilities on a building energy performance.

Longer term perspectives

This thesis provided a new methodology for precise prediction of actual users energy profiles, and for the forecast of the leverage of occupant behaviour. In spite of these advances there is a considerably scope for further improvements in behavioural modelling and its applications in dynamic building energy simulation tools.

Based on the results and their implication the following researches seem to be promising:

- The outcomes of this research showed that occupant behaviour is not only influenced by various external factors: Energy consumption patterns are a complex technical and social topics and by consequence to fully understand this phenomenon, it must be viewed from both engineering and social science perspectives. As consequence a shift in the direction of engineering research related to energy and environmental performance of buildings is needed towards a focus on human-centred concerns
- The analysis presented so far were done for one single action, such as open the widow or turn up the heating set-point. As mentioned previously, the occupant has to choose between several options to achieve thermally comfort conditions. In order to integrate this choice analysis or other statistical methods, the concept of utility used in discrete choice analysis will be interesting to come up with a more complete model of occupant behaviour.
- In the present research it has been highlighted a first of improvement for the building energy simulation software regarding the input and output parameters related to the occupant behaviour. Moreover, improvements of simulation tools could be achieved in the field of control and action logics. Controls regard HVAC systems and in general, equipment, actions regards occupant behaviour. Calculation tools should be used to set up different control and action scenarios, developed in order to maintain the required indoor environmental quality levels with minimum energy consumption at different design stages of the building.

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VIII. Ph.D. Publications

PAPER I

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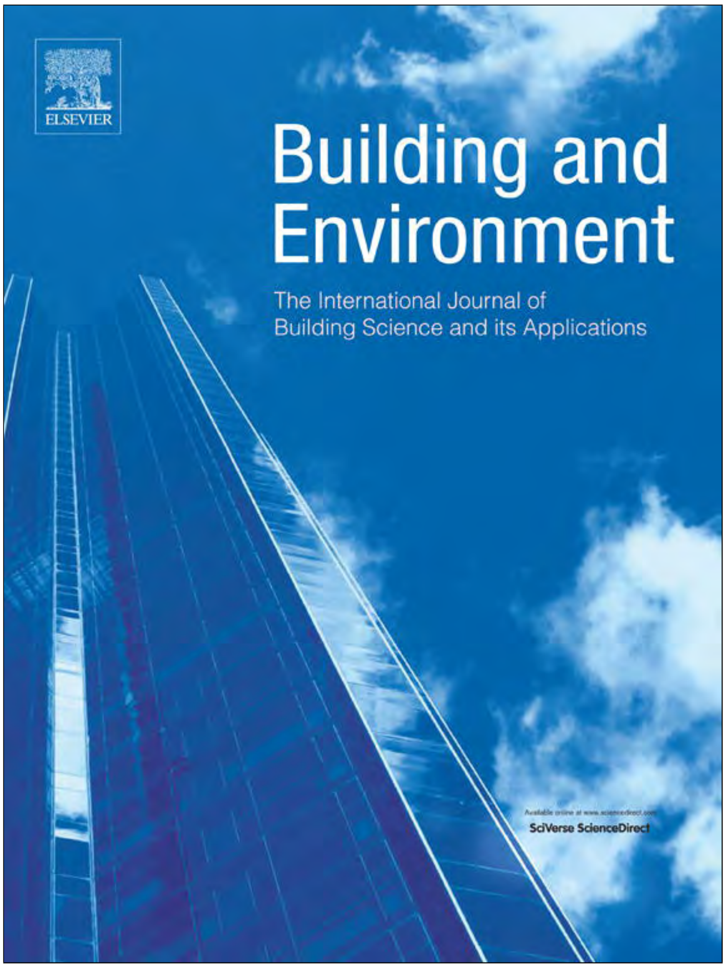
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Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models

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ABSTRACT

Energy consumption in buildings is influenced by several factors related to the building properties and the building controls, some of them highly connected to the behaviour of their occupants.

In this paper, a definition of items referring to occupant behaviour related to the building control systems is proposed, based on studies presented in literature and a general process leading to the effects on energy consumptions is identified.

Existing studies on the topic of window opening behaviour are highlighted and a theoretical framework to deal with occupants' interactions with building controls, aimed at improving or maintaining the preferred indoor environmental conditions, is elaborated. This approach is used to look into the drivers for the actions taken by the occupants (windows opening and closing) and to investigate the existing models in literature of these actions for both residential and office buildings. The analysis of the literature highlights how a shared approach on identifying the driving forces for occupants' window opening and closing behaviour has not yet been reached. However, the reporting of variables found not to be drivers may reveal contradictions in the obtained results and may be a significant tool to help direct future research.

1. Introduction

The behaviour of building occupants can have large effects on building energy use, and it results in huge gaps between real and predicted energy performance of buildings. The differences between real and predicted energy use depends on differences between the predicted and actual final realisation of the construction, technical installations, and the real use of the built systems operated by occupants [12,49,55]. Recently, it has been shown that occupant behaviour plays a fundamental role on the amount of energy used in buildings, e.g., by the time and type of window opening, the use of air-conditioning (AC) units or the choice of indoor temperature set point [4,29,34,62,66]. Consequently, the occupant has a great influence on the variation of energy consumption in different kinds of buildings: several studies [20,48,69,71] have shown that the behaviour of the household members may vary to such an extent that residential energy use differs by a factor of two, even when the equipment and appliances are identical [11,28,57]. Haas et al. [31], and Filippìn et al. [24] state that occupant behaviour affects energy use to the same extent as mechanical parameters, such as equipment and appliances: in an experimental study conducted over 3 years in multifamily buildings in Switzerland, Branco et al. [12] noted that the real energy use was 50% higher than the estimated energy use (246 MJ/m^2 as opposed to 160 MJ/m^2). The differences between the two values were due to the real conditions of utilisation, the real performance of the technical system and the real weather conditions. In the case described by Branco et al. [12], assumptions made about the behaviour of the occupants were not in agreement with the real behaviour of the occupants. In that case, a more realistic model of the occupants' behaviour patterns would have narrowed the gap between predicted and actual energy use. A vital part of developing such models is to know which variables to take into account, i.e., the variables that affect the occupants' behaviour patterns.

In literature, different energy end-uses determined by technical and architectural characteristics and by the occupants' behaviour have been studied. In this paper, a literature review regarding the relationship between occupants' interactions with building controls and the effects on the indoor environment and energy consumption is presented. Specifically, the paper is focussed on the topic of natural ventilation, and in particular on window opening behaviour, taking residential and office buildings into account. In

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the paper, the literature for evidence of factors with an influence on occupants' window opening behaviour is surveyed.

2. Occupant behaviour: a complex process

Much is still unknown about the motivation of the building control related occupant behaviour. Occupant behaviour is influenced by quite a large number of causes, both "external" to the occupant itself (e.g., air temperature, wind speed), and internal or "individual" (e.g., personal background, attitudes, preferences) and building properties (e.g., ownership, available heating devices) [5,67].

It is worth to highlight, that occupants' interactions with building control systems are only one aspect of human behaviour. Human behaviour can be expressed throughout the results of a continuous combination of many factors crossing different disciplines, from the social to natural sciences.

Concerning the building science area, occupant behaviour related to building control systems has traditionally been connected above all to indoor and outdoor thermal conditions. In early studies, the outdoor air temperature accounts for most of the variations in the interaction of the occupants with the elements of the built environment (e.g., windows or radiators) [13,17]. These parameters can be named as "external factors" as proposed by Schweiker [67] and the number of studies concerning them have increased in the last years [5,32,51,52,66].

In the field of social sciences, human behaviour is set in relation with causes which could be called "internal or individual factors" (Schweiker [67],), such as preference, attitudes, cultural background and so on. In addition to external factors, they influence the occupant behaviour with a range of cognitions and actions in a very complex way. Research on the individual factors leading to one action rather than another has been conducted in the field of behavioural psychology [1,2,27,61].

The theoretical basis of the following analysis is the so-called "adaptive approach", which states that "if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort" [54]. According to the adaptive approach, if an individual is in a state of discomfort, then she/he will take actions that would restore a state of wellbeing.

The adaptive approach [16] is based on the notion that the occupants' level of adaptation and expectation is strongly related to outdoor climatic conditions: in this way, at the base of adaptive model of comfort is the belief that the occupants consciously or unconsciously, play an active role in realizing indoor environmental conditions. In general, research has demonstrated that occupants are more comfortable and suffer fewer SBS symptoms when they have a high degree of control opportunities and a freedom of choice to adapt their conditions in a clear and intuitive way [72,73]. Furthermore it has been demonstrated that small adaptive changes (for instance clothing or posture) can lead to dramatic differences in physiological comfort [7,53].

It is important to note that to choose the adaptive approach for a building at the design stage implies by consequence to provide building occupants with rich opportunities of interacting with controls. However, the higher level of satisfaction and lower level of SBS symptoms also apply for buildings designed using the conventional approach [72]. By consequence, providing the occupants with rich opportunities seems to be beneficial, regardless of the design approach. But doing so implies a larger degree of influence by the occupants on the indoor environment and energy consumption.

As a consequence, the behaviour of the occupants becomes increasingly important and the consideration of occupants' behaviour in the design process becomes a necessity.

Hoes et al. [35] conducted a study on the effects of occupant behaviour on the simulated energy performance of buildings and concluded that the simple approach used nowadays for design assessments applying numerical tools are inadequate for buildings that have close interactions with the occupants. The approach of analysis through simulation has been used by Corgnati et al. [15] for the assessment of categories of indoor environmental quality and building energy demand for heating and cooling. They highlight that the comfort requirements by occupants in terms of thermal conditions and indoor air quality in buildings represent a high expense of energy. So in the challenge of reducing the environmental impact, it is important to understand the occupant interactions with the indoor environment in order to provide comfortable conditions in the most efficient ways.

2.1. Steps of behaviour

The general process leading from occupant behaviour driving forces to energy consumption can be identified as shown in Fig. 1 [22] and described in the following.

Factors influencing occupant behaviour, both external and individual, that could be named with the general term *"Drivers"*, are the reasons leading to a reaction in the building occupant and suggesting him or her to act (they namely "drive" the occupant to an action).

These drivers have been divided into five groups: physical environmental factors, contextual factors, psychological factors, physiological factors and social factors.

- Physical environmental:

Examples of physical environment aspects that drive occupant behaviour with an effect on energy consumption are temperature, humidity, air velocity, noise, illumination, and odour.

- Contextual:

Contextual drivers are factors that have an indirect influence on the human being. They are determined by the context. The insulation of buildings, orientation of façades, heating system type, thermostat type (e.g., manual or programmable), etc. are examples of contextual drivers.

- Psychological:

Occupants tend to satisfy their needs concerning thermal comfort, visual comfort, acoustical comfort, health, safety, etc. Furthermore, occupants have certain expectations of e.g., the indoor environmental quality (temperature, etc.). Other examples of psychological driving forces are awareness (e.g., financial concern, environmental concern), cognitive resources (e.g., knowledge), habit, lifestyle and perception.

- Physiological:

Examples of physiological driving forces are age, gender, health situation, clothing, activity level, and intake of food and beverages. These factors together determine the physiological condition of the occupant.

- Social:

Social driving forces refer to the interaction between occupants. For residential buildings this depends of the household composition (e.g., which household member determines the thermostat set point or the opening/closing of windows).

With reference to indoor environmental quality, the occupant reacts consciously or unconsciously to an external or internal stimulus ("Occupant Stimulus" in the flux diagram proposed in Fig. 1) in order to improve, restore or maintain the comfort conditions (thermal, lighting, acoustics, indoor air quality,…). In this way, the occupant becomes the central operator with control of the energy consumption. In such a way, occupant behaviour can be defined as proposed by Schweiker (2010) [67] "*a human beings unconscious and conscious actions to control the physical parameters of the surrounding built environment based on the comparison of the perceived environment to the sum of past experiences*". The physical parameters can be different: visual, auditory, olfactory and, in particular, thermal.

This is a quite exhaustive definition, but it only takes the perceived environment into account and in this sense is restricted to the field of physical environmental sciences. It does not describe the connection with the environmental education and social science. For example, Andersen [3] found that some people ventilated by opening the windows for 10 min at the same time every day, regardless of the environmental conditions. This behaviour was driven by concerns about health effects of poor indoor climate and was not based on perception or past experience, but rather on knowledge and education.

The third point in the Fig. 1 is represented by the action scenarios. This term indicates the occupant reactions since she/he was stimulated by a driver or a combination of them. Window opening or closing, set-point changes, clothing changes are all examples of this kind of actions. In general, behavioural actions cannot be regarded singular, because they continuously interact with each other and the borders cannot be distinguished in every case. The reactions could be determined both by some "action logics" operated by the occupants themselves and by the system and equipments controls and partly by the building behaviour itself. Consequently, the term *"action scenarios"* has been chosen.

There are several possibilities for the occupants to control the indoor environment.

The control related actions performed by the occupants can be divided into changes that alter the environment to make it more comfortable, into changes that adapt the occupant to the prevailing environment and finally into actions that have an effect on the indoor environment indirectly. The first might be to adjust the heating set-point, to open/close a window, to turn lights on or off or to adjust the solar shading, while adjusting clothing, adjusting body posture and consuming hot or cold drinks fall into the second category. The third category include actions related to the chance of internal heat gains/energy use: operations of this second kind are the use of appliances and equipment (use of TV, refrigerator, etc.), use of hot water (taking bath or shower) and cooking [58].

All the operations aimed by the occupants to improve or maintain the indoor environmental quality have a consequence on the indoor environment. A variation in air change rates or room air temperature are examples of the "parameter variation" due to the window opening. Different action scenario outcomes could have a direct influence on both indoor environmental quality and on the energy consumption.

Indoor environmental quality and energy consumption are the "process output": their variability range could be very wide, as shown before, and depending on many variables.

It is significant to observe how this whole process is not a closed system, i.e., the changes brought by the effects of the action scenarios on energy use and indoor environmental quality are themselves an element of influence on "the drivers". Pushed to the desire to emphasize this continuity that is an inherent part of the process, it is more accurate to argue for a cycle of processes that influence user behaviour. In this way the energy consumption becomes a driver that affects the behaviour along with the environmental quality. The energy output could be minimum if actions scenarios are managed in a prudent way or maximum if the users follow actions logics scenarios maximizing the energy wasting. In this way, it is possible to identify different users' behaviour typologies depending on the way the actions sequences are performed. From an energy perspective occupants could be named "energy saving users" or "energy wasting users". From an indoor environmental perspective, occupants could be divided into air quality users or thermal comfort users or both.

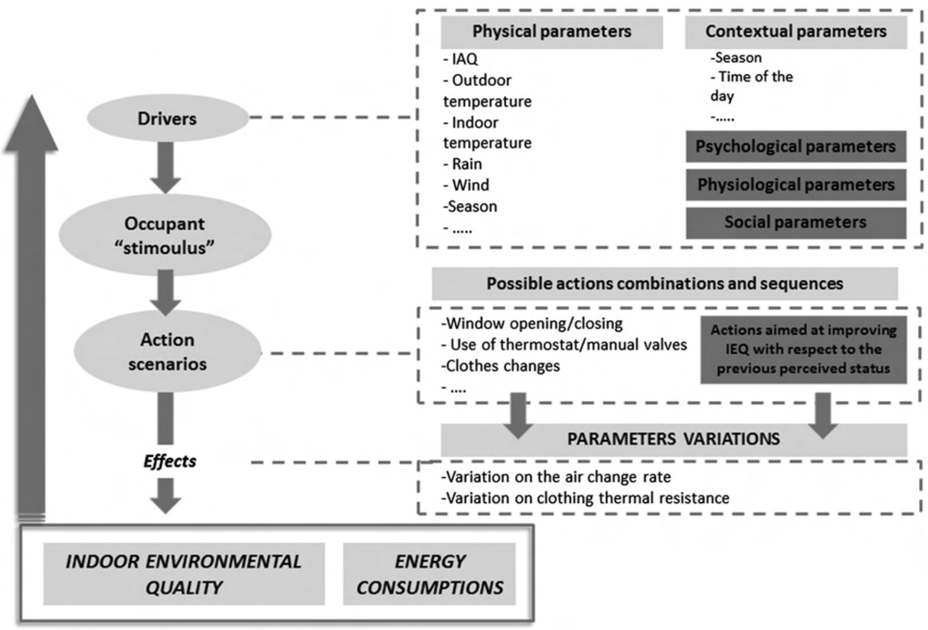

Fig. 1. Flux diagram: from drivers to energy consumption and indoor environment.

3. Effect of occupant behaviour on energy consumption in buildings

One way of highlighting and investigating the influence of occupant behaviour on the energy performance of a building is by comparing energy consumption of identical buildings.

Socolow [69] used this method, and the same approach was used by Sonderegger [70] and Seligman et al. [68]. They were amongst the first to point out that the behaviour of occupants had a significant impact on the energy performance of a building. In his paper Socolow [69], investigated energy consumption in 28 identical town houses and found the largest variation in energy consumption to be two to one. Furthermore, the energy consumption of the houses depended on the occupants. Sonderegger [70] measured gas consumption used for heating in 205 town houses located in the same group of houses as the study of Seligman et al. [68] and Socolow [69]. He found the highest consumption to be more than three times as high as the lowest consumption. 54% of the variance in gas consumption was explained by design features of the houses, such as number of rooms, area of windows etc. which left 46% of the variance unexplained by the design features. By comparing changes in gas consumption between two heating seasons of occupants who moved into the houses with that of occupants who stayed in the houses, they concluded that 71% of the unexplained variance was due to occupant related consumption patterns.

Also Gartland et al. [26] used the method of energy consumption comparisons. They monitored energy consumption in four houses of identical layout in Washington from 1987 to 1992. Two of the houses were built so they represented construction practices in the 1980s while the other two were better insulated and more air tight. They found that changes in heating set-point patterns accounted for as much as 27% of the total energy used for heating, while variations in the door and window opening behaviour accounted for up to 17%. The houses had a monthly average infiltration rate of 0.6–1.9 h^{-1} which is much higher than what was found by Offerman [56] and Price and Sherman [59] in Californian homes. A comparison of the energy consumption in the four houses revealed that the behavioural variations became more significant in the buildings that were better insulated and more air tight. As such, a lower infiltration rate would conserve energy but increase the impact of occupant behaviour on the energy consumption.

In a more recent study, Juodis et al. [41] compared energy consumption for space heating and domestic hot water in 2280 similar apartment buildings in Lithuania. They found the factor between highest and lowest consumption to be between 1.22 and 1.7, when comparing identical buildings. The comparison was made on a building level and did not include analysis of differences between apartments. The authors conclude that the observed differences originate from differences in initial design and construction uncertainties and they do not discuss differences in occupants behaviour patterns. While the diversity of the apartments' construction will have an effect on the different energy performances of the buildings, it seems evident that the occupants' different behaviours significantly affect the consumption. As a consequence, it would be worth to take the occupants' behaviour into account in the analysis.

Maier et al. [48] used the method of comparing identical buildings on 22 houses in Germany, comparing energy consumption over a two year period. Apart from the ventilation principle, the houses were identical. Amongst the 12 houses that were ventilated identically, the highest consumption was 2.84 times higher than the lowest consumption. The house with the lowest consumption of energy had the lowest average temperature implying that the occupants had a behaviour aimed at conserving energy by having a lower heating set-point in the heating season.

While some scientists use energy consumption comparisons to infer the effects of occupant behaviour on energy consumption, others have used questionnaire surveys to investigate the determinants for energy consumption. This method was employed by Sardianou [65]. She found that the age of the respondent, family size, annual income, and size and ownership status of the dwelling impacted the consumption of oil used for space heating. This indicates that the socioeconomic status has an impact on the behaviour patterns of occupants.

Also Guerra-Santin and Itard [30] conducted a questionnaire in Dutch households. With a response rate of 5% they were able to explain 11.9% of the variance in energy consumption using three behaviour variables. Furthermore they found that the type of heating system and ventilation system had an influence on the behaviour of the occupants.

A further analysis that could allow an overall view of both the performance of buildings and the subjective indications given by users could be to compare the data obtained through questionnaires with the results of analysis of real measurements in field.

These studies showed that occupant behaviour does indeed have a very large effect on the energy performance of buildings (Table 1). This underlines the need for guidelines or models of behaviour patterns for implementation in simulation programs.

3.1. Influence of window opening behaviour on air change rate

One parameter having a high influence both on the energy consumption and on indoor environmental quality is the air change rate. Since the thermal load for ventilation is related to the air change rate, a close examination of this indicator is important to consider when investigating the effects of the occupant behaviour.

The air change rate is affected by the occupants' behaviour, indoor environment and weather, but how dependent is the air change rate on the behaviour of the occupants?

As early as 1943 Bedford et al. [8] conducted 358 measurements of the air change rate in six properties in London using the decay of coal-gas (containing about 50% of hydrogen) liberated into the air. They discussed the effects of flues, air gratings, cracks and leakages

Table 1
Major findings in literature about variation of energy consumption due to the occupants.

Paper	Number and type of dwellings	Measured consumption	Max/min consumption [-]	Variance in consumption explained by occupant behaviour [%]
Seligman et al. (1977/78)	28 town houses	Gas and electricity	2	
Sonderegger (1977/78)	205 town houses	Gas used for heating	3	33
Socolow (1977/78)	28 town houses	Gas used for heating	2	
Gartland et al. ASME 1993	4 houses	Electricity used for heating		
Juodius et al. EaB 2009	2280 similar apartment buildings		Between 1.22 and 1.7	
Maier et al. (2009)	22 houses		2.84	
Gerra-Santin and Itard BRaI 2010	Questionnaire survey of 313 households	District heating and gas for heating		11.9

on the air change rate in the houses and finally noted that any reasonable amount of ventilation could be obtained if liberal window openings were provided. They obtained as many as 30 air changes per hour by means of cross-ventilation in experimental rooms. Since then, houses have been tightened and sealed, increasing the relative effect of window opening on the air change rate. In fact, when Wallace et al. [74] measured air change rates in a house in Virginia during a year, they found that the window opening behaviour had the largest effect on air change rates, causing increases ranging from a few tenths of an air change per hour to approximately two air changes per hour. In another paper describing the same measurements Howard-Reed et al. [36] stated that opening of a single window increased the air change rate by an amount roughly proportional to the width of the opening, reaching increments as high as 1.3 h^{-1}. Multiple window openings increased the air change rate by amounts ranging from 0.10 to 2.8 h^{-1}.

Bedford et al. [8], Wallace et al. [74], Howard-Reed et al. [36] and Offerman et al. [56] focussed on the exposure to contaminants at low air change rates. While Bedford et al. [8] found an average air change rate of 0.8 h^{-1} and with only 11% of the measurements under 0.4 h^{-1} in London, Offerman et al. [56] found that 75% of homes without mechanical ventilation had air change rates lower than 0.35 h^{-1}, suggesting that homes had been tightened to such an extent that occupants needed to actively adjust building controls to obtain adequate supply of fresh air. Also, Price and Sherman [59] found that, depending on season, between 50% and 90% of Californian homes had air change rates lower than 0.35 h^{-1}. The results of Offerman et al. [56] and Price and Sherman [59] suggest that many houses in California are under-ventilated according to local standard recommendations because ventilation systems are too small and because the occupants do not operate the windows adequately. This was especially evident in the winter months implying that the occupants opened windows to a smaller degree in winter than in summer (Table 2).

According to Keiding et al. [42] who conducted a questionnaire survey in Danish Dwellings, 53.1% slept with an open window during autumn while 25.2% had a window open during the night in winter time, which in most situations should ensure an air change rate of more than 0.35 h^{-1}. They found that 91.5% of the respondents vented by opening one or more windows each day throughout the year. The results showed that a large proportion of Danish occupants use windows to adjust the supply of fresh air to the dwelling. Since the lowest temperatures occur during night time in winter, the effects of this behaviour on the energy consumption might be substantial. However, when Bekö et al. [9] measured ventilation rates in 500 bedrooms, they found that 57% of the bedrooms had a lower air change rate than 0.5 h^{-1}. In a later paper Bekö et al. [10] attempted to model air change rates based on the same measurements. Their best model explained 46% of the variance in the air change rates. This model contained variables related to both building characteristics and behaviour, while models inferred only from variables that are related to building characteristics or occupant behaviour explained 9% and 30% of the variation, respectively (Table 2).

Kvistgaard et al. [43] measured air change rate and temperature in 16 Danish dwellings and found an average air change rate of 0.68 h^{-1} (Table 2). They suggested a classification of air change rates as follows:

- Basic air change: Air change of unoccupied house with all windows and door closed. Varies with wind velocity and interior/exterior temperature differences.
- Air change from ventilation system: air change from a mechanical ventilation system, if it exists in the building.
- User-influenced air change: air change caused by window and door opening.
- Total air change: the sum of the three categories above.

In a later paper Kvistgaard and Collet [44] noted that there was considerable difference in the total air change between the individual dwellings. As the basic air change was fairly similar in the dwellings, it was concluded that it was the user influence on air change (i.e., the behaviour of the occupants) that caused these large differences. This conclusion was confirmed by Weihl [76], who concluded that a substantial variation in ventilation behaviour found among seven households, reflected different occupant functions and management strategies.

Iwashita G and Akasaka [38] were able to quantify the effect of occupant behaviour on air change rate. They investigated the relationship between occupants' behaviour and the energy consumption used for air conditioning, by means of tracer gas measurements and questionnaire surveys in Japan, and concluded that 87% of the total air change rate was caused by the behaviour of the occupants.

The studies mentioned above show that air change rates vary significantly from home to home and the window opening behaviour of the occupants has a considerable effect on the air change rate. We have not been able to find studies investigating the direct connection between air change rate and energy consumption, but since the air change rate has a big impact on the energy consumption it is evident that different behaviour patterns will result in differences in energy consumption. One aspect that affects the air change rate is how often and for how long the windows are opened but also the degree of opening will have an impact.

4. Windows opening behaviour: identification of driving forces

Several studies have been carried out in recent years regarding air change rates, indoor air quality and window opening habits in

Table 2
Major findings in literature about variation of air change rate due to the occupants.

Paper	Number and type of dwellings	Measurement method	Average air change rate [h^{-1}]	Percentage of measurements lower than 0.4 h^{-1}
Bedford et al. (1943)	358 observations in 6 properties	Decay of Hydrogen	0.8	11%
Wallace et al. (2002)	1 single family house	One year (SF6 as tracer gas)	0.65	–
Offerman et al. (2008)	73 new naturally ventilated single family houses	24 Hours (PFT tracer gas)	Not stated (median: 0.25)	75% lower than 0.35 h^{-1}
Price and Sherman (2006)	1515 new single family houses	Questionnaire survey	–	Between 50% and 90% lower than 0.35 ACH
Kvistgaard et al. (1985)	16 single family houses	205 days (N_2O and SF6 as tracer gas)	0.68	20%
Bekö et al. (2010)	3–5 days of measurements in 500 bedrooms	Build-up of CO_2 emitted by occupants	0.46	–

residential buildings [18,46,47,64]. These studies revealed that in residential buildings with natural ventilation the occupants' ventilation behaviour is the most important variable in the determination of the air change rate.

In particular, the topic of occupant behaviour with regard to control of the indoor environment has mainly been studied with two aims: investigating the window opening and ventilation behaviour to find if occupants are provided with adequate fresh air, and energy related investigations of occupant behaviour. The former category of studies has usually been carried out in dwellings and has had a health or a comfort perspective, while the latter category has focussed on studied in offices with a comfort, and energy performance perspective.

Even though dwellings are responsible for consuming more than a quarter of the total primary energy in the EU member states [19], the studies that are aiming at implementing realistic behaviour patterns in simulation programs have been based mainly on occupant behaviour in offices [32,34,62].

Analysing the results of several studies conducted both in residential and in office buildings [18,29,33,34,38,62,63,71], there is a distinction to be made within the factors influencing the occupant behaviour in relation to the natural ventilation. These factors can be named as "drivers" of the behaviour as discussed before (Fig. 1). In the following Tables 3 and 4, the major parameters found in literature driving the occupant behaviour aimed at controlling the indoor environment in relation to natural ventilation are split into five categories of influencing factors for residential and office buildings.

4.1. Residential buildings

Since the effectiveness of natural ventilation is strongly dependent on characteristics of ventilation openings and their controllability (aspects closely related to the type and size of the windows and its placements within facade) the window opening and closing behaviour is strictly connected to the building characteristics. Type of dwelling (single house or apartment), orientation and type of the room (bedroom, living room or kitchen) are the main parameters found to have an influence on occupant behaviour related to window opening and closing [18].

The study of IEA – ECBCS Annex 8 [18] on occupant behaviour with respect to ventilation involving Belgium, Germany, Switzerland, the Netherlands and the United Kingdom focussed on a combination of questionnaires and observations to determine which action is taken by occupants to ventilate their homes and to evaluate their reasons for these actions. The study showed that the type of dwelling (house or apartment) influences the length of time windows are open and has an effect also on how wide windows are left open. In the same research it appeared that in houses compared to apartments' windows in living rooms and kitchens were open on average for shorter periods, whereas windows in bedrooms were open for longer. The type of the dwelling (detached one-storey residence) was found to affect the residential openness in a pilot study conducted by T. Johnson and T. Long [40] in North Carolina between October 2001 and March 2003.

According to the study of IEA – ECBCS Annex 8 [18] the main ventilation zones are bedrooms, while the greatest percentages of windows never opened are in living rooms, kitchens and bathrooms. This finding is consistent with the findings of H. Erhorn [21] in 24 identical flats in Germany. Even in the extreme winter weather, bedrooms were ventilated more frequently than all of the rooms on averageand the windows opening time in bedrooms exceeded the average for all rooms by some 50% during the entire measuring period. The orientation of rooms is important as well. The IEA – ECBCS Annex 8 project [18] found that, when the sun was shining, south facing living rooms and bedrooms were more likely to be ventilated for longer periods than similar rooms orientated in other directions. It seems most likely that it is the effect of solar radiation and temperature, rather than the orientation itself that affected the occupants' window opening behaviour.

The investigations have shown different daily patterns for the different types of the rooms. Typically, the maximum of window openings occur in the morning. During early afternoon (when cooking) the number of open windows is still relatively high but gradually decrease during the afternoon till the return home of working inhabitants (at about 5 p.m.) [18]. Time of the day is found to determine the transition probabilities (closed to open and open to closed) in the aforementioned study of Johnson and Long [40].

Looking at opening frequency and transition probability are quite different approaches. The strengths to analyse the open frequency is that it is easier to measure. Noting the window position and the present conditions every hour (or even every day) results in a dataset that could be used to infer the probability of having a window open. But since the indoor conditions are affected by the window position, it is problematic to use these as explanatory variables in the model.

This problem can be overcome by inferring the probability of opening and closing a window (transition probabilities) instead of looking at the window state probability. On the other hand the problem of this method is that it can only be used if the conditions just before an opening/closing event are known. As a consequence, data with a much smaller timely resolution is needed to acquire data on the environment before the transition.

The window opening behaviour is strongly related with the perception of comfort with respect to the microclimate in dwellings. Due to this correlation the most important environmental parameters are investigated in many studies.

Not surprisingly the outdoor temperature had a considerable impact on the window opening behaviour. An early study of J.B. Dick and D.A. Thomas [17] found that the outdoor temperature was

Table 3
Driving forces for energy-related behaviour with respect to ventilation/window operation in residential buildings.

Physiological	Psychological	Social	Physical environmental	Contextual
Age	Perceived illumination	Smoking behaviour	Outdoor temperature	Dwelling type
Gender	Preference in terms of temperature	Presence at home	Indoor temperature	Room type
			Solar radiation	Room orientation
			Wind speed	Ventilation type
			CO_2 concentrations	Heating system
				Season
				Time of day

Table 4
Driving forces for energy-related behaviour with respect to ventilation/window operation.

Physiological	Psychological	Social	Physical environmental	Contextual
		Shared offices	Outdoor temperature	Window type
			Indoor temperature	Season
			Solar radiation	Time of day
			Wind speed	
			Rain	

the single most important explanatory variable when investigating the number of open windows in 15 houses. Most of the investigation in the IEA – ECBCS Annex 8 project [18] have shown that in the temperature range between −10 °C and +25 °C a direct linear correlation exists between window use and outdoor temperature. Brundrett [13] found the temperature (mean monthly temperature and average temperature swing) to be an important explanatory variable for the occupant's opening of windows. Erhorn [21] found that a change in ventilation behaviour was stated at temperature of 12 °C. Below 12 °C, daytime ventilation increased by 75% per degree temperature differences and by 1.1% per °C. above 12 °C. In terms of ventilating frequency this represents an increase of about 50%. The results of Andersen [3] are consistent with these findings. The statistical analysis related to the questionnaire survey carried out in 2006 and 2007 in Danish dwellings has shown that window opening behaviour is strongly linked to the outdoor temperature. Recently, the results of logistic regression model based on a long-term monitoring of behaviour and environmental variables into 15 dwellings confirm that outdoor temperature, indoor temperature, solar radiation and the indoor CO_2 concentration were the most influencing variables in determining the opening/closing probability [6].

Erhorn [21] tried to correlate the season with window opening behaviour and found that windows were open longest in summer and shortest in winter This finding was supported by the successive study conducted by Herkel et al. [34] in office buildings, where the percentages of open windows were highest in summer, lowest in winter and intermediate in autumn and spring. Regarding the seasonal variations, the open question is if the season itself or the changes in outdoor conditions that drive the occupant behaviour.

The IEA – ECBCS Annex 8 [18] showed that windows are opened more often and for longer periods in sunny weather. The finding of Andersen et al. [6] fit with these earlier studies. In Erhorn's investigation [21] a distinct dependence on solar radiation cannot be confirmed, as the influences of outdoor air temperature and global irradiance are superimposed.

The influence of wind speed was investigated in the aforementioned studies [18,21], and the results show a significant decrease in the prevalence of open windows at high wind speed. Dubrul [18] found that nearly all windows were closed at wind speeds above 8 m/s.

Based on an average wind velocity of 3 m/s Erhorn [21] proposed to introduce the wind influences as a correction term for temperature-related window ventilation periods. While this might be viable way forward, it would give a clearer picture of the relation, if multiple regression is used, which would allow for the inclusion of wind speed as an explanatory variable.

The interaction between occupant's gender and perceived illumination had a statistical impact on the window opening behaviour [5]. Since the influence of perceived illumination has not been investigated by others, this result has neither been confirmed nor challenged.

The investigation of Guerra-Santin and Itard [30] of households in the Netherlands in autumn 2008 showing that the behaviour of elderly people significantly differed from that of younger people, fit with the results of IEA – ECBCS Annex 8 [18], who reported that the window position was affected by the presence of children.

IEA – ECBCS Annex 8 project [18] highlighted a clear correlation between smoking behaviour and the airing and ventilation of living rooms. Moreover, the longer the dwelling is occupied the more the windows, especially the bedroom windows were kept open, and in this way the Annex 8 concluded that the presence of the occupants in the home and use of the windows were related. No other of the surveyed studies took into account the occupant lifestyle as explanatory variable of the model.

Finally, Dubrul [18] noted that indoor climate preferences in terms of temperature are one key driver of the behaviour of the occupants, but this driver is strongly connected to the occupant's perception of comfort.

In summary, the previously identified driving forces for energy-related behaviour with respect to ventilation/window operation in residential buildings are grouped and listed in Table 3.

4.2. *Office buildings*

Based on field surveys many studies have focussed on monitoring user behaviour in offices to identify the influential variables. These studies have focussed on energy consumption and thermal comfort, which are affected by the use of manually-controlled windows.

Field studies about window operation and its impact on energy consumption (heating, primarily) date back to the 1980s in office buildings. Since studies in homes found that weather (temperature, humidity, wind) could explain a majority (∼65–70%) of window interactions [13,17], Warren and Parkins [75] applied similar methods to five naturally-ventilated office buildings in the UK and found outdoor air temperature to explain 76% of variance in window state, and that solar gain and wind speed also played a role (8% and 4% respectively). In addition to field monitoring, the study asked occupants why they used windows, and found fresh air to be the most common reason for opening windows in both winter (51%) and summer (74%) and of equal importance to "keeping cool" during the summer. Although air quality wasn't used as an independent variable for analysing behaviour, an analysis of small/slightly open windows compared to large open windows led to the conclusion that there are two control modes for windows, one related to air quality and the other to temperature. Moreover, Warren and Parkins [75] differentiated between small and large openings. Small windows were open to satisfy indoor air quality requirements, while large windows were strongly affected by outdoor temperature and solar gain.

Until recently, subsequent attempts to characterize window operation have been based exclusively on outdoor and/or indoor temperatures [25,37,51,52,60]. The analyses are based on control actions collected predominantly from buildings without cooling systems in Europe and the UK. The focus on temperature makes intuitive sense given that windows aren't likely to be opened if it is too hot or cold outside, and given the important role of indoor temperature in maintaining occupant comfort. However, this single sided focussing on temperature as the only driver seems to exclude any other variables as drivers, even though these cannot be ruled out a priori.

Raja et al. [60], studying the use of building control in 15 naturally ventilated offices in UK, reported that the proportion of open windows increased with an increase in indoor and outdoor temperature. Only few windows were open when the outdoor temperature was below 15 °C, whereas most windows were open when temperatures exceeded 25 °C. Nicol [50] conducted a survey on the use of windows, lighting, blinds, heaters and fans in different countries and showed how the use of each control varies with outdoor temperature. Although significant variation was found between different climates, occupants opened windows when the outdoor temperature was above 10 °C in all countries where the surveys were conducted. As outdoor temperature increases there is an increase in the probability of an open window. These results fit with the results of Herkel et al. [34] who analysed 21 offices in Germany and found that the highest percentage of open windows was reached at a temperature of 20 °C. At higher temperatures the percentages of open windows seemed to decrease. Moreover, they found that the correlation of the percentages of open windows to the indoor temperature was smaller than the correlation with the outdoor temperature.

However, consensus has not been reached about whether to use indoor temperature, outdoor temperature or both as the independent variable when simulating window use, because of the inherent interactions between indoor and outdoor temperature in naturally-ventilated buildings. For instance, rising indoor temperatures might drive the opening of windows, but how long the window stays open might depend more on outdoor temperature. Haldi and Robinson [32] argued that indoor temperature would be a better predictor of window opening behaviour than the outdoor temperature because indoor temperature is a driver for opening and closing windows to a much larger extent than outdoor temperature. However, the indoor temperature is affected by the windows' state, which makes the analysis of window state based on indoor temperature difficult to interpret. The problem is that the predictive variable is influenced by the state that it is trying to predict. In a cold climate the low indoor temperatures would occur when the windows are open and not when they are closed. In such a case the result of the analysis would be that the inferred probability of a window being open increases with decreasing indoor temperature, with the illogical implication that the probability of opening a window would increase with decreasing indoor temperatures.

On the contrary, Schweiker [67] stated that neither outdoor nor indoor temperature are suitable predictors because from the viewpoint of perceptual control theory, the best predictor would be the controlled value itself (thermal comfort). From one hand, occupants cannot control the outdoor temperature, which depends on the weather conditions. On the other hand, also the indoor temperature alone cannot be the value to be controlled by the full range of occupant behaviour, because e.g., thermal comfort depends also on mean radiant temperature, air speed, relative humidity, clothing insulation and metabolic rate [23].

In office buildings, user behaviour was found to be strongly correlated with the *season* [34,39,74]: the percentages of open windows are lowest in winter, highest in summer and intermediate in autumn and spring, suggesting that the behaviour may be influenced by long-term experience.

Wind is a driver for closing the windows and occupants are likely to close windows if the sensation of draft in the office is producing a predominant discomfort: Roetzel et al. [63] reported an inverse linear correlation between wind velocity and window opening.

Researchers have found a strong correlation between window adjustment and time of arrival and departure [33,34,78]. Although these studies use this analysis to modify algorithms for predicting behaviours, one implication of their observations that is not further studied is that many window control actions could be a function of routine, habit or state of mind rather than simple environmental response. In fact, related research on thermostat control has found that major differences in control patterns were largely related to the habits and routines of households [77]. Warren [75], Yun [78], Herkel [34] and Haldi [33] found a strong link between time of day and the windows controls activities. During the night the percentages of completely open windows was around zero, and actions on windows mostly occurred on arrival of the occupants. In the survey conducted by Herkel [34], in 21 offices in Germany intermediate window switching during the day was found to be relatively low, so windows were usually left in the same position for long periods of time, till discomfort occurred. In naturally ventilated buildings, this behaviour could be interpreted as an avoidance of discomfort that has evolved to become a daily routine.

The current state of the window also plays a role in how likely it is to be adjusted. Several studies find that windows that are opened tend to stay that way [25,62,78]. Once the occupant has taken action, they usually will not revert back to the original state once comfort has been restored, but are more likely to wait until another crisis of discomfort is reached [45]. Moreover, this parameter was found significant in the context of night ventilation [63].

Type of windows influences the length of time the window is open. Herkel et al. [34] found that small openings were opened less frequently but remained open for longer periods of time, while large openings were opened more frequently, but generally closed after less than a working day.

The social dynamics of shared office space can also have a dramatic impact on window operating behaviour. As observed by Cohen et al. [14], manual controls (windows, blinds, lights) in open-plan offices tend to "lapse into default states that minimize conflict and inconvenience but are not optimal, e.g., 'blinds down, lights on." In part, this phenomenon points to differences in office inhabitants' natural disposition towards or awareness of their environment while they are working.

4.3. Identification of driving forces: key points

From the analysed studies it is clear that there is not a shared approach to the identification of driving forces for occupants' window opening and closing behaviour. In particular, it emerges how there is still a disagreement as to whether indoor or outdoor temperature or both are best predictors when simulating the actions on windows. Moreover, some parameters are not considered in any of the surveyed studies. There is a lack of understanding in the relationship between indoor air quality and the window opening behaviour of occupants. The behaviours of the occupants' towards night ventilation is generally poorly understood and the degree of openings are ignored in most studies, even though these are crucial for reliable air flow prediction.

In office buildings, almost all data were collected in buildings without ventilation systems and physiological (like gender or age) or psychological aspects are not investigated to the same degree at the physical drivers.

Moreover, the case of offices with several occupants is not specifically treated (single behaviour or shared behaviour).

Most studies focus on determining the most important drivers and put little emphasis on the variables that do not show up as drivers. However, highlighting variables found to have little or no impact on the occupants' window opening behaviour reveal contradictions between the studies and may help directing future research. Behind the parameters that are found to have an impact on occupant behaviour, Table 5 shows the variables that were included in the surveys, but found not to be drivers.

Table 5
List of variables that have been found not to drive window opening behaviour. The column 'Presence in "drivers tables" ' indicates if the variable has also been found to be a driver in other papers.

Parameter	Building type	Driver type	Presence in "drivers tables"
Wind speed	Residential	Physical Environmental	Yes
Wind direction	Office, Residential	Physical Environmental	No
Solar Radiation	Office, Residential	Physical Environmental	Yes
Rainfall	Office, Residential	Physical Environmental	No
Age	Residential	Physiological	Yes
Income	Residential	Social	No
Thermal sensation	Residential	Psychological	No
Day of week	Residential	Time	No
Wood burning stove	Residential	Building properties	No

From the table it appears clear that there are parameters that distinctly are not drivers, like wind direction or income, but there are other investigated variables which appear to have an impact on the window opening behaviour (Table 3 and Table 4) as well, indicating that they cannot be applied to models for any building, since they cannot be generalised. Unfortunately, the table is far from being exhaustive because many papers only report the variables that have an impact on the occupant behaviour.

From the table it appears evident that the following variables are clearly not drivers:

- Wind direction
- Rainfall
- Income
- Thermal sensation
- Day of week
- Wood burning stove

Haldi and Robinson [32] and Herkel et al. [34] in office building and Johnson and Long [40] in residential building did not observe any particular variations with wind direction and rainfall (which was correlated with relative humidity in the study of Haldi and Robinson [32]), thus they were not found to affect window opening behaviour significantly. Herkel et al. [34] reported a low correlation between wind direction and the percentage of open windows ($r = 0.16$).

Johnson and Long [40] reported in their survey that income (particularly related to poverty level, used in the investigation as an indicator of the socioeconomic level of Durham population) and the day of week (week day or weekend) were not found to impact the residential openness significantly.

With regard to thermal sensation, which is found not to be a statistical predictor for the interactions with windows in Andersen et al. [5], it is also explained in the paper that the reason could be the feedback mechanism occurring between the window opening and the thermal sensation. If a window was opened because the occupants felt too warm, it would probably stay open until they would start to feel cold. Because of this, occupants with open windows might have a thermal sensation anywhere between warm and cold.

The other parameters of Table 5 that appears not to be drivers are:

- Wind speed
- Age
- Solar radiation

Andersen et al. [5] found that age and wind speed did not affect the proportion of dwellings with open windows. These results are not coherent with other studies [18,21] where a significant decrease of open windows for high wind speed emerges. This inconsistency might be explained by the fact that Andersen et al. [5] used wind speed recorded at weather stations throughout the country at a height of 10 m above ground level, which may be different from local wind speeds. Herkel et al. [34] reported a low correlation between the percentages of open windows and wind speed ($r < 17$).

Regarding solar radiation, both Herkel et al. [34] in office buildings and Erhorn [21] in residential buildings cannot confirm a statistical significance for the correlation with solar radiation and the percentage of open windows. Herkel et al. [34] found that the correlation of window openings and solar radiation was small ($r < 0.5$) if compared to the correlation with temperatures both indoor ($r = 0.72$ for small windows and $r = 0.76$ for large windows) and outdoor ($r = 0.81$ for small windows and $r = 0.79$ for large windows). Erhorn [21] reported that while a strong influence appeared with solar radiation, it was not possible to determine a distinct dependence because the influences of outdoor air temperature and solar radiation were superimposed in the overall duration of window ventilation as function of daytime/night-time outdoor temperatures.

The aim of most existing studies is the window state instead of the action of opening and closing the windows (transition from one state to another). This is an important distinction, since the window state influences the indoor environment. If the indoor environmental variables are used to infer models of window state, the predictive variables are influenced by the state that they are trying to predict. In a cold climate low indoor temperatures would occur when the windows are open and not when they are closed. In such a case the result of the analysis would be that the inferred probability of a window being open increases with decreasing indoor temperature, with the illogical implication that the probability of opening a window would increase with decreasing indoor temperatures.

Another problem with focussing on the state rather than the transition is that the drivers for opening and closing windows might be different. Indeed, Andersen et al. [6] found that the CO_2 concentration was the most important driver for opening of windows, while the outdoor temperature was the most dominant driver for closing of windows.

The problems listed above are overcome, when the focus of the analysis is shifted from state to transition.

Further studies are then required focussing on the driving forces for the actions on windows (opening and closing) rather than keeping the state of the windows as the aim of the research.

5. Conclusions

This literature review highlights that what seems to be a simple task, to open or close windows, is in reality a task that is influenced by many factors, which interact in complex ways. It is evident that the window opening behaviour has a very big impact both on the indoor environment quality and on the energy consumed to sustain the desired indoor environmental quality level.

In this paper, we have reviewed the existing studies on the topic of window opening behaviour and elaborated a theoretical framework to deal with occupants' interactions with building controls, aimed at improving or maintaining the indoor environment. This approach is used to look into the drivers for the actions taken by the occupants (windows opening and closing) and to investigate the existing models in literature of these actions for both residential and office buildings. In general, the driving forces are multidisciplinary and can be categorised in five main categories (Physical Environmental, Contextual, Psychological, Physiological and Social). The analysis of the literature highlight how a shared approach on identifying the driving forces for occupants' window opening and closing behaviour has not yet been reached. Most studies focus on determining the most important drivers and put little emphasis on the variables that do not show up as drivers. However, the reporting of variables found not to be drivers may reveal contradictions in the obtained results and may be a significant tool to help direct future research.

Moreover, existing studies on window opening behaviour are aimed at investigating the state of the window itself instead of the transition from one state to another (opening and closing). This might be problematic, since the indoor environment is affected by the state of the window with the consequence that the predictive variables are influenced by the state that they are trying to predict. Further studies are required focussing on the driving forces for the transition of windows state (open and closing) rather than keeping the state of the windows as the aim of the research.

A significant effort should be addressed in the following years to better understand the dynamics of the relationship between indoor environment, occupant behaviour and energy consumption. More accurate, reliable and realistic occupant behaviour models need to be developed. The description of the dynamics regulating the relationship between occupant behaviour and energy consumption is still an unresolved problem. In this sense, it is fundamental to apply approaches in the interpretation of the phenomena shared as much as possible.

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PAPER II

Window opening behaviour modelled from measurements in Danish dwellings

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Abstract: A method of defining occupant window opening behaviour patterns in simulation programs based on measurements is proposed.
Measurements of occupant's window opening behaviour were conducted in 15 dwellings in Denmark in the period from January to August 2008. Indoor and outdoor environmental conditions were monitored in an effort to relate the behaviour of the occupants to the environmental conditions. The dwellings were categorized in four groups according to ventilation type (natural or mechanical) and ownership (owner-occupied or rented) in order to investigate common patterns of behaviour. Logistic regression was used to infer the probability of opening and closing a window.
The behaviour related to window operation of the occupants was governed by different but distinct habits in the four groups, and in each dwelling within the groups. However, common patterns were also identified in the analysis: Indoor CO2 concentration (used as an indicator of indoor air quality) and outdoor temperature were the two single most important variables in determining the window opening and closing probability, respectively.
The models could be implemented into most simulation programs which would enable a better chance of mimicking the behaviour of the occupants in the building and thus getting the indoor environment and energy consumption correct.

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Window opening behaviour modelled from measurements in Danish dwellings

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Abstract

A method of defining occupant window opening behaviour patterns in simulation programs based on measurements is proposed.

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The models could be implemented into most simulation programs which would enable a better chance of mimicking the behaviour of the occupants in the building and thus getting the indoor environment and energy consumption correct.

Highlights

We inferred four models of occupants' window opening behaviour

The models were inferred based on measurements of window position, indoor environment and weather in residential buildings.

Measurements revealed different but distinct habits between dwellings

Models can be implemented in building energy performance simulations programmes, to increase validity of simulation results

Keywords

Occupant behaviour; building controls; adaptation; window opening; Building energy performance simulation; Air quality

1 INTRODUCTION

Occupants who have the possibility to control their indoor environment have been found to be more satisfied and suffer from fewer building related symptoms than occupants who occupy environments in which they have no control [1, 2, 3]. These studies emphasize the significance of providing occupants with rich opportunities of interacting with building controls. In doing so, the control of the building is to some extend left in the hands of the occupants. However, occupant behaviour varies significantly between individuals which results in large variation of the energy consumption of buildings [4, 5, 6, 7]. Because of this, it is important to take occupants' interactions with building controls into account when designing buildings.

Most building simulation programs provide possibilities of regulating the simulated environment by adjusting building controls (opening windows, adjusting temperature set-points etc.). However, discrepancies between simulated and actual behaviour can lead to very large offset between simulation results and actual energy use [8, 9]. Indeed, Andersen et al. showed that differences in occupant behaviour might lead to differences in energy consumption of over 300 % [10]. Thus there is a need to set up standards or guidelines to enable comparison of simulation results between simulation cases. One method that can provide this is to define standard behaviour patterns that can be implemented in building simulation programs. This would significantly improve the validity of the outcome of the simulations. A definition of such standard behaviours should be based on the quantification of real occupant behaviour.

Two important parameters influencing energy consumption in dwellings are indoor temperature and air change rate. Wallace et al. measured air change rates in a house during one year and found that the opening and closing of windows had the largest effect on the air change rate [11]. Also Howard-Reed et al. found that opening of windows produced the greatest increase in air change rates compared with temperature differences and wind effects [12]. In Danish dwellings mechanical cooling is almost never used, which means that the indoor temperature depends on the heating set-point in winter and on the air change rate in the summer. As a consequence, window opening behaviour and heating set-point behaviour of occupants play an important role in determining the energy consumption and indoor environment of a household.

Recently, the effect of indoor and outdoor temperature on the window opening behaviour in offices has been investigated by means of logistic regression [13, 14, 15, 16, 17, 18, 19, 20]. The general trend has been to infer the probability of the window state as a function of indoor and outdoor temperature, while some have investigated the probability of opening a window (change from one state to another) as a function of temperature [16, 17, 19]. Haldi and Robinson argued that the indoor temperature would be better a predictor than the outdoor temperature because indoor temperature is a driver for opening and closing windows to a much larger extent than outdoor temperature [14]. In a later paper Haldi and Robinson addressed the differentiation between indoor and outdoor stimuli for openings and closings and tested several modelling approaches [19]. Since indoor environmental parameters are influenced by the state of the windows, it is problematic to infer the latter based on indoor parameters e.g. indoor temperature. The problem is that the predictive variable is influenced by the state that it is trying to predict. In a cold climate the low indoor temperatures would occur when the windows are open and not when they are closed. In such a case the result of the analysis would be that the inferred probability of a window being open increases with decreasing indoor temperature, with the illogical implication that the probability of opening a window would increase with decreasing indoor temperatures.

Another problem with this approach is that the driving forces for opening and closing a window might be different. The window might be opened due to IAQ and closed because of low indoor temperature.

Most recent studies have been limited to the investigation of thermal stimuli [13, 14, 15, 16, 17, 18] although other studies have found that many other stimuli play an important role in determining the window opening behaviour [21, 22, 23, 24].

In this paper we have inferred the probability of opening and closing a window (change form one state to another) separately, rather than investigating the state of the window. In this way the most dominating drivers for each action was derived and the problem of feedback on indoor environment from window state, overcome.

2 METHOD

Andersen et al. [21] quantified behaviour of occupants in Danish dwellings by means of a questionnaire survey. A definition of standard behaviour patterns was attempted, but a link to the indoor environment was missing due to the effects of behaviour of the occupants on the indoor environment. As a follow up to the questionnaire survey and to fill this gap, simultaneous measurement of occupant behaviour, and indoor and outdoor environment was carried out in (and outside) 15 dwellings during the period from January to August 2008.

2.1 Measurements

The following variables were measured continuously in all 15 dwellings.

Indoor environment factors measured every 10 minutes

- Temperature (°C)
- Relative humidity (RH) (%)
- Illuminance (Lux)
- CO_2 concentration (ppm)

Outdoor environment acquired from meteorological measuring stations in 10 minute intervals [27]

- Air temperature (°C)
- RH (%)
- Wind speed (m/s)
- Global Solar radiation(W/m^2)
- Sunshine hours (daily values) (Number of hours with sunshine (insolation higher than 120 W/m^2))

Behaviour

Window position (open/closed)*

*In three of the dwellings, the actual opening angle of the window was measured

The indoor environment measurements were carried out with Hobo U12-012 data loggers [25]. The CO_2 concentration was measured using a Vaisala GMW22 sensor [26] connected to the Hobo logger as depicted in figure 1. Both the CO_2 sensors and the Hobo data loggers were newly calibrated from the factory. The CO_2 sensors were tested against a newly calibrated Innova multigas analyser both before and after the measuring period. The temperature sensors in the hobo data loggers were also tested before the measurements. The outdoor environmental variables were obtained from the Danish meteorological institute [27]. Data from the meteorological station closest to each of the dwellings was used. The closest meteorological stations did not measure precipitation and since local wind direction is very sensitive to local conditions it was decided not to include the direction of the wind.

The window position (open/closed) was measured using a Hobo U9 sensor [25]. Three of the windows were hitched in the top and tilted outwards when opening. In these cases the tilt was measured using an accelerometer (HOBO UA-004-64 Pendant G) [25] attached to the window frame. In this way the opening angle of the window was measured.

Figure 1. Pictures of the instruments used to measure the indoor environmental variables and window opening behaviour. Top left: CO_2 monitor connected to a data-logger with built in temperature, relative humidity and illumination sensors. Top right: Window state sensor (open/closed). Bottom: window state sensor (open/closed) and window position sensor.

Generally, all measurements were carried out in the (main) living room and the (main) bedroom in each dwelling. The window sensors were installed on windows that inhabitants used most often when ventilating the dwelling.

2.2 Place of Measurement

Our measurements were limited to two rooms in each dwelling. Brundrett [28] found that open windows were most commonly found in the bedroom, particularly the main bedroom, while the sitting room, kitchen and the dining room had the lowest frequency of open windows. This was later supported by Dubrul [29] who found that bedrooms were the main ventilation zone, whereas the majority of windows which were never opened was in the living rooms. Furthermore, the percentage of open windows in kitchens and bathrooms was similar to that of living rooms. Based on these findings we chose to conduct the measurements in the main bedroom and in the main living room in each dwelling. This choice was made in an effort to select the rooms with the highest and lowest window opening frequency.

2.3 The dwellings

Measurements were carried out in 10 rented apartments and 5 privately owned single family houses. Five of the apartments were naturally ventilated (apart from an exhaust hood in the kitchen) while the other five were equipped with constantly running exhaust ventilation from the kitchen and bathroom. Three of the single family houses were naturally ventilated while the other two were equipped with exhaust ventilation.

With the exception of one (located 60 km from Copenhagen) all dwellings were located less than 25 km from Copenhagen.

Features of the dwellings are described in Table 2.

All dwellings used waterborne radiators/convectors and natural gas boilers as a primary means of heating and two of the dwellings (number 10 and 16) had a wood burning stove.

3 PROCESSING AND PREPARATION OF DATA

The indoor environment sensors were placed on internal walls at a height of roughly 1.8 m above the floor. We attempted to place the sensors so that they would not be hit by direct sunlight, but due to acceptance of the occupants in the dwellings and other practicalities this was not always possible. In the cases when direct sunlight fell on the sensors the temperature measurements were corrected for the heating of the sensor. This was done in periods when the measured illuminance was larger than 1000 lux. In these cases the temperature was corrected by linear interpolation between temperature measurements 30 minutes prior to and one hour after direct sunlight fell on the sensor.

The CO_2 concentration was used as an indicator of the occupancy of the rooms where the measurements took place. If the CO_2 concentration was below 420 ppm and the window was closed the room was classified as being unoccupied. Furthermore, if the CO_2 concentration was higher than 420 ppm, but decreased and continued to decrease until reaching values below 420 ppm and the window was closed in the entire period, the room was classified as unoccupied during the period of concentration decay.

The value of 420 ppm was chosen since earlier observations had shown that the outdoor concentrations might reach levels of up to 400 ppm. To ensure that long unoccupied periods were not classified as occupied an uncertainty range of 20 ppm was added to the highest observed outdoor concentration.

The room was classified as occupied if the window was open. This classification was based on a questionnaire survey conducted by Andersen et al. [30] who found that the statement “I had to leave the dwelling” was mentioned amongst the most common reasons for closing windows.

If the bedroom and the living room were both unoccupied, the dwelling was classified as unoccupied. Periods when the dwelling was unoccupied were not taken into consideration in the analysis.

When analysing the window opening data the database was divided depending on the state of the window (open/closed) to infer the probability of opening and closing the window (change from one state to another) separately. The 15 dwellings were divided into four groups on the basis of the ownership (owner-occupied or rental) and the ventilation type (natural ventilation or mechanical ventilation) (table 1).

Table 1. description of groups investigated related to the ownership and ventilation type

Group	*Ownership*	*Ventilation type*	*Dwelling index*
1	Owner-occupied	Natural	3, 4, 16
2	Owner-occupied	Mechanical	1, 10
3	Rental	Natural	6, 8, 9, 11, 12
4	Rental	Mechanical	5, 7, 13, 14, 15

Table 2 shows the relation in each of the four groups between inhabitants (age and number), dwelling characteristics (building construction or renovation years and the dwelling size) and the frequency of openings.

Table 2. Description of residents and characteristics of the dwellings

Group	*Dwelling number*	*Number of openings in period*	*Average age of the residents*	**Number of residents**	*Year of construction (and renovation)*	*Floor area (m^2)*
1	3	82	57	2	1928	145
	4	235	70	2	1956 (1976)	130
	16	153	26	2	1967	139
2	1	334	65	1	1994	126
	10	65	59	2	1901 (1957)	190
3	6	337	78	2	1945	86
	8	258	55	2	1945	109
	9	25	35	3	1945	87
	11	82	71	2	1945	77
	12	1	64	1	1945	109
4	5	73	76	2	1981 (2001)	83
	7	718	63	1	1981 (2001)	83
	13	341	60	3	1981 (2001)	80
	14	241	28	2	1981 (2001)	85
	15	166	60	4	1981 (2001)	84

3.1 Statistical Analysis

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 in formula 1.

$$\log\left(\frac{p}{1-p}\right) = a + b_1 \cdot x_1 + b_2 \cdot x_2 + \cdots + b_n \cdot x_n \qquad (1)$$

Where,

p	is the probability of an opening/closing event
a	is the intercept
b_{1-n}	are coefficients
x_{1-n}	are variables such as temperature, CO_2 concentration etc.

However, the probability might depend differently on x_1 at one level of x_2 as compared to another level of x_2 (e.g. an increase in temperature might increase the probability of opening a window at high CO_2 levels, whereas the same increase might result in a lower probability at low CO_2 levels). An example like the one described above would not be well described by a model based on equation 1. Equation 2 deals with interactions between variables by adding interaction terms to the model.

$$log\left(\frac{p}{1-p}\right) = a + b_1 \cdot x_1 + b_2 \cdot x_2 + \cdots + b_n \cdot x_n + c_{12} \cdot x_1 \cdot x_2 + c_{13} \cdot x_1 \cdot x_3 + \cdots \qquad (2)$$

Equation 2 was used to infer the probability of windows being opened or closed. The Akaike information criterion (AIC) was used as a basis for forward and backward selection of variables in the regression models [31]. Each individual variable was first fitted to the measured window opening data and then AIC was calculated for each fit. The variable with the lowest AIC was selected and the remaining variables were then tested one by one on a bivariate level, to see if any of the bivariate models resulted in a lower AIC. If this was the case, the remaining variables were tested in a model with three variables and so on (forward selection). At each step, the AIC was also calculated for models, where each of the selected variables was removed from the models (backward selection). In this way, the final model included variables and interaction terms that resulted in the lowest AIC. To limit the complexity of the model, only interaction terms between continuous and nominal variables, e.g. indoor temperature and day of week were included in the analyses.

The statistical analyses were conducted using the statistical software “R” and the models were inferred using the ‘step’ function in R. [32]

In the interpretation of the coefficients, the sign, the size and the scale of the corresponding variable have to be taken into account. For example, a coefficient for solar hours of 0.057 might seem to impact the probability more than an outdoor relative humidity coefficient of 0.029 (group 4, opening model). However, the scales of the two variables (solar hours: 0 to 16.1, outdoor RH: 28% to 100%) should be taken into account: Schweiker et al. [33] suggested to multiply the scale of the variable with the coefficient, to get an indication of the magnitude of the impact from each variable. In the example described above the magnitude of the impact was $0.057 \cdot (16.1-0) = 0.91$ and $0.029 \cdot (100-28) = 2.08$ for the solar hours and the outdoor relative humidity respectively, revealing that the outdoor RH had a higher impact on the probability than the solar hours.

When using logistic regression, it is required that all variables are independent. Since the data was obtained in 15 dwellings with different physical properties and different inhabitants, all variables could not be assumed a priori to be independent of the dwelling it was obtained from. Variable independency was tested by assigning an index to each of the dwellings, which was used as a factor in the analyses. If an interaction term between a variable and the dwelling number was retained in the model, it was taken as an indication of dependence and the variable was removed from the model. All variables which did not interact with the dwelling number were assumed to be independent of the individual dwelling.

Correlations between explanatory variables may result in inflation of the estimated variance of the inferred coefficient, which in turn will result in too wide confidence intervals. To estimate the size of the inflation due to correlations between all explanatory variables (multicolinearity), generalized variance inflation factors (GVIF) were calculated for coefficients of all continuous explanatory variables. The GVIF estimates the inflation of the variance, due to multicolinearity as compared to no multicolinearity. Since the GVIF is an estimate of the inflation of the variance, the $\mathrm{GVIF}^{\frac{1}{2 \cdot \mathrm{DF}}}$ is an estimate of the factor by which the standard error and confidence interval is inflated due to multicolinearity between explanatory variables.

Prior to the regression analyses, four variables were transformed to obtain a better distribution. Table 3 describes how the variables were transformed.

Table 3: Variable transformations

Variable	**Transformed variable**
CO_2 concentration [ppm]	Log(CO_2) [Log(ppm)]
Illumination [Lux]	Log(Illumination) [Log(Lux)]
Wind speed [m/s]	Log(Wind speed+1) [Log(m/s)]
Solar radiation [w/m²]	Log(Solar radiation+1) [Log(W/m²)]

4 RESULTS

In this section the main results of the statistical analysis are presented. Table 4 presents descriptive statistics of all measured variables in each of the four groups.

Table 4. Descriptive statistics of the monitored variables

		Indoor temperature	Indoor R.H.	CO_2	Outdoor temperature	Outdoor R.H.	Lux	Wind	Solar Radiation	Solar Hours
GROUP 1										
windows closed	Max	30.3	69	3065	26.9	100	16063	13.2	918	16.1
	Min	17.1	24	355	-6.9	24	4	0.0	0	0.0
	Mean	22.1	46	862	9.6	76	159	2.8	199	8.5
	Median	21.8	45	773	9.3	76	51	2.5	63	8.1
	St. Dev.	2.0	7	369	6.2	18	458	2.1	252	5.0
windows open	Max	29.2	67	2229	25.5	100	8077	9.1	904	16.1
	Min	17.2	26	328	-1.4	30	4	0.0	0	0.0
	Mean	22.9	38	520	13.5	61	278	3.1	413	10.8
	Median	22.8	38	464	13.6	58	99	3.0	437	13.0
	St. Dev.	1.8	6	175	5.1	18	447	1.7	272	4.7
GROUP 2										
windows closed	Max	27.3	49	4453	24.0	100	1494	17.3	904	14.9
	Min	13.5	24	377	-6.0	25	4	0.0	0	0.0
	Mean	22.3	36	722	7.5	75	111	3.3	165	6.9
	Median	22.6	35	648	7.0	78	36	2.7	23	6.1
	St. Dev.	2.0	4	310	5.1	18	183	2.6	234	4.8
windows open	Max	27.3	53	1959	24.0	100	32280	17.3	883	14.9
	Min	12.0	25	363	-6.0	25	4	0.0	0	0.0
	Mean	18.1	40	516	8.0	74	295	4.3	203	6.7
	Median	17.2	40	468	7.0	78	43	3.7	91	6.3
	St. Dev.	3.2	5	142	5.4	19	1500	2.9	240	4.8
GROUP 3										
windows closed	Max	31.2	63	3634	26.3	100	32280	13.0	904	15.3
	Min	14.1	21	338	-5.8	24	4	0.0	0	0.0
	Mean	22.3	37	780	7.4	73	179	3.3	164	6.1
	Median	22.3	37	612	6.8	76	43	2.9	36	5.5
	St. Dev.	2.0	5	462	5.2	18	888	2.2	230	5.0
windows open	Max	27.7	54	3295	26.3	100	2456	13.0	883	15.2
	Min	11.5	22	333	-5.8	25	4	0.0	0	0.0
	Mean	19.9	38	590	7.9	75	80	3.3	141	6.7
	Median	19.1	38	520	6.3	80	43	2.9	6	5.7
	St. Dev.	3.5	5	232	6.0	19	130	2.2	229	5.4
GROUP 4										
windows closed	Max	28.8	73	4636	28.6	100	23442	13.5	918	16.1
	Min	9.8	21	333	-7.7	28	4	0.0	0	0.0
	Mean	20.9	42	702	7.9	80	85	3.0	138	6.6
	Median	20.8	42	628	7.1	84	36	2.5	11	6.2
	St. Dev.	2.2	8	292	5.9	17	206	2.3	208	4.7
windows open	Max	29.1	69	3530	29.4	100	13935	13.5	918	16.1
	Min	11.9	22	328	-7.2	28	4	0.0	0	0.0
	Mean	22.0	44	492	14.1	71	132	3.1	293	9.2
	Median	22.2	43	437	14.6	71	59	2.7	238	9.4
	St. Dev.	2.4	8	142	5.9	19	229	2.1	276	5.0

The number of the dwelling affected the impact of some of the explanatory variables as concerns the probability of opening and closing a window. This indicates different habits in the different dwellings included in the four groups, which were not described by the measured variables. For example, the CO_2 concentration interacted with the dwelling index in the model for closing windows in group 3, indicating that the windows were closed at different (but distinct) concentrations of CO_2 in each dwelling. The variables that interacted with the dwelling number were removed from the models where the interaction occurred. In the further analyses, the number of the dwelling was not included, since we were not interested in the behaviour in each single dwelling, but in the overall behaviour in all of the surveyed dwellings.

Table 5 shows a list of variables that were removed from the models due to interactions with the dwelling number.

Table 5. A list of variables that interacted with the dwelling number indicating that they were not independent of the dwelling where they were measured. The table states in which models (Open and/or close) the interactions were found.

Model	**Indoor temperature**	**Outdoor temperature**	**Solar radiation**	**CO_2 concentration**	**Time of day**	**Illumination**
Group 1	None	None	None	None	None	None
Group 2	Open and Close	Open	Open	None	None	None
Group 3	None	None	Close	Close	None	None
Group 4	Close	None	None	Close	Open and Close	Close

Group 1: Owner-occupied, naturally ventilated dwellings

As expected, CO_2 concentration, indoor temperature and solar radiation were positively correlated with the probability of opening the window, while Outdoor Temperature was negative correlated with the probability of closing windows. In the bedroom, the CO_2 concentration was the most important variable for the probability of opening windows, while it did not have a significant effect in the living room (the confidence interval for the coefficient contains the number 0). The indoor relative humidity had the biggest effect on the closing probability in the living room, but did not have a significant effect in the bedroom. Both the opening and closing probabilities were influenced by the season and by the time of day. Since no window were opened during the winter time, the seasonal effects only take spring and summer into account. During winter, the inferred probability of opening a window was 0.

Table 6. Coefficients and magnitudes of the opening and closing models inferred based on data from Group 1. The magnitude is a measure of the impact of the variable on the probability. It was calculated as the coefficient of the variable multiplied by the scale of the variable.

Variable	Time/ room	Open Window				Close Window			
		Coefficient	Confidence interval		Magnitude	Coefficient	Confidence interval		Magnitude
			2.5%	97.5%			2.5%	97.5%	
Intercept Spring - Bedroom	Night	-23.83	-27.78	-19.88		-1.93	-3.67	-0.19	
	Morning	-23.04	-27.06	-19.03		-0.84	-2.71	1.03	
	Day	-24.06	-28.10	-20.03		-1.22	-3.09	0.65	
	Afternoon	-24.32	-28.35	-20.29		-1.00	-2.87	0.87	
	Evening	-24.47	-28.49	-20.45		-0.38	-2.25	1.48	
Intercept - Spring - Living Room	Night	-10.58	-16.40	-4.76		-5.31	-7.76	-2.87	
	Morning	-9.80	-15.66	-3.93		-4.22	-6.76	-1.69	
	Day	-10.82	-16.69	-4.94		-4.61	-7.15	-2.07	
	Afternoon	-11.08	-16.95	-5.20		-4.39	-6.93	-1.85	
	Evening	-11.22	-17.09	-5.35		-3.77	-6.31	-1.23	
Intercept - Summer - Bedroom	Night	-24.72	-28.69	-20.75		-0.77	-2.59	1.05	
	Morning	-23.94	-27.97	-19.91		0.32	-1.62	2.26	
	Day	-24.96	-29.00	-20.91		-0.06	-2.01	1.88	
	Afternoon	-25.22	-29.26	-21.17		0.16	-1.79	2.10	
	Evening	-25.36	-29.40	-21.33		0.77	-1.17	2.72	
Intercept - Summer - Living Room	Night	-11.47	-17.35	-5.60		-4.15	-5.98	-2.32	
	Morning	-10.69	-16.58	-4.80		-3.06	-5.02	-1.11	
	Day	-11.71	-17.60	-5.82		-3.45	-5.40	-1.49	
	Afternoon	-11.97	-17.85	-6.09		-3.23	-5.19	-1.27	
	Evening	-12.12	-17.95	-6.28		-2.61	-4.56	-0.66	
CO_2 concentration [Log(ppm)]	Bedroom	1.87	1.37	2.37	4				
	Living Room	0.23E-03	-0.81	0.81	0.00				
Indoor Temperature [°C]		0.163	0.11	0.22	2.15				
Solar Radiation [Log(W/m²)]		0.501	0.14	0.86	3.42				
Outdoor Temperature [°C]						-0.15	-0.19	-0.12	-4.07
Outdoor Relative Humidity [%]						1.16	1.15	1.17	81.1
Indoor Relative Humidity [%]	Bedroom					0.037	-0.003	0.077	1.56
	Living Room					0.104	0.046	0.162	4.34

The results in table 7 indicate that the confidence intervals of some variables may be inflated due to multicolienarity (the $GVIF^{\frac{1}{2 \cdot Df}}$ is a measure of inflation due to multicolinearity). Especially the standard error of the categorical variable Room and the interaction terms were inflated due to multicolinearity. This indicates that some variables were biased by the room they were measured in.

Table 7. Results of performed VIF analysis for variables of group 1.

Variable	Opening window			Closing window		
	GVIF	Df	$GVIF^{\frac{1}{2\cdot Df}}$	GVIF	Df	$GVIF^{\frac{1}{2\cdot Df}}$
Time	3.7	4	1.2	1.9	4	1.1
Solar Radiation	3.5	1	1.9			
Season	1.1	1	1.0	1.9	1	1.4
Room	353	1	18.8	52	1	7.2
Indoor Temperature	1.1	1	1.1			
CO_2 Concentration	3.0	1	1.7			
Room:CO_2	338	1	18.4			
Relative Humidity				6.4	1	2.5
Outdoor Temperature				2.4	1	1.6
Outdoor Relative Humidity				3.0	1	1.7
RH:Room				60	1	7.7

Group 2: Owner-occupied, mechanically ventilated dwellings

Due to interaction with the dwelling number, indoor and outdoor temperature and solar radiation were removed from the window opening model and indoor temperature was removed from the window closing model.

The CO_2 concentration was the most important variable in the determination of the window opening probability, while Outdoor temperature and illumination turned out to be the most important variables in the window closing model. From the confidence intervals it is evident that all the variables, except the outdoor temperature for the bedroom and the solar radiation for the living room had a statistically significant impact on the opening/closing probabilities (Table 8).

Since the outdoor relative humidity is related to the outdoor temperature, the correlation of outdoor relative humidity gives a perception of the outdoor temperature as well: the higher the outdoor relative humidity is, the lower the outdoor temperature is. On the other hand an increasing illumination, number of solar hours per day and outdoor temperature were correlated with a decreasing probability of closing windows.

Table 8. Coefficients and magnitudes of the opening and closing models inferred based on data from Group 2. The magnitude is a measure of the impact of the variable on the probability. It was calculated as the coefficient of the variable multiplied by the scale of the variable.

		Open Window				**Close Window**			
		Coefficient	**Confidence interval**		**Magnitude**	**Coefficient**	**Confidence interval**		**Magnitude**
Variable	**Time/ Room**		**2.5%**	**97.5%**			**2.5%**	**97.5%**	
Intercept	Bedroom	-13.49	-15.64	-11.33	-	-4.75	-5.53	-3.98	-
	Living Room	-13.49	-15.64	-11.33	-	4.19	3.03	5.34	-
Illumination [log(Lux)]	-	0.27	0.17	0.37	2	-0.62	-0.67	-0.57	-6
CO_2 Concentration [Log(ppm)]	-	1.40	1.10	1.71	3	-			-
Outdoor Relative Humidity [%]	-	-0.02	-0.03	-0.01	-1.5	-			-
Solar Hours [h]	-	-			-	-0.06	-0.09	-0.02	-0.86
Outdoor Temperature [°C]	Bedroom	-			-	0.03	-0.02	0.08	0.90
	Living room	-			-	-0.26	-0.34	-0.19	-7.85
Solar Radiation [Log(W/m²)]	Bedroom	-			-	0.59	0.45	0.74	4.04
	Living room	-			-	0.04	-0.17	0.26	0.30

The Variance inflation factors turned out to be small (lower than 5) for all the variables in the models (Table 9).

Table 9. Results of performed VIF analysis for variables of group 2.

Variable	**Opening window**			**Closing window**		
	GVIF	**Df**	$GVIF^{\frac{1}{2 \cdot Df}}$	**GVIF**	**Df**	$GVIF^{\frac{1}{2 \cdot Df}}$
Lux	1.4	1	1.2	1.9	1	1.4
CO_2	1.3	1	1.1			
Outdoor RH	1.4	1	1.2			
Solar Radiation				6.8	1	2.6
Sun Hours				1.7	1	1.3
Room:OutdoorTemperature				7.1	1	2.7
Room:Solar Radiation				8.9	1	3.0
Room				9.8	1	3.1
Outdoor Temperature				3.0	1	1.7

Group 3: Rented, naturally ventilated dwellings

All of the variables in the window opening model were assumed to be independent from the dwelling they were measured in since none of them interacted with the dwelling number. The CO_2 concentration was the only continuous variable having an impact on the opening window behaviour.

The variables Solar Radiation and CO_2 concentration were removed from the model of closing behaviour since they interacted with the dwelling number. Indoor and outdoor temperature were found to be the most important variables driving the closing behaviour. As expected, they had a negative correlation with the exception of the indoor temperature in the bedroom, which was positively correlated with the probability of closing window.

Table 10. Coefficients and magnitudes of the opening and closing models inferred based on data from Group 3. The magnitude is a measure of the impact of the variable on the probability. It was calculated as the coefficient of the variable multiplied by the scale of the variable.

Variable	Time/ room	Open Window				Close Window			
		Coefficient	Confidence interval		Magnitude	Coefficient	Confidence interval		Magnitude
			2.5%	97.5%			2.5%	97.5%	
Intercept for Bedroom	Night	-17.69	-18.80	-16.59		-2.68	-6.50	1.14	
	Morning	-15.51	-16.63	-14.38		-0.51	-6.37	5.36	
	Day	-17.09	-18.24	-15.94		-7.67	-13.84	-1.50	
	Afternoon	-18.23	-19.40	-17.05		-12.78	-20.94	-4.63	
	Evening	-17.13	-18.26	-15.99		-13.22	-20.81	-5.64	
Intercept for Living Room	Night	-17.69	-18.80	-16.59		14.68	9.90	19.45	
	Morning	-15.51	-16.63	-14.38		16.85	10.32	23.38	
	Day	-17.09	-18.24	-15.94		9.69	2.88	16.50	
	Afternoon	-18.23	-19.40	-17.05		4.57	-4.07	13.22	
	Evening	-17.13	-18.26	-15.99		4.13	-3.98	12.24	
CO_2 Concentration [Log(ppm)]		1.75	1.60	1.90	***4.16***				
Indoor Temperature [°C] Bedroom	Night					0.40	0.29	0.52	***6.55***
	Morning					0.15	0.03	0.27	***2.39***
	Day					0.21	0.08	0.33	***3.38***
	Afternoon					0.70	0.57	0.83	***11.36***
	Evening					0.60	0.48	0.73	***9.79***
Indoor Temperature [°C] Living room	Night					-0.25	-0.37	-0.13	***-4.05***
	Morning					-0.51	-0.69	-0.32	***-8.21***
	Day					-0.45	-0.65	-0.25	***-7.22***
	Afternoon					0.05	-0.23	0.33	***0.75***
	Evening					-0.05	-0.29	0.19	***-0.81***
Outdoor Temperature [°C] Bedroom	Night					0.01	-0.08	0.09	***0.19***
	Morning					0.12	0.03	0.21	***3.85***
	Day					-0.13	-0.23	-0.04	***-4.28***
	Afternoon					-0.07	-0.16	0.03	***-2.10***
	Evening					-0.09	-0.18	0.01	***-2.77***
Outdoor Temperature [°C] Living room	Night					-0.13	-0.22	-0.04	***-4.09***
	Morning					-0.01	-0.11	0.08	***-0.43***
	Day					-0.27	-0.36	-0.17	***-8.56***
	Afternoon					-0.20	-0.30	-0.10	***-6.37***
	Evening					-0.22	-0.32	-0.12	***-7.05***
Indoor Relative Humidity [%]	Night					-0.25	-0.32	-0.17	***-7.75***
	Morning					-0.16	-0.24	-0.08	***-4.93***
	Day					0.06	-0.02	0.14	***1.84***
	Afternoon					-0.15	-0.24	-0.07	***-4.88***
	Evening					-0.07	-0.15	0.02	***-2.14***
Solar Hours [h]						-0.08	-0.11	-0.06	***-1.27***

closed during the next 10 minutes. In the simulation program, a comparison with a random number can determine if the window is opened/closed or not. Since the models predict the probability of an opening/closing event during the next 10 minutes, the random number should change in 10 minute intervals.

When introducing the models and comparisons with random numbers into the simulation software, the results of identical simulations may differ, since the random numbers change between simulations. By running several simulations it is possible to obtain probability distributions of the performance indicators, rather than a single number. As a consequence, the implementation of the models in simulation software will transform the software from a purely deterministic tool to a simulation tool with capabilities of simulation stochastic behaviour patterns.

The multicolinearity analysis for group 3 (Table 11) revealed highly inflated standard errors of the variables time, room and the time-room interaction terms. This indicates higher levels of uncertainty in the coefficients. But the predictive power of the model will only be affected by this if the model is used on data that falls outside the ranges in table 4.

Table 11. Results of performed VIF analysis for variables of group 3.

Variable	**Opening window**			**Closing window**		
	GVIF	**Df**	$GVIF^{\frac{1}{2\cdot Df}}$	**GVIF**	**Df**	$GVIF^{\frac{1}{2\cdot Df}}$
CO_2	1.1	1	1.0			
Time	1.1	4	1.0	7.07E+09	4	17.0
Room				230	1	15.2
Indoor Temperature				11.7	1	3.4
Sun Hours				2.2	1	1.5
Relative Humidity				15.1	1	3.9
Outdoor Temperature				22.0	1	4.7
Room: Indoor Temperature				263	1	16.2
Time: Indoor Temperature				774.3E+06	4	12.9
Time: Relative Humidity				110.6E+06	4	10.1
Outdoor Temperature: Time				18.6E+03	4	3.4
Room: Outdoor Temperature				7.3	1	2.7

Group 4: Rented, mechanically ventilated dwellings

Both in the window opening and window closing model, the variable "Time" interacted with the dwelling index and were removed from the model. In the closing model indoor temperature, CO_2 concentration and illumination depended on the dwelling and were removed.

Table 12. Coefficients and magnitudes of the opening and closing models inferred based on data from Group 4. The magnitude is a measure of the impact of the variable on the probability. It was calculated as the coefficient of the variable multiplied by the scale of the variable.

Variable	Season/ Room	Open Window				Close Window			
		Coefficient	Confidence interval 2.50%	Confidence interval 97.50%	Magnitude	Coefficient	Confidence interval 2.50%	Confidence interval 97.50%	Magnitude
Intercept - Bedroom	Winter	-18.53	-20.55	-16.51		-4.28	-5.21	-3.35	
	Spring	-18.53	-20.55	-16.51		-2.98	-4.18	-1.78	
	Summer	-18.53	-20.55	-16.51		-4.94	-6.24	-3.63	
Intercept - Living Room	Winter	-3.56	-6.82	-0.30		-0.62	-1.72	0.48	
	Spring	-3.56	-6.82	-0.30		0.68	-0.66	2.01	
	Summer	-3.56	-6.82	-0.30		-1.28	-2.71	0.15	
Outdoor temperature - Bedroom	Winter	-0.019	-0.04	0.003	-0.68	-0.038	-0.161	0.084	-1.41
	Spring	-0.019	-0.04	0.003	-0.68	-0.147	-0.321	0.027	-5.38
	Summer	-0.019	-0.04	0.003	-0.68	-0.057	-0.233	0.119	-2.09
Outdoor temperature - Living Room	Winter	0.059	0.03	0.09	2.16	-0.17	-0.29	-0.04	-6.06
	Spring	0.059	0.03	0.09	2.16	-0.27	-0.45	-0.10	-10.04
	Summer	0.059	0.03	0.09	2.16	-0.18	-0.36	-0.01	-6.75
Solar radiation	Bedroom	0.18	0.14	0.23	1.24	0.13	0.09	0.16	0.86
	Living Room	0.35	0.28	0.42	2.39	0.13	0.09	0.16	0.86
Solar hours		0.057	0.043	0.070	0.91	-0.089	-0.103	-0.075	-1.43
Outdoor relative humidity		0.029	0.024	0.033	2.08	-0.028	-0.033	-0.023	-2.01
Illumination		0.26	0.20	0.33	2.30				
Indoor temperature	Bedroom	0.10	-1.92	2.12	1.93				
	Living Room	-0.38	-0.47	-0.29	-7.25				
CO2 concentration	Bedroom	1.16	0.91	1.40	3.04				
	Living Room	0.30	-0.12	0.71	0.78				
Indoor Relative humidity	Bedroom					0.063	0.051	0.075	2.99
	Living Room					0.036	0.017	0.056	1.72

The results in table 13 show that the confidence interval for many of the coefficients was highly inflated. This might explain the unexpected negative correlation between indoor temperature in the living room and opening probability. Since the interaction between room and indoor temperature was inflated up to 14 times, the impact of the room on the indoor temperature coefficient was not as certain, compared to the case with no multicolinearities.

The impact of outdoor temperature on the closing probability was inflated up to 13 times due to multicolinearity. As a consequence, the outdoor temperature coefficients in the closing model may be uncertain. The uncertainties created by the mulitícolinearities will only affect the model's predictive power if the models are used on data that is outside the ranges listed in table 4 (assuming similar colinearities).

Table 13. Results of performed VIF analysis for variables of group 4.

Variable	Opening window			Closing window		
	GVIF	Df	$GVIF^{\frac{1}{2 \cdot Df}}$	GVIF	Df	$GVIF^{\frac{1}{2 \cdot Df}}$
Solar Radiation	4.0	1	2.0	1.7	1	1.3
Outdoor Relative Humidity	2.0	1	1.4	2.7	1	1.6
Room	530.0	1	23.0	27.0	1	5.2
Sun Hours	1.3	1	1.1	1.5	1	1.2
Indoor Temperature	3.1	1	1.8			
Lux	1.8	1	1.3			
CO_2 Concentration	3.0	1	1.7			
Outdoor Temperature	5.5	1	2.3	175.9	1	13.3
Solar Radiation: Room	8.3	1	2.9			
Room: Indoor Temperature	203.3	1	14.2			
Room:CO_2 Concentration	363.5	1	19.1			
Room: Outdoor Temperature	9.0	1	3.0	6.8	1	2.6
Indoor Relative Humidity				3.5	1	1.9
Season				98.3	2	3.1
Outdoor Temperature :Season				1968.8	2	6.7
Room: Indoor Relative Humidity				34.2	1	5.8

Generalized patterns

Generally the occupants' window opening and closing behaviour was governed by different variables indicating that the occupants had different reasons for opening and closing windows.

From the four opening and closing models it appears that some common patterns of behaviour exist. In all four groups of dwellings, the CO_2 concentration had an impact on the window opening probability while the outdoor temperature affected the closing probability.

Interestingly, wind speed did not affect window opening/closing behaviour in any model of the four groups.

BEHAVIOUR PATTERNS IN SIMULATION PROGRAMS

The results from the analysis provide a possibility of defining window opening behaviour patens for simulation purposes. Tables 6, 8, 10 and 12 provide a method for calculating the probability that the window will be opened or

6 CONCLUSIONS

Based on measurement of window opening behaviour and indoor/outdoor conditions in 15 dwellings during winter, spring, and summer it was shown that behaviour differed between dwelling type (rented or owned, mechanical or natural ventilation) and within dwelling type. The indoor CO_2 concentration and the outdoor temperature were the two single most important variables in determining the probability of opening and closing windows respectively.

Based on the measurements, four models of occupants' window opening and closing behaviour patterns in building simulation programs was proposed. When implemented into simulation programs, this definition will significantly increase the validity of the simulation outcome.

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5 DISCUSSION

Rijal et al. [13] 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 our proposed models 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 getting the indoor environment and energy consumption correct.

Occupancy

The occupancy of the dwellings was determined using the monitored CO_2 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. Since most of the periods without occupancy were removed, any correlations between behaviour and CO_2 concentration indicate relationships between air quality and behaviour.

Statistical approach

We have used logistic regression to infer the probability of a window opening or closing event. In using this method we have assumed that the probability function looks like formula 2. Additionally we have assumed that all observations were independent of each other. This assumption is questionable as the observations were gathered in 15 dwellings. Essentially the assumption would hold true if all inhabitants of the dwellings reacted similarly to the conditions they were subjected to. In any other case the observations in each dwelling will be influenced by the habits of the inhabitants of the individual dwelling and as a result they would not be independent from each other. We have dealt with this problem by using a dwelling index as a factor in the first attempts to infer models. Interactions between variables and dwelling index were taken as signs of dependence and the variables were removed from the final models. In doing so, we may have removed variables that had an influence on the opening/closing probabilities.

We chose to use the Akaike information criterion (AIC) as a basis of variable selection in the inference of the models. Another option would be to use Wald tests to test the significance of each term and use this as a selection criterion. We chose to use the AIC, since selecting variables based on their significance does not take the risk of overfitting into account. This risk increases with the number of observations. The AIC includes a penalty that increases with the number of estimated variables in the model, which discourages overfitting.

Seasonal variations

The measurements were made during the winter, spring and summer. As a consequence the results in this paper are only valid for these seasons. There is, however, no evidence that the behaviour of occupants depends differently on the measured variables in the autumn than in spring (or other parts of the year if the model does not include seasonal effects). When implementing the models into simulation programs, the models without seasonal effects (table 8 and 10) can be used for the entire year. In models including seasonal effects the spring season can be used as a representation in autumn.

Variables for determination of window opening behaviour

Indoor relative humidity influenced the opening/closing probability (table 6, 10 and 12), even though it was in the range 30% to 70 %, where humans are modestly sensitive to relative humidity. On the other hand, the relative humidity does affect both thermal sensation and perceived air quality and this might be why it affected the opening/closing probability. Johnson and Long [22] conducted a visual survey of residential window and door positions in North Carolina. They found that the window and door opening behaviour was affected by a number of variables including weather, dwelling characteristics and anthropological variables. An AIVC report [29] concluded that there were considerable differences in the ventilations behaviour's weather dependency, which indicates that other variables play a significant role in determining the ventilation behaviour. These results are in accordance with our work and underline the importance of taking more than the temperature into account when investigating the behaviour of occupants.

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PAPER III

A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings

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A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings

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Research Article

Abstract

An energy simulation of a building is a mathematical representation of its physical behaviour considering all the thermal, lighting, acoustics aspects. However, a simulation cannot precisely replicate a real construction because all the simulations are based on a number of key assumptions that affect the results accuracy. Above all, the real energy performance can be affected by the actual behaviour of the building occupants. Thus, there are great benefits to be derived from improving models that simulate the behaviour of human beings within the context of engineered complex systems. The occupant behaviour related to the building control potentialities is a very complex process that has been studied only in the last years with some focuses related to natural ventilation (window opening behaviour), space heating energy demand (in particular the adjustments in the temperature set-point) and natural light (focusing on window blinds adjustments). In this paper, a methodology is presented to model the user behaviour in the context of real energy use and applied to a case study. The methodology, based on a medium/long-term monitoring, is aimed at shifting towards a probabilistic approach for modelling the human behaviour related to the control of indoor environment. The procedure is applied at models of occupants' interactions with windows (opening and closing behaviour). Models of occupants' window opening behaviour were inferred based on measurements and implemented in a simulation program. Simulation results were given as probability distributions of energy consumption and indoor environmental quality depending on user behaviour.

Keywords

occupant behaviour,
energy modelling,
building energy performance,
probabilistic approach

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1 Introduction

In recent decades governments worldwide have implemented energy requirements in their building regulations in order to reduce levels of buildings energy consumptions and to promote more energy-efficient housing. Since 2002 the Energy Performance Building Directive (EPBD) has required all EU member states to enhance their building regulations by implementing performance-based energy requirements and by introducing energy-label certification schemes to decrease the energy spent on heating, cooling, ventilation, lighting and domestic hot water in buildings. Even so, various studies have shown large differences in energy consumption in similar buildings (Branco et al. 2004; Emery et al. 2006; Marchio and Rabl 1991; Nordford et al. 1994; Seligman et al. 1978; Sonderegger 1978), suggesting that among the various factors occupant behaviour determines a strong influence. Actually, there is often a significant discrepancy between the designed and the real total energy use in buildings. The reasons of this gap are generally poorly understood and largely have more to do with the role of human behaviour than the building design (Fabi et al. 2012). Differences in users' attitudes, preferences in thermal comfort and reactions to the indoor environment determine great variations in energy consumptions. An investigation of energy consumption for heating in 290 similar houses revealed that there was considerable variation between houses (Henningsen 1999; Andersen 2012): since the houses were "identical" (apart from orientation) the variation was largely due to the way the houses were used. The comparison of energy consumption

Architecture and Human Behavior

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of identical buildings (Branco et al. 2004; Emery et al. 2006; Marchio and Rabl 1991; Nordford et al. 1994; Seligman et al. 1978; Sonderegger 1978) highlights that the difference between real and predicted energy use depends on both the final realisation of the construction, the technical installations, and the real use of the built systems operated by occupants. Knowledge of such user actions is crucial for better understanding and for more valid predictions of building performance (energy use, indoor climate) and effective operation of building systems (Hoes et al. 2009).

In current practice the results of dynamic simulation tools cannot provide realistic results. Simulation programmes use standard/fixed occupant behaviour to predict the energy requirements of buildings but in reality occupant behaviour may differ from the scheduled actions.

The ability of a simulation program to calculate real energy use in buildings is undermined by a poor representation of stochastic variables that relate human interactions with the control of the indoor environment. One reason of the discrepancy between simulated and real energy use in buildings lies in the fact that simulation tools are only able to describe control actions deterministically, e.g., following predefined, fixed and unrealistic schedules (Fabi et al. 2011b).

A number of studies have been conducted in the past decades to understand how building occupants interact with buildings' environmental control systems such as windows, blinds, heating set-point. Based on field investigations several models have been developed (Fritsch et al. 1990; Nicol and Humpherys 2004; Rijal et al. 2007; Haldi and Robinson 2008; Yun and Steemers 2008; Herkel et al. 2008; Page et al. 2008; Reinhart 2004) in order to describe the occupant behaviour related to some specific topics (window or blind operation, heating set-point) and to implement it into building simulation programs.

The results of the above mentioned studies cannot be generally applied to any buildings, since variables like climate, culture, building structure, space typology (e.g., residential or office building) play an important role. In literature driving forces for user behaviour (like in the case of window operation, the noise level or indoor air quality reported either as not recorded or as evaluated by questionnaires) indicate the importance of such factors but does not contribute to formulate generalizable behavioural models. Nevertheless, previous work provides a good basis for formulating a suitable models according to the aim and the object of the analysis.

In this paper, the problem of modelling the users' interaction with building indoor environmental control systems into building energy simulation programs is first dealt with, and the existing models of windows operation are briefly described aiming at providing an impression of the kinds and scope of the relevant research efforts.

A methodology is then presented to model the user behaviour in the context of real energy use and applied to a case study. The methodology, based on a medium/long-term monitoring, is aimed at shifting towards a probabilistic approach for the modelling the human behaviour related to the control of indoor environment.

The procedure is finally applied at modelling occupants' interactions with windows (opening and closing behaviour). Models of occupants' window opening behaviour were inferred based on measurements and implemented in a building energy simulation program. The results of the simulations results were probability distributions of the performance indicators (energy consumption, overheating hours etc.) rather than a single number.

2 Occupant behaviour models

The first issue emerging from the literature regards the facts that models for human behaviour and for energy simulation are based on two fundamentally different approaches.

Models of human behaviour are based on statistical and probabilistic algorithms that predict the probability of an action or event. For example, like other representations of human behaviour, the emerging empirical models of window operation tend to be based on statistical algorithms that predict the probability that an event occurs, for example opening a window, given certain environmental conditions. They are based on observations of windows in existing buildings that allow to find out statistical correlations between the "window state" (open, partially open, closed, etc.) and outdoor temperature, time of day, season, indoor environmental conditions, etc. In other words, they consider window operation as a stochastic (probabilistic) process where the probabilities of control events are based on environmental (indoor and outdoor) factors.

Building simulation tools, on the other hand, are based on heat transfer and thermodynamic equations, and they typically model human actions (e.g., operation of lights, blinds, and windows) by means of predefined fixed schedules or rules (e.g., the window always open, if the indoor temperature exceeds a certain limit). Building simulation tools often model building dynamics using numerical approximations of equations: they are capable of modelling only deterministic (fully predictable and repeatable) behaviours.

This is an important limitation of energy simulation tools for modelling occupant's interactions with buildings, and it highlights that the results are essentially unrealistic: for example, lots of simulation codes do not model the control of windows but they use as input the possible effect (through air change rate variation each hour).

Clarke et al. (2006) analyzing this issue, stated that for given environmental conditions people could feel comfortable or uncomfortable and they could control the indoor environment in several ways, without having the certainty to behave exactly in the same manner in another occasion given the same stimulus. Thus, since a deterministic model is not able to manage to give these natural uncertainties, they proposed to develop a probabilistic model. In particular, they suggested a probabilistic model of the discomfort and a second probabilistic model of actions taken in response to that discomfort to model stochastic occupant behaviour in buildings. This approach, however, will only model actions taken as a direct consequence of discomfort (typically only thermal discomfort). Many actions may be taken in anticipation of discomfort (before the uncomfortable state occurs) or for reasons that are not related to comfort (a window might be opened to hear the birds singing). A single stage model focusing on a direct relation between the environment to actions will overcome this problem.

Currently, the most common means used to consider occupant presence and behaviour within simulation tools is the "diversity profile" (Herkel et al. 2008; Page et al. 2008; Haldi et al. 2009; Hoes et al. 2009). This is used to estimate the impact of internal heat gains (from people, office equipment and lighting) on heating and cooling load calculations of a single building. The profiles depend on building type (typical categories: "residential" and "commercial") and on the occupants type (for example, size and composition of a household).

The papers from literature here presented refer to two specific building typologies: residential and office buildings. Although residential buildings are responsible for a quarter of the total primary energy in EU member states, studies with the purpose of implementation of realistic model of human behaviour in simulation tools have generally been conducted in offices (Haldi and Robinson 2008; Rijal et al. 2007; Herkel et al. 2008). However in the last years dedicated literature studies (Brundrett 1977; Kvistgaard and Collet 1990; Weihl and Gladhart 1990; Wallace et al. 2002; Keiding 2003; Price and Sherman 2006; Offerman et al. 2008; Xu et al. 2009; Andersen et al. 2009) have increased and different questionnaire surveys, monitoring and statistical approaches are investigated. Since the application at a case study is regarding the topic of natural ventilation, and in particular of window opening behaviour, existing models of human behaviour related to the window opening behaviour are presented in the following section.

2.1 Window opening behaviour models in residential buildings

In general, the existing models of window opening behaviour that are expressing the probability of actions will be performed on windows in office buildings, therefore they are not calibrated and validated for residential buildings. So far, there are only two published models regarding the window opening behaviour in dwellings and they are here discussed.

As early as 2005 Johnson and Long (2005) developed a linear regression model: a series of stepwise linear regression analysis were performed on the data to identify factors associated with open windows and doors. The statistical analysis is focused on identifying the variables that can be used to predict when a residence will have one or more open windows or doors.

In 2011 Andersen et al. (2011) developed a logistic model inferring the probability of opening and closing a window (change from one state to another) separately to determine the most dominating drivers for each action. For each variable the coefficients for the logistical regression is identified for different times of day and days of week, The magnitude described as a measure of the maximum impact of each variable on the probability of opening or closing a window, was presented.

Schweiker et al. (2012) have recently validated models developed for office building in residential buildings. The basis is data analysis from two distinct measurements campaigns in residential indoor environments in Japan and Switzerland. The previous models for office occupants' use of windows are related to the study of Haldi and Robinson (2009) and Schweiker and Shukuya (2009). In particular, they tested the Bernoulli process, Markov Chain and hybrid model. Totally the combination of these distinct approach results in nine types of models for the prediction of actions on windows. From the results it seems that models require specific calibration in the case of buildings equipped with an air-conditioning unit as was the case of Japanese database.

2.2 Window opening behaviour in office buildings

Various window opening models have been developed in recent years, based on relationship with indoor and/or outdoor temperature (Fritsch et al. 1990; Nicol 2001; Nicol and Humphreys 2002; Herkel et al. 2008; Yun and Stemeers 2008).

Fritsch et al. (1990) proposed a model based on Markov chains (probabilities of window operation based on current state) for random window opening prediction. They investigated personal use of operable windows in four offices and found that the probability of finding a window in a certain position depends on its preceding position yet not on any others. The authors chose discrete Markov chains as the basis of a suitable predictable model. A Markovian process has no memory; the next state will depend only on the present state and no others: capturing all the particularities of an investigated room (e.g., size, inhabitant behaviour, etc.), yet it requires a unique set of observations for every office.

Herkel et al. (2008) used Monte-Carlo (multiple runs with randomly determined outcomes consistent with the observed probabilities used to explore all the outcomes that are within the range of expected behaviour) simulations to predict user behaviour. Herkel et al. (2008) developed a window opening model based on outdoor temperature and occupancy levels.

In cases where a dependent variable assumes a continuum of values, conventional regression analysis is appropriate to link the observed outcome to the values of certain driving or explanatory variables. Here, the use of controls is instead binary in nature (windows are either opened or closed, blinds either retracted or lowered, etc.) rather than being part of any continuum. Nicol and Humphreys (2002) linked the use of controls to either outdoor or indoor globe temperature using binomial logit regression. The resulting function provides the probability of a state of the particular controls (window open or closed, blinds activated or not, etc.).

While most studies have investigated the number of open windows and the probability of opening a window, only few have examined the degree of opening. Fritch et al. (1990) measured the opening angle of four windows in four offices every half an hour during the heating seasons of 1983–1984 and 1984–1985. Monitored variables included indoor and outdoor temperature, wind speed and solar radiation interfering with the window. The data analysis excluded the wind speed and solar radiation as significant drivers for determining the angle of opening. The indoor temperature was discarded as the indoor temperature was relatively constant and due to the fact that it dropped when the supply of fresh air was increased as a consequence of opening the window[1]. This left the outdoor temperature as the only significant variable in the determination of the window angle. Fritch et al. (1990) found that windows were usually left in the same position for long periods of time which is consistent with the findings of Herkel et al. (2008). They found that large windows that were opened completely remained open for a short time, while large windows that were tilted open and small open windows usually remained open for the entire day.

Some algorithms, for example the Yun algorithm (Yun and Steemers 2008), classify building occupants into active, medium and passive users of windows based on the frequency at which they arrange the window position. They are capable of quantifying the effects on building thermal performance: it is demonstrated that the variation between active and passive window user is of the same order as the difference between low and high thermal mass constructions.

Although the studies mentioned above provide an accurate analysis of what drives occupants to change window status, it is necessary to consider how these models could be applied in energy simulation. The analysis of main drivers emerging from the literature clearly indicated that the interactions of the users with the building control (windows or heating set-point) is not only influenced by perceived thermal conditions but also by the response to perceived indoor air quality (IAQ), draughts, rain, outdoor noise levels, the desire to conserve energy, etc (Fabi et al. 2012). However, reliable values of key drivers, such as rain or psychological variables, are difficult to obtain, while others, such as draught levels, are subject to great uncertainty.

Behavioural models predicting the probability of opening window are largely based on indoor/outdoor air temperatures; however when other variables are investigated they often turn out to be significant drivers.

[1] This was problematic since the predictive variable was influenced by the state it was trying to predict.

2.3 Window opening behaviour models: Key points

The crucial point lies in the fact that human behaviour is not deterministic, but common tendencies are recognizable in the data that has been collected. Models based on the probability of observed phenomena (like window opening and closing) are suited to capture such behaviour.

At the same time, stochastic (probabilistic) models can take different forms. Some of these models can be simple functions giving the probability of a window being open given a set of environmental conditions as inputs, while others like Markov chains and survival analysis can use the current state of the window or other time varying factors to influence the outcome.

The analysis of drivers showed that the time of a day is a very important parameter influencing users to act. In offices, most opening and closing behaviour is associated with arrival and departure from the room (Herkel et al. 2008). Moreover, windows tend to be left in the state they are. The conclusion is that occupants do not adjust their windows very actively or regularly throughout the day. These facts introduce a time dimension into models of occupant actions and suggest that different times of day or different "window states" might require their own probability functions. Some models focus on the temporal aspects of window control (occupant arrival and departure, and evolution given a particular window state), others focus on the thermal comfort aspects (indoor temperature, outdoor temperature, adaptive comfort modelling, etc.), and some account for both.

Temperature is still the most important driver in most models, but context really does matter. It is a point of discussion if it is better to take into account outdoor temperature or indoor temperature. They tend to co-vary in naturally ventilated buildings, and even as indoor temperature produces the discomfort that triggers window opening, the acceptability of an open window will be determined by the conditions outside.

Moreover, window opening angles are often not taken into account in models and in the simulation.

From the literature review it emerges that so far, existing models and simulations are regarding mostly office buildings and behaviour in residential environment is not specifically treated, and published studies do not provide any common robust cross-validation procedure, which prevents any comparison of quality between published models.

3 A procedure for modelling the energy related human behaviour

3.1 Procedure details

The traditional approaches look at human behaviour as if they would behave in a fully deterministic way: that's to say in a fully repeatable manner. Moreover, in the first design stage, "design conditions" are simulated, implying that when the building is realized the occupants interactions with the indoor environment will exactly coincide with the design values during the entire operational time.

However, if what happens in the real world is analysed more carefully, it is easy to discover that, actually, many parameters influence the environmental conditions and the human behaviour varies significantly and unpredictably during the whole building life. This implies that, for smaller or larger amounts of time, not all the interactions of the building occupants to control the indoor environmental parameters would satisfy the assumed requirements in all building rooms.

The proposed procedure to simulate the human behaviour realistically is based on a probabilistic approach for the evaluation of both input and output parameters. This probabilistic approach is related to variability and unpredictability during the whole building operation. Figure 1 shows the different steps representing the proposed approach and described in the following sections. The philosophy behind this method accounts for stochastic factors, and the result of the design process will not be a "single value" for the system performance, but a probability to fulfil a certain performance over the time (Corgnati et al. 2006).

From the practical point of view, the proposed approach means to start with continuous measurements of both indoor environmental parameters and external climate conditions and the behaviour of the building occupants (window opening, thermostatic radiator valves' set-point, occupancy sensors, etc.), performed in a sufficient number of areas and rooms representing different zones in the building.

Different suitable user behavioural patterns (models) were defined by means of statistical analysis (logistic regression, Markov chain, etc.) and could be implemented in many of the actual simulation tools (Esp-r, IDA ICE).

Finally, a probabilistic distribution instead of a single value is preferred as a representation of energy consumptions.

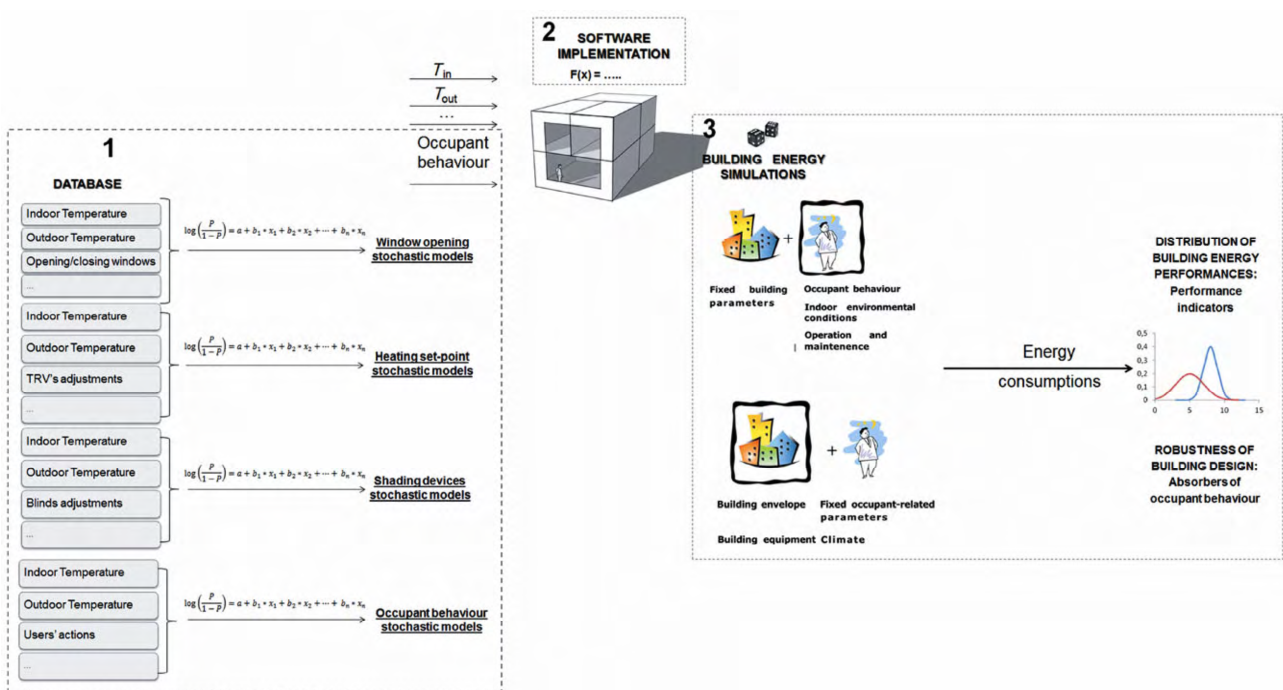

Fig. 1 The probabilistic approach to model the human behaviour related to the control of indoor environment

3.2 Database

A complete database should include all the parameters regarding the possible occupant's behaviour driving forces. In particular, as explained in (Fabi et al. 2011a), both external parameters (physical environmental and contextual variables) and internal parameters (social, psychological and physiological variables) should be collected.

Typically, the data to be elaborated to assess the behavior of the building occupants can be obtained by setting up a measurement campaign and questionnaires given to be answered by the occupants. Even if the majority of the existing studies mainly focused on monitoring activities through measurements, it is important to point out that also surveys and questionnaires addressed to occupants are in important tool to characterize properly users' behaviour.

A series of variables concerning indoor (temperature, relative humidity, CO_2 concentrations, etc.) environmental conditions are to be monitored and meteorological data (wind velocity, global solar radiation, rainfall precipitations, etc.) should be obtained from national meteorological stations in the buildings proximity. The measurement campaign addressed to evaluate the external factors could be applied only to one parameter (for example, room operative temperature), but may include measuring of many other quantities (related to the thermal and IAQ environment).

Occupants' interactions with the controls, as heating set-point temperatures or window positions, should be gathered by measurements of the most representative zones and rooms of the building, for example, one thermostatic radiatior valve in the bedroom and one in the living room of each dwelling.

Internal driving forces should be collected by means of surveys and questionnaires, aimed at investigating the factors strictly connected to individual and subjective data. In particular, they should be included in the database users' preferences, users' thermal background, users' behavioural background, and attitudes, lifestyle, activity, age or gender as well.

Moreover, as reported in (Fabi et al. 2012), there are some specific "drivers" having the greatest influence leading the occupant to make an action. These "preeminent" drivers are crossing the different field of study, highlighting the complexity of the research regarding occupants, but they should be gathered in order to characterize as much as possible the behaviour of the building occupants.

All the data collected by means of both objective procedure and subjective procedure, should be analysed in a statistical way. As a result of the monitoring data analyses by means of the statistical analysis, the probability of doing a certain action (opening or closing the window, turning up/down the heating system) was inferred for a defined behavioural models. Users control actions are deduced by means of logistic regression with interaction between variables or Markov chain or other typologies of statistical analysis. The results are "occupant behaviour descriptors" to integrate within a building energy simulation software.

3.3 Software

In order to investigate the effect of occupants behaviours both on energy consumption and indoor environmental quality, simulations should be run in thermal zones maintaining location, weather file and building construction of the monitored buildings. In the occupancy schedule the occupant could be still considered as always present but the control of building indoor environment is now probabilistic in nature, it doesn't follow pre-defined controllers or fixed rules. The probability of adjusting temperature set-point or opening a window is calculated in the simulation software on the basis of the equations previously used to describe statistically the behaviour. Most of simulation programs are deterministic in nature, so there is the need to translate the probability of an event to a deterministic signal. A way of doing this is to compare the probability to a random number to determine if the event takes place or not. As the given probability is the probability of doing a certain action in a certain time period, the comparison is to be made with a random number that changes with the same interval. The action occurs when comparing the random number with the calculated probability, the former was smaller than the latter.

3.4 Simulations

A probabilistic distribution of energy consumptions depending on user type is obtained by running several simulations.

Fixing all the parameters related to the energy performance of the building (i.e. climate, building envelope, building equipment), the simulations are aimed at verifying the influence of the characterized users behaviour on energy consumptions. Running a high number of simulations it is possible to have a curve of energy performance of the building in different situations and for different occupant typologies. In this way, it's preferable to have a probabilistic distribution (a "*probabilistic output*") instead of a single value as a representation of energy consumptions.

Indeed this approach aims to represent a procedure that could be extended to all the users' interactions with the indoor environmental control systems, like window operations, heating set-point adjustments, solar shading operations.

A further step is represented by the application of user models into simulation programs to verify the "robustness" of the building with respect to the users. Once the user behaviour has been characterized by a model and its impact on energy performance is verified with a number of simulation, it is interesting to check what happens changing the building properties and equipment with the same user behavioural pattern.

Based on (Ferguson et al. 2007), Hoes et al. (2011) defined the performance robustness as the ability of a building to handle changes (or disturbances) in the building's environment and maintain the required performance. Therefore, it is important to take performance robustness into account during the design process (Leyten and Kurvers 2006).

Nevertheless factors involved in the energy programs implementations can be extended to thermal mass, facade percentage of transparency, shading devices or window opening with the aim to understand which of these have the most influence in energy use and so, constitute recommendations for improved buildings design with regard to energy reduction. This allows the designers (engineers, architects or technicians) to select the most robust solution for the building design.

4 Application of the procedure

4.1 Case study description

The proposed procedure was applied for modelling the occupant behaviour related to window opening and closing, and its implementation in the simulation tool IDA ICE so that the results obtained are probabilistic in nature.

Based on previous monitoring in Danish dwellings in Copenhagen (Denmark) a database was elaborated in order to get all the required information of occupants interactions with controls. Through the statistical software R it was possible to determine window opening influencing factors within indoor climate variables and outdoor weather conditions. Dwellings were grouped on the base of their ownership (owner occupied or rental) and the ventilation type (natural or mechanical). The probability of opening/closing the windows was inferred by logistic regression. A linear model gave the measure of the degree of opening. Four different users' behavioural patterns were defined that could be implemented in many existing simulation tools. In this paper, IDA ICE (Indoor Climate and Energy) simulation tool was used and the equation describing the probability of user interfering with the control of the indoor environmental quality and the event taking place was inserted in the program.

4.2 The Danish database

A monitoring of indoor and outdoor climate variables and occupant's control actions was conducted in 15 Danish dwellings in the period from January to August 2008 in Copenhagen (Andersen et al. 2009). Measurements were carried out in 10 rented apartments and 5 privately owned single family houses. Half of the apartments were naturally ventilated, while the other half were equipped with constantly running exhaust ventilation in the kitchen and in the bathroom. Three single family houses were naturally ventilated while the other two were equipped with exhaust ventilation. A series of variables concerning indoor and outdoor environmental conditions were monitored and meteorological data were obtained from 2 Danish meteorological stations in the dwellings proximity. Occupants interactions with the windows (in the bedroom and living room) were monitored.

Danish dwellings were divided into 4 groups for the data analysis (Table 1), depending on ownership (owner-occupied or rented) and ventilation type (natural or mechanical).

In the analyses the probability of opening and closing the windows was inferred for the four behavioural models.

Occupants' control actions was deduced by means of logistic regression with interaction among variables according to the following equation:

$$\log\left(\frac{p}{1-p}\right) = Q + b_1 \times x_1 + b_2 \times x_2 + \cdots + b_n \times x_n + c_{12} \times x_1 \times x_2 + \cdots \tag{1}$$

where,
p: the probability of an opening/closing event,
a: the intercept,
$b_{1\cdots n}$: coefficients,
$x_{1\cdots n}$: variables such as temperature, CO_2 concentration etc.,
$c_{12\cdots nn}$: coefficients of interaction among selected variables.

Backward and forward selection of variables based on the Akaike information criterion was used in the selection of the models (Schweiker and Shukuya 2009). The statistical analyses were conducted using the statistical software "R" and the models were inferred using the "step" function in R. The magnitude of the variable is a measure of the maximum impact of the variable on the probability of opening or closing a window.

Table 1 Description of groups related to the ownership and ventilation type

Group	Ownership	Ventilation type	Number of dwelling
I	Owner-occupied	Natural	3, 4, 16
II	Owner-occupied	Mechanical	1, 10
III	Rental	Natural	6, 8, 9, 11, 12
IV	Rental	Mechanical	5, 7, 13, 14, 15

The results were models capable of predicting probabilities of opening and closing the windows. A model that predicts the degree of opening was inferred using linear regression. For reasons of brevity, all the models are not presented here, but a model of window operation resulting from the analysis is presented:

$$\log\left(\frac{p}{1-p}\right) = a + 0.501 \times x_1 + 1.87 \times x_2 + 0.163 \times x_3 \qquad (2)$$

where,
p: the probability of an opening event,
a: the intercept, assuming different values for different times of the day as follows:
night: −23.83
early morning: −23.04
late morning: −24.06
afternoon: −24.32
evening: −24.47
x_1: the solar radiation (W/m^2),
x_2: the CO_2 concentration (ppm),
x_3: the indoor temperature (℃).

Figure 2 represents the probability of opening windows for different times of a day and CO_2 concentration for this analysed group of dwellings. This field survey highlighted that for all the examined groups the inhabitants have generalized patterns regarding the time of the day: the probability of opening windows is highest in the morning (6–9 a.m.) when they wake up (Fig. 2).

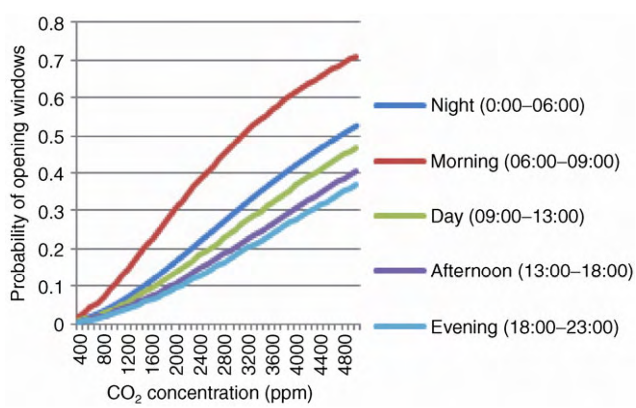

Fig. 2 Probability of opening windows for different times of a day and CO_2 concentration for an analysed group of dwellings

4.3 Software

To estimate the influence of occupant behaviour on dwelling energy consumption, stochastic models of energy-related occupants' behaviour were implemented in the dynamic building simulation software IDA ICE [version 4.1]. IDA ICE is a dynamic multi zone simulation software application for accurate study of thermal indoor climate and energy consumption of the entire building, developed by EQUA. This open source program allows modellers to manage occupant behavioural patterns, by implementing statistical equations (IDA ICE 2009).

4.4 Simulations

Results of the statistical analysis provide the possibility of defining behavioural models of windows use to be implemented in simulation tool for energy simulations.

In the occupancy schedule, the occupant is still considered as always present but window control is now probabilistic in nature, it doesn't follow fixed controllers for opening and closing. The probability of opening and closing the windows was calculated based on the logistic regression previously described. Specifically, four behavioural patterns were simulated.

The occupant behaviour equations were implemented in the simulation program using a model with a living room and a bedroom. The use of two different rooms reflected the circumstances under which the measurements were collected. A typical room was adopted for both living room and bedroom to evaluate the influence of windows control related to occupant behaviour on total energy use. European Standard EN 15265/2005 "Thermal performance of buildings—Calculation of energy use for space heating and cooling—General criteria and validation procedures" provided a test room suitable for the simulations.

The room area was 19.8 m^2 and the dimensions were: length = 3.6 m; depth = 6.5 m; height = 2.8 m. The external wall was facing west with a window area of 3.5 m^2. The thermo physical properties of the opaque components are summarized in Table 2. The transparent component was a double pane glass (4 mm of pane of glass, 12 mm of air, 4 mm of pane of glass) and its solar and thermal characteristics were: U value: 2.9 W/(m^2·K); solar transmittance, T = 0.7; solar heat gain coefficient, g = 0.76.

Since the location was Copenhagen in Denmark (55.63°N, 12.67°E), the meteorological data used in the simulations refers to the Danish design reference year.

Both bedroom and living room were equipped with of a waterborne radiator supporting the HVAC plant in providing the required thermal comfort with a constant heating set-point of 21℃ from September to June, working with a dead band of 2℃ and a maximum power of 2500 W placed under the windows in the rooms. None of the rooms had a cooling system. Cracks were added to the two rooms, inducing an average infiltration rate of respectively 0.4 h^{-1} in the living room and 0.2 h^{-1} in the bedroom (calculated in IDA ICE). Both the living room and the bedroom had

Table 2 Thermo physical properties of the opaque components

	Material	Thermal conductivity (W/(m·K))	Density (kg/m³)	Specific heat capacity (J/(kg·K))	U value (W/m²)	Thick-ness (cm)
External wall	Internal plastering	0.70	1400	0.85	0.49	0.365
	Masonry	0.79	1600	0.85		
	Insulation layer	0.04	30	0.85		
	Outer layer	0.99	1800	0.85		
Internal wall	Gypsum plaster	0.21	900	0.85	0.36	0.125
	Mineral wool	0.04	30	0.85		
	Gypsum plaster	0.21	900	0.85		
Floor	Acoustic board	0.06	400	0.84	0.241	0.40
	Mineral wool	0.04	50	0.85		
	Concrete	2.10	2400	0.85		
	Mineral wool	0.04	50	0.85		
	Concrete	1.40	2000	0.85		
	Floor covering	0.23	1500	1.5		
Roof	Rain protection	0.23	1500	1.3	0.438	0.284
	Insulating	0.04	50	0.85		
	concrete	2.10	2400	0.85		
External floor	Concrete	2.10	2400	0.85	0.76	0.284
	Mineral wool	0.04	50	0.85		
	Concrete	1.40	2000	0.85		
	Plastic floor covering	0.23	1500	1.5		

only one wall facing the exterior environment in the west orientation and only one operable window (Fig. 3).

As internal source, one person was considered present in each of the rooms with a house living schedule (from 0:00 to 8:00 and from 17:00 to 24:00) at an activity level of 70 W/m², corresponding to a metabolic activity of 1.2 met. The lighting schedule followed the presence of people (100%) from Monday to Sunday, from 6:00 to 8:00 and from 15:00 to 23:00. Furthermore, the light in the room, with an emitted heat per unit equal to 50 W, was automatically switched on if the minimum work plane illuminance was lower than 100 lx based on the study of the Lightswitch-2002 (Reinhart 2004); the light was automatically switched off at an illuminance level of 500 lx. The equipment emitted 50 W heat from 18:00 to 22:00 from Monday to Friday, and from 15:00 to 22:00 on weekends. There was no solar shading, since this is typically not used in Danish dwellings (Andersen et al. 2009).

According to the mechanical ventilation type of the database dwellings, two "deterministic reference" models were set differing only for the ventilation type: one model was realized for naturally ventilated buildings and another one for mechanically ventilated building (exhaust ventilation).

IDA Indoor Climate and Energy, as most the simulation programs, is deterministic in nature. Therefore there was a need to translate the probability of an event to a deterministic signal. Based on the model of Reinhart (2004) and Newsham et al. (1995), two time series of evenly distributed random numbers of a rectangular distribution between 0 and 1 with an interval of ten minutes were located in the simulation program, one series for opening and another for closing. The windows were opened or closed when the probability of the action was larger than the random number. In the event that both the random open number and the random close number were smaller than the calculated probabilities, the window state remained unchanged.

Two stochastic processes were needed in order to predict the state of the window. First of all, the probability of opening the window for four user profiles was determined in relation to the explanatory variables. The closing probability was calculated in the same way.

Secondly, the linear model gave the degree of opening. Using the probability of opening and closing the windows, quantitatively controlled by the linear model, the degree of opening was then predicted.

5 Results

The results of the statistical analysis on the Danish database confirmed that there is no 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. Even if the dwellings were divided for the statistical analysis into four groups on the basis of ownership and

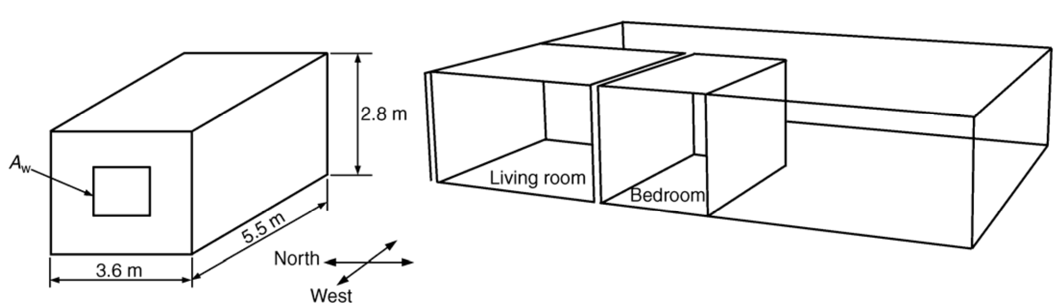

Fig. 3 The simulated rooms in IDA ICE

ventilation type, from the results it appeared that some common patterns of behaviour exist: the three most important variables determining the probability of opening a window in the four window opening models were CO_2 concentration, outdoor temperature and indoor illumination. For the outdoor temperature and indoor illumination, this was also the case for closing of a window, although the direction was different.

To get an indication of the performance of the four probabilistic models and their ability to predict window opening behaviour, simulations were run for each model comparing the results with the corresponding models where a reference deterministic window control (on/off temperature control + schedule) was used. In a deterministic way, IDA ICE has a schedule for window opening. Windows opened if the indoor temperature exceeded a certain value (25℃ ± 2℃) and the outdoor temperature was lower than the indoor temperature. This schedule was used in the deterministic simulations of the building.

Results are given in the form of primary energy, accordingly with the European Standard EN 15603 that establish the conversion factors as $f_{\mathrm{pfuel}} = 1.36$ for heating and as $f_{\mathrm{pelectricity\ mix\ UECPTE}} = 3.14$ for other electric systems and appliances.

The air change rate was used as a first indicator of the size of the change in performance caused by a shift in window opening behaviour. Fluctuations on air change rate were signs of a shift in the window opening behaviour governed by a change in the indoor climate large enough to influence the window opening behavioural models.

From the data reported in Table 3 and Table 4, the existing relationship among probabilistic window control for the groups and air change rates, ventilation losses and energy consumption can be noted.

A significant difference can be appreciated in the comparison between the groups with natural ventilation (I and III) and groups with mechanical (exhaust) ventilation (II and IV). Ventilation rates for the mechanically ventilated buildings were up to 57% higher than in the naturally ventilated ones (for groups I and II in the bedroom and for groups III and IV in the living room). Major differences were found in the ventilation losses in the bedroom where the groups with mechanical ventilation had up to 101% higher losses than the natural ventilated buildings (bedroom, groups I and II). There were small differences in the space heating between groups, due to the fact that the building envelope was the same for all the four groups. This was especially true for the primary energy values, where lighting facilities, equipments and domestic hot water were exactly the same for all the groups.

From Tables 3 and 4 it is evident that the probabilistic approach used for the simulations of the four user types was different from the deterministic approach.

The air change rate in the naturally ventilated buildings was up to 33.8% higher in the bedrooms, and the ventilation losses was 9.9% less in the buildings where the probabilistic approach was used.

The predefined schedule for the window control underestimated the opening and closing events compared to the window opening models for mechanically ventilated buildings (groups II and IV). This result fits with the existing studies on the topic, where bedrooms are the rooms where windows are most frequently opened (Fabi et al. 2012). By consequence, space heating demand is often underestimated if the control on windows is regulated by a fixed schedule.

Table 3 Air change rates, ventilation losses, space heating energy demand and primary energy for naturally ventilated buildings

User types	Air change rate ($m^3/(s\cdot m^2)$)		Ventilation losses (kWh/m^2)		Heating, PE (kWh/m^2)	Total energy, PE (kWh/m^2)
	Bedroom	Living room	Bedroom	Living room		
I	0.58	0.65	70	72	266	393
III	0.58	0.64	71	70	266	392
Deterministic NV	0.87	0.86	77	76	281	407

PE: primary energy

Deterministic NV: naturally ventilated deterministic building energy simulation

Table 4 Air change rates, ventilation losses, space heating energy demand and primary energy for mechanically (exhausted) ventilated buildings

User types	Air change rate ($m^3/(s\cdot m^2)$)		Ventilation losses (kWh/m^2)		Heating, PE (kWh/m^2)	Total energy, PE (kWh/m^2)
	Bedroom	Living room	Bedroom	Living room		
II	0.91	0.59	140	96	349	479
IV	0.73	1.00	112	80	321	451
Deterministic MV	0.81	0.78	90	87	299	429

PE: primary energy

Deterministic MV: mechanically ventilated deterministic building energy simulation

6 Discussion

A probabilistic distribution of energy consumption depending on user types was obtained by running 20 simulations of the same model. Since the random numbers (that were compared with the predicted probabilities) changed in each simulation, the results of the 20 simulations were not identical (as would have been the case had a deterministic approach been used).

The results of the twenty simulations were similar to each other, in particular in the case of the groups with natural ventilation only (groups I and III).

The probabilistic distribution curve in Fig. 4 showed that the air change rate for group IV (with mechanical exhaust ventilation) ranged from 0.87 h^{-1} to 1.14 h^{-1} in the bedroom (variation equal to 24%). In the case of space heating demand, this shift in air change rate was reflected in a range of 10 kWh/m^2 per year (ranging from 313 to 323 kWh/m^2 per year).

This was an unexpected narrow range of variability, and could be attributed to the degree of the windows opening that was sometimes very small causing a small variability on the air change rate. The degree of opening was calculated with a linear regression based on the measures coming from only three windows. Only the window opening was simulated with the probabilistic approach, while the other

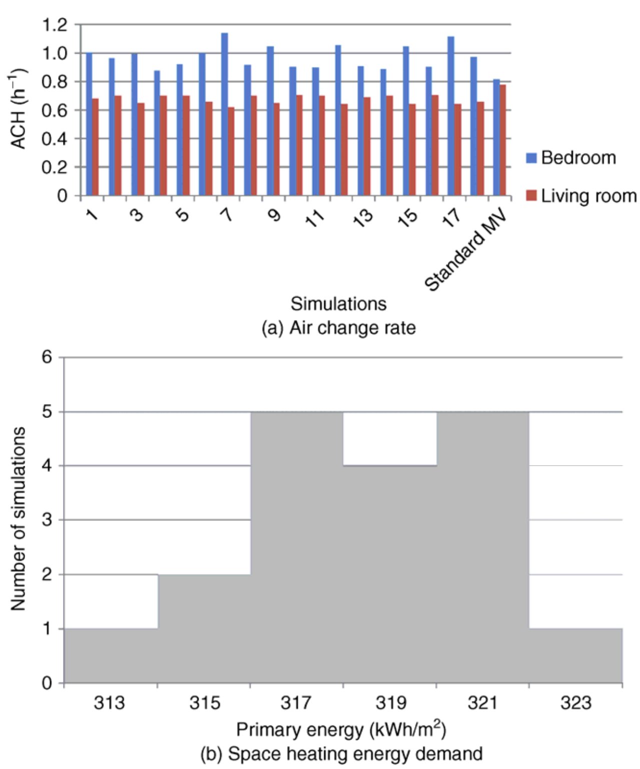

Fig. 4 Distribution of air change rate (a) and space heating energy demand (b) for group IV user type

user interactions with building (heating set-point, artificial lighting, blind adjustments, occupancy profiles) were simulated with the standard approach. This could have contributed to the unexpectedly narrow range of variability. Moreover, by merging the dwellings in groups inner dynamics of a single dwelling is lost and the specific behaviour is flattened in the groups as well. Further research to deepen this topic is required and it should analyse in a statistical way the single behaviour of each dwelling in order to obtain a specific model of user behaviour and randomly simulate these different behaviours in order to better represent users' variability.

The approach proposed here can be extended to cover heating/cooling set-points, use of solar shading and other actions that occupants take with an influence on indoor environment and energy consumption. The approach can be used to study variations in thermal mass, facade percentage of transparency or shading devices with the aim of constituting recommendations for improved buildings design with regard to energy reduction.

A fundamental step to be deepened in a further research is the comparison of simulation results with measured data, to ensure the validity of the models. The aim of our paper was to propose a shift on the research about modelling the occupant behaviour energy related factors from a deterministic approach to a probabilistic one, which was to verify that the proposed approach to simulation could actually work with existing building energy simulation tools.

7 Conclusions

In this paper, the issue related to users' interactions with indoor environmental control systems in building energy simulation tools are dealt with. Then, a probabilistic approach is proposed and applied to simulate the occupants' behaviour related to the window opening and closing. The main existing models of window opening and closing behaviour are briefly described, and then four window opening behaviour models based on actual, measured window opening behaviour are derived. Logistic regression analysis is used to infer the probability of the window being found open. This means that only values leading up to the opening/closing event were included and not values influencing the window state that was to be predicted. They were implemented in IDA ICE and the energy performance was simulated for a bedroom and living room. The use of probabilistic models resulted in a large variations range between behaviour patterns in the groups with natural ventilation and mechanical ventilation. The probabilistic approach results in simulation outputs as probability distributions, rather than a single number: probabilistic distributions of energy consumptions and air change rates for different real users' types have been determined.

This approach is reflected in distributions of energy performance indicators rather than one exact value. Even if calculated consumptions in the analysed Danish dwellings do not significantly vary within different behaviour patterns, they are definitively higher (in the case of mechanically ventilated buildings) or lower (in the case of naturally ventilated buildings) compared with the simulation results in accordance with the reference a deterministic control of windows. This range of results represent the variety in window opening behaviour often found between dwellings and therefore formed a good basis to improve the analysis of actual building energy performance.

Future field studies should include other aspects of occupants control on building systems in order to enhance a more accurate representations of reality by simulation tool prediction methods.

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PAPER IV

Influence of Occupant's Heating set-point preferences on Indoor Environmental Quality and Heating Demand in Residential Buildings

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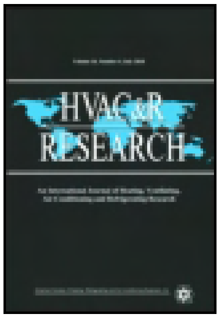

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Influence of Occupant's Heating set-point preferences on Indoor Environmental Quality and Heating Demand in Residential Buildings

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Influence of Occupant's Heating set-point preferences on Indoor Environmental Quality and Heating Demand in Residential Buildings

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The aim of this study was to switch from a deterministic approach of building energy simulation toward a probabilistic one that takes the occupants' interactions with the building controls into account. A probabilistic approach is proposed and applied to simulate occupant behaviour realistically. The methodology was based on probabilistic evaluation of both input and output variables of building energy simulations. The developed methodology can be applied in all aspects of occupant's interactions with building controls such as window openings, shading devices, etc. to achieve more realistic predictions of energy consumptions. The aim was to compare the obtained results with a traditional deterministic use of the simulation program.

Based on heating set-point behaviour of 13 Danish dwellings, logistic regression was used to infer the probability of adjusting the set-point of thermostatic radiator valves. Three different models of occupant's interactions with heating controls were obtained and implemented in a building simulation tool. The models of occupant's behaviour patterns were used to investigate how different behaviour patterns influence indoor climate quality and energy consumptions.

Simulation results were given as probability distributions of energy consumption and indoor environmental quality depending on occupant's behaviour.

Introduction

The ability of a simulation program to calculate real energy use in buildings is undermined by a poor representation of the stochastic variables that relate human's interactions with the control of the indoor environment. Consequently, the results of dynamic simulation tools cannot provide realistic results in current practice. One reason of discrepancies between simulated and real energy use in buildings lies in the fact that simulation tools are only able to simulate control actions following predefined, fixed and unrealistic schedules or rules. While simulation tools are based on deterministic equations and mimic user behaviour in a very static way, models of occupant's behaviour are generally described by statistical models which predict the probability of a state or an action. In the current practice, assumptions are generally applied to describe occupant's presence and actions in the building, but occupant's behaviour is much more complex (Hoes et al., 2009). It is therefore necessary to take occupant's interactions into account in order to obtain results that are closer to real energy use. Moreover, probabilistic modelling may quantify the inherent uncertainty and provide not only a number but also an interval on possible outcomes. In modelling there is a need to move toward a probabilistic approach. Equations describing human behaviour need to be implemented in simulation programs, and methods for a better prediction of energy demands have to be defined. Several studies proved that building occupants can have large influence on building energy use (Emery and Kippenhan, 2006; Maier et al., 2009; Socolow, 1977-78; Steemers and Yun, 2008). Differences in occupants' attitudes, preferences in thermal comfort and reactions to the indoor environment determine great variations in energy consumptions. An investigation of energy consumption for heating in 290 similar houses revealed that there was considerable variation between houses (Andersen 2012): since the houses were "identical" (apart from orientation) the variation was largely due to the way the houses were used. It was demonstrated that the total energy consumption in dwellings can be reduced by 10–30% by changing occupants' behaviour alone (Cordes, 1990, Mullaly, 1998). The number of occupants and their age influences energy consumption, for example, households where there are no children or where couples work consumes less energy than a household with children or older people (Guerra Santin et al. 2009). Dwelling size, family size, climate, appliance ownership, lifestyle and behaviour are all defining factors of households' energy consumption patterns. Therefore, the energy demand of dwellings varies greatly between households and with time on an hourly, monthly and yearly basis according to an "occupant's profile". By consequence, there is a need to consider the occupants' interactions with control systems in buildings to obtain values that are closer to real energy use.

In this paper we have focused on heating set-point adjustments and their consequences on energy demand for residential buildings.

The simple action of adjusting the thermostatic radiator valve (TRV) is influenced by many factors that interact in complex ways. Specifically, we have dealt with heating set-point adjustments and their effects on energy demand for residential buildings. Differences in users' attitudes, preferences in thermal comfort and reactions to the indoor environment bring great variations in energy consumptions. In the first phase we have surveyed literature of research on heating behaviour highlighting the main driving forces for occupants to interact with heating systems. Afterwards, we have presented a probabilistic approach in building energy modelling with the purpose of defining behaviour patterns to be implemented in simulation tools. The approach was constituted on two steps: first the development of probabilistic occupant's behaviour models from an existing database and consequently their implementation in a building energy simulation software comparing them with conventional deterministic definitions of occupant behaviour.

Literature survey of investigation on heating behaviour in residential buildings

Variations in set-point and in frequency of adjustment between inhabitants lead to significant difference in heat consumption. It is common practise amongst some users of building simulation programs to define the heating set-point temperature so it is constantly set to 20°C while in reality they vary, even on a daily basis, depending on occupant's preferences. Due to presence and activities in the building occupants control actions have impact on indoor environmental conditions (Hoes et al.2009). Indoor climate quality (ICQ), in its dual aspect of indoor air quality (IAQ) and indoor thermal comfort (ITC), has an impact on occupant's comfort perception but also affect energy use and saving potentials (Rehva Guidebook, 2011). Higher levels of ICQ may correspond to higher indoor temperatures set-point and air change rates: three levels of thermal comfort and indoor air quality categories (ranges from I to III) are introduced by the European Standard EN 15251 (2008). Since the user behaves in order to maintain or improve the comfort level (Fabi et al. 2012), and comfort categories are related to the users' expectations (EN 15251, 2008), it is evident that they have a strong impact on energy consumptions.

In literature, the use of thermostatic radiator valves (TRVs) have been investigated by Xu et.al., (2009) by means of questionnaire survey and field observation to study how occupants interact with heating controls. Occupants were grouped in reason of their behavioural patterns regarding TRVs set-point and the frequency of adjustments was analysed discovering large differences in habits among occupants. In this paper, we have referred to factors influencing occupants' behaviour with the general term "Drivers", representing the reason leading the building occupant to a certain reaction (Fabi et al., 2012). "Drivers" have been investigated by several researchers and have been grouped into "external" factors connected with indoor/outdoor conditions (Seligman et al., 1977-78, Nicol, 2001, Schweiker et al., 2009, Andersen et al., 2009) and "internal" factors connected with the field of social science, like antropology or psychology areas (Ajzen et al. 2005, Refsgaard et al., 2009). In addition to external factors, they influence the occupant behaviour with a range of cognitions and actions in a very complex way. Research on the individual factors leading to one action rather than another has been conducted in the field of behavioural psychology. As defined in Fabi et al. 2012, this kind of "internal" factors influencing heating and cooling behaviour ("Drivers") include physical, psychological, social and contextual factors. In particular, variables influencing energy use for heating are mainly related to household characteristics, regarding both social and physiological and contextual drivers. Social driving forces refer to the interaction between occupants. For residential buildings this depends of the household composition (e.g. which household member determines the thermostat set point or the opening/closing of windows).Examples of physiological driving forces are age, gender, health situation, clothing, activity level, and intake of food and beverages. These factors together determine the physiological condition of the occupant. According to several papers (Sardianou, 2008 Guerra Santin et al., 2009, Andersen et al., 2009), age is an important characteristic determining energy use: in general, the presence of elderly people or children is related to more hours of use of radiators. Gender differences in the adjustments of thermostat set point have been found in the use of thermostat. Results (Karjalalainen, 2007, Andersen et al., 2009) have shown that females are less satisfied with room temperatures than males and preferred a higher set point, but males adjust the thermostat set point more often than females. Household income has proven to be an important factor in determining energy use for heating. In a study based on the expenditure and energy use of 2800 households in the Netherlands, Vringer (2007) found that a 1% increase in income results in a 0.63% increase in energy use. Biesiot and Noorman (1999), using data from household budget surveys, energy prices and the primary energy requirements of goods in the Netherlands, found an almost linear relationship between expenditure and energy use, confirming that the higher the disposable yearly income, the higher the energy requirements. Psychological drivers are related to the occupant preferences on indoor temperature. Results of a survey conducted in a student house in Japan (Schweiker et al. 2009), including people coming from several countries, have shown that also the "thermal background" of occupants, related to climate region of origin, and the "behavioural background", related to the habits in childhood, are drivers leading to different heating behaviour. Dwellings size (Sardianou 2008), type and ownership are contextual parameters found to be drivers of heating behaviour. Guerra Santin's investigations (2009) lead to the result that single-family houses are connected with highest chosen temperature and more hours with radiators on. Andersen (2009) found that the heating tended to be on more often in rented dwellings compared to those which are owner-occupied. Thermostat type is an important aspect in the determination of how occupants interact with thermostats: households with programmable thermostat were associated with higher temperature settings during the night and with more hours with radiators on (Guerra Santin et al., 2009). Shipworth et al. (2010) found that in dwellings with thermostats, the mean temperature setting is slightly lower than in dwellings without a thermostat. They also found that households with a programmable thermostat keep the heating system on for longer than households with manual thermostats. The most influential physical environmental driver on the heating set-point is the indoor temperature. Several studies (Haas et al., 1998, Guerra Santin et al., 2009, Schweiker et al., 2009, Andersen et al., 2009) have indicated strong evidence for a linear relationship between space heating energy demand and indoor temperature.

Outdoor temperature, wind speed, solar radiation and outdoor relative humidity have an impact on the heating behaviour, but with different patterns. They have been found to be negatively correlated with the heating set-point on Thermostatic Radiator Valves (TRV) (Andersen et al., 2011), indicating that heating set-point increases when these variables decrease. The method used by Andersen et al. (2011) was a linear model for defining the heating set-point directly. As described in their paper, this may not be the most adequate method since indoor temperature cannot be used as predictor as it is affected by the heating setpoint that the model is trying to predict.

Mean outdoor temperature of the foregoing night has been found (Schweiker et al., 2009) to have a major impact on occupant behaviour during the summertime (cooling behaviour regarding the AC usage), but a minor one in wintertime.

In summary, the previously identified driving forces for energy-related behaviour with respect to heating set-point adjustments in residential buildings are grouped and listed in Table 1.

Methodology

The present work undertook a theoretical and empirical study of the uncertainty of energy consumption assessment related to occupants' behaviour in residential buildings. The goal was to determine occupant behaviour patterns describing occupant's interaction with the controls and in particular with TRVs.

The probability of turning up/down the heating controls was interfered by logistical regression. A linear model gave the measure of set-point change. Three different users' behavioural patterns, named "active", "medium" and "passive" were defined and implemented in the simulation tool IDA ICE (Indoor Climate and Energy) (ICE 4, 2009), inserting in the software the equation describing the probability of the user to interact with the control of the temperature. A probabilistic approach was adopted in the simulations to investigate how probabilistic user's patterns influence indoor environmental quality and energy consumptions improving accuracy of calculated energy performance in buildings simulation tools. Simulations were ran for three different user patterns: active users, medium users and passive users. In each timestep, the processes in the flow chart of figure (figure 1) were executed.

The logistic models were used to calulate the probability of turning up and down the setpoint (step 1). These probabilities were compared to random numbers to translate the stochastic probabilities to deterministic signals (step 2). Following the logics of the diagram, the sice of the setpoint change was calculated based on the linear regression model. If the sign of the setpoint change corresponded to the action (positive corresponded to the actioln of turning up and negative setpoint change corresponded to turning down), the setpoint was changed. If the sign of the setpoint change contradicted the action, the setpoint wasnot changed.

To compare energy calculations results of the deterministic method with the probabilistic approach, simulations were conducted maintaining constant location, building construction and thermal zone ICQ settings. Evidently in these simulations, Indoor Thermal Comfort (ITC) was not determined by set-point controller by fixing maximum and minimum operative temperature in the simulation program but indoor set-point temperatures were influenced by behavioural patterns identified by the statistical models. When, in the probabilistic approach, models of user behaviour are implemented the energy simulations show improved accuracy and validity of the results. A probabilistic distribution instead of a single value was preferred as a representation of energy consumptions: energy distribution curves were calculated by running several simulations of the same models.

Figure 1. The methodology used for the modelling and simulation of the occupant behaviour

Beside energy consumptions, also quality of the indoor environment needs to be taken into account and indoor thermal comfort represented. Probabilistic distributions of ITC are evaluated and probability of comfort category for different user type is presented.

A probabilistic approach

The method developed in this research was based on the assumption that only switching from a determinist approach to a probabilistic one, a better measure of the impact of occupant’s behaviour on the performance indicators will be provided. This probabilistic approach is related to variability and unpredictability during the whole building operation. The aim of this study was then to switch from a deterministic approach of building energy simulation toward a probabilistic one that takes into account the occupants' presence and interactions with the building and systems. These tools often reproduce building dynamics using numerical approximations of equations modelling only deterministic (fully predictable and repeatable) behaviours. In such a way, "occupant behaviour simulation" could refer to a computer simulation generating "fixed occupant schedules", representing a fictional behaviour of a building occupant over the course of a single day. Often, the occupant behaviour is not specifically addressed in the simulation programs, but only modelled by means of its effect. For example, the infiltration rate might be modelled as a fixed value that does not vary over time, with the assumption that occupants will manipulate windows in order to reach this infiltration rate.

In this paper, probabilistic approach was proposed and applied as an input to a simulation tool. The approach is based on probabilistic evaluation of both input and output variables in the building energy simulation software.

This approach consisted of two different steps of modelling the behaviour (Figure 2). The first step is represented by the statistical modeling of the occupant's behaviour, defining a probabilistic model of the input parameters: using a database of indoor/outdoor environment variables and behaviour it was possible to infer models of occupant's interactions with the building envelope and systems. These models can be used to provide probabilistic input for the simulation software (in this case, heating set-points). The second step of the proposed approach is defined when the statistical models were implemented into the building energy simulation software and used to run several simulations providing probabilistic outputs.

Figure 2. The two steps of the probabilistic modelling

A probabilistic model of the input parameters

Database. A monitoring campaign of indoor and outdoor climate variables and occupant's control actions was conducted in 13 Danish dwellings in the period from March to August 2008 in Copenhagen. Measurements were carried out in 10 rented apartments and 5 privately owned single family houses. Half of the apartments were naturally ventilated while the other half were equipped with constantly running mechanical exhaust ventilation in the kitchen and in the bathroom. Three single family houses were naturally ventilated while the other two were equipped with exhaust ventilation. A series of variables concerning indoor and outdoor environmental conditions were monitored and meteorological data were obtained from two Danish meteorological stations in the dwellings proximity. Occupants' adjustments of heating set-points temperatures were monitored by measurement of the setting of one TRV in the bedroom and one in the living room of each dwelling.

The dwellings were divided into three groups selected by inhabitants' frequency of TRVs manipulation: the three groups were named active, medium and passive users. As shown in table 2, in the period from March to August (six months) "passive users" interfere with heating controls from 0 to 5 times, "medium users" from 6 to 50 times and "active users" more than 50 times.

In the analyses the probability of turning up/down the heating was inferred for the three user types. Set-point dependency on indoor and outdoor environment and users control actions was

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deduced by mean of logistic regression with interaction between selected variables accordingly to the following equation:

$$\log(P/(1-P)) = a + b_1 \cdot x_1 + b_2 \cdot x_2 + \ldots + b_n \cdot x_n + c_{12} \cdot x_1 \cdot x_2 + c_{13} \cdot x_1 \cdot x_3 + \ldots \quad (1)$$

Where p is the probability of turning up or down the setpoint, a is the intercept, x_1, x_2 etc. are background variables such as indoor temperature, solar radiation and b_1, b_2 etc. are coefficients of the variables. c_{12}, c_{13} etc. are coefficients of the interactions between variables x_1 and x_2, x_1 and x_3 etc.

Backward and forward selection based on the Akaike information criterion (AIC) was used to select models (Schweker et al. 2009, Akaike H, 1973). The results were models that predict probabilities of turning up and down the set-point. A model that predicts the size of the set-point change was inferred using linear regression. The statistical analyses were performed using the statistical software “R”.

The statistical models of the users’ interactions with TRVs. Even if the sample of this application is limited to few dwellings, it was possible to apply the proposed method and verify its working. Findings of the statistical analysis are presented in Table 3 and in Table 4 in the form of coefficients of the logistical regression and the linear model for all the variables in the models . Indoor relative humidity, outdoor temperature, solar radiation, wind speed and time of the day were the variables that influenced mostly the set-point temperatures.

The statistical analysis revealed that for active users the most important variables in determining the probability of turning up the set-point were indoor relative humidity, time of the day and outdoor temperature. Indoor relative humidity turned out to have an influence on the increasing of set-point even though it was in the range 30% to 70 %, where humans are insensitive to relative humidity. On the other hand, the relative humidity does affect the thermal sensation and has an impact on thermal comfort being one of the variables included in Fangers' PMV model (ISO 7730, Fanger, 1972, ASHRAE 55/2004). An increase in solar radiation resulted in a decrease in the probability turning down the heating. This is probably a result of the relation between solar radiation and time of the day and may indicate that some occupants decreased the heating set-point before going to bed. For medium users outdoor temperature and wind speed were negatively correlated with the TRV set-point indicating that the heating set point was increased when these variables decrease while the time of the day was the most influential variable in the determination of turning down the heating. The model for passive users showed no significant variable influencing the probability of increasing the heating set-point whereas wind speed was positively correlated with the probability of turning down the heat, indicating that an increase of wind speed increased the probability of turning down the heating.

Table 3 shows the relations between factors and changing the TRV such as the wind speed, the outdoor temperature, etc. The occupants may have changed the TRV setpoint as a direct consequence of all the factors. However, since some of the factors are correlated (outdoor and indoor conditions), the setpoints may also have been changed as an indirect consequence (for instance, the outdoor temperature may have affected the indoor temperature, which then affected the occupants TRV setpoint prefferences). In the statistical model interaction terms between the variables were not taken into account, so it is not possible to say if the effects are due to direct or indirect effects. .

As shown in Table 3, indoor temperature was not considered as an influencing variable.

The reason could be because heating set-point and indoor temperature are inter-correlated (for example if the heating set-point is turn up the indoor temperature increases) and affect each other. Due to this interaction indoor temperature is not always included in investigations of many researchers. From the histogram of the monitored values of temperatures (Figure 3) it appears that the highest percentage of observations lies between 19-24°C, meaning that for most of the time the indoor temperature lies in the comfort range.

Figure 3. Histogram of the monitored values of indoor temperature.

Building energy simulation implementation

Results of the statistical analysis in Table 3 and Table 4 provide the possibility of defining behavioural models of thermostatic radiator valves use to be implemented in simulation tool for energy simulations.

Most of simulation programs are deterministic in nature, so there is the need to translate the probability of an event (changing the TRV set-point) to a deterministic signal. A way of doing this is to compare the probability of an event to a random number to determine if the event takes place or not. As the given probability of the models in table 3 is the probability of doing a certain action in a certain time period, the comparison is to be made with a random number that change with the same interval. The action occurs when the probability of the action is larger than the random number. But since the random numbers change between simulations, the actions may not occur at the same time in each simulation with the consequence that the results of two simulations of identical models will be different. By running several simulations it is possible to obtain a distribution of the performance indicators of interest, rather than a single number for each performance indicator.

The simulated building. Simulations were run in a typical mechanically ventilated residential room: this was simulated to evaluate the influence of indoor environmental quality levels on total energy use.

The room area was 16 m^2 and the dimensions were: length = depth= 4 m; height= 2.8 m. The two external walls were facing south and east, the window area was 2m x 2m facing east. The thermo physical properties of the opaque components are resumed in Table 5. The transparent component had the following thermal characteristics: U value=1.1 W/(m^2K); solar transmittance, T= 0.54; Solar factor , g= 0.62. The window was considered as not operable and a water radiator was supporting the HVAC plant in providing the required thermal comfort. The location was Copenhagen in Denmark (55.63° N, 12.67° E) and the meteorological data used in the simulations refers to the Danish Design Reference Year.

As internal heat gain, one person was considered always present at an activity level of i.e. 1.2 met (70W/m^2). Lighting schedule was connected to the people presence and based on the study of the Lightswitch-2002 (Reinhart, 2004), the light (50W per unit) was switched on if the minimum work plane illuminance was lower than 100 Lux. It was switched off at an illuminance level of 500 Lux. A building equipped with a mechanical Air Handling Unit (AHU) was chosen to avoid the influence of occupants' window opening behaviour. The AHU was equipped with a heat exchanger for heat recovery. Temperature and ventilation are controlled by a CAV control, with a constant 0.5 ACH and the air supply temperature was constantly 16 ° C.

The "deterministic" model. Energy consumptions were calculated accordingly to the comfort levels recommended in the EN 15251 EN 15251(2007) "Indoor environmental input parameter for design assessment of energy performance of buildings - addressing indoor air quality, thermal environment, lighting and acoustics". The specific issue of the standard are the category of indoor environmental quality (ICQ). In general, the 15251 specifies how the criteria on ICQ can be established and adopted in the design phase. Calculation results were compared in term of heating and AHU systems primary energy requirements. Since there was no cooling system, the AHU energy consumption depended only on the heat exchanger. These simulations were run in the deterministic way on the base of schedules assumptions decided a priori describing occupancy, lighting and equipment load. Thus, the results were unrealistic and far from representing real occupant behaviour.

The implemented probabilistic model. In the occupancy schedule the occupant was considered always present, but heating control was probabilistic in nature, it doesn't follow maximum and/or minimum set-point controller. The probability of adjusting the temperature set-point was calculated basing on the logistic regression previously described. Specifically, three behavioural patterns were simulated.

A probabilistic model of the output parameters: simulation results

Results were given in the form of primary energy, accordingly with the Standard EN 15603 establishing the conversion factors as fp_{fuel}= 1.36 for heating and as $fp_{electricity\ mix\ UECPTE}$= 3.14 for electric systems and appliances. Not surprisingly, higher levels of indoor environmental quality resulted in higher energy consumptions. An increase in air flow rates and in operative temperature set-point rised energy consumption: switching from category I to category III, there was a gap of 77% of energy consumption for space heating, and of 27% of AHU primary energy. A significant difference could only be appreciated in primary energy demand for heating, while energy demand for AHU is lightly changing (Table 6).

Since IEQ comfort categories of the European Standard 15251 are used for the simulations, the results showed higher energy demands at higher comfort levels. When using implement behavioural patterns, a significant difference was appreciated on energy demands for the three different cases.

Energy consumption did not linearly increase accordingly to occupants’ frequency of interaction with set-point controller. Active users did not always represent the most energy wasting user type.

Generally, deterministic energy consumptions were lower than probabilistic users’ consumptions as summarized in Table 7. In the deterministic simulation, set-point for categories I-II-III have been set respectively on 18-20-21°C accordingly to operative temperature of EN15251 for energy calculations while in the probabilistic approach users statistically control indoor temperatures according to the results of the statically analysed building sample. Even if the specific position (1,2,3,4,5) of TRV is not a input in the simulations, during the simulations the set-point in the implementation of the probabilistic simulations.rangeed around 23 °C, definitively higher than the values recommended by EN 15251. The recommendations in EN 15251 are based on thermal comfort models and assumptions of activity levels and clothing, whereas the model presented here is based on measurements. The discrepancy between the model results and the EN 15251 recommendations indicate that the assumptions of clothing and activity level did hold true in the monitored apartments. From the histogram of the simulated values of indoor temperatures (Figure 4) it appears that the highest percentage of observations appears in the range between 20°C - 28°C with a maximum within 24°C – 26°C, meaning that for most of the time the indoor temperature lies in the comfort range, according to the EN 15251.

Figure 4. Histogram of the simulated values of indoor temperatures during the heating season.

Influence of users' types on final energy demand could be evaluated by a factor (ratio between the higher energy consumption and the deterministic one) ranging from 1.10 to 1.30 (Table 7).

The implemented probabilistic model. In this part of the research the II category of EN 15251 (table 6) was chosen for energy consumption investigation. The probabilistic distribution curve reported in Figure 5 and Figure 6 show that the probability of primary energy consumption for active users in comfort category II range from 82 kWh/m^2 to 85 kWh/m^2. This could be attributed to the frequency in manipulating thermostatic radiator valves but also to indoor temperature preferences or even to saving measures.

Figure 5. Distribution of primary energy consumptions for active user type.

Figure 6. Distributions of primary energy consumptions for different user types.

Inarguably an infinite number of scenarios could have been simulated, each different in comfort category, representing a different user's profile and therefore more outcomes could have been found. Indeed the approach of this study aim to represent a procedure method that could be extended to the window opening behaviour (to open and to close the windows), or the window blind adjustments (to raise or to lower the shading elements). Nevertheless factors involved in the energy programs implementations could be extended to shading devices or window opening with the aim to understand which of these have the most influence in energy use and so, constitute recommendations for improved buildings design with regard to energy reduction.

The implemented probabilistic model. One of the common forgetfulness in energy calculation is focusing especially on energy consumptions forgetting the quality of the indoor space. The random numbers method applied to probability user's pattern in IDA ICE allows to represent, beside more realistic results, also indoor environmental quality in probabilistic ways. In fact it is possible to define statistical graphics representing the indoor thermal comfort as: the probability of predicted percentage of dissatisfied PPD or predicted mean vote PMV, the percentage of probable hours with thermal dissatisfaction, the percentage of probable hours with operative temperature above 27 °C, the probability of comfort category. In Figure 7, referring the results of three of the previous simulations in terms of ITC, a certain stability of comfort category permanence could be noted for the three user types throughout the year.

Figure 7. Distribution of thermal comfort categories for different user's types with II comfort category setting in the year.

Discussion

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Since the sample was limited to a few case studies (13 dwellings), the main goal at this stage of this research was to propose a procedure based on a probabilistic approach and to apply it to a case study. The analysis was based on logistic regression to infer the probability of an adjustment of the TRV's setting. Using this method, we have assumed that the probability function looks like equation (1). Additionally, as a first step, we have assumed that all observations were independent of each other. This assumption is questionable as the observations were gathered in 13 dwellings. Essentially the assumption would hold true if all inhabitants of the dwellings reacted similarly to the conditions they were subjected to. In any other case the observations in each dwelling will be influenced by the habits of the inhabitants of the individual dwelling and, as a result, they would not be independent from each other. An improvement on the coefficient and the variables could lead to a more reliable results on set-point preferences. Nevertheless, the model demonstrated that the methodology was successful in obtaining simulation results as probability distributions, obtaining a significant discrepancy when compared with the deterministic simulations results.

A fundamental step to be deepened in a further research is the comparison of simulation results with measured data, to ensure the validity of the models. Unfortunately, the simulated positions of the valves were not saved during the simulations, so a comparison with the measured data is not possible. The aim of our paper was to propose a shift on the research about modelling the occupant behaviour energy related factors from a deterministic approach to a probabilistic one, which was to verify that the proposed approach to simulation could actually work with existing building energy simulation tools..

Conclusions

A simulation study on the effects of ICQ categories and occupant interactions with the heating control on energy demands to control ICQ has been conducted in a typical residential room by using the deterministic approach used nowadays in simulation programs. Since the sample was limited to a few case studies (13 dwellings), the main goal of this research was to propose a procedure based on a probabilistic approach and to apply it to a case study, analysing its effects on terms of energy consumptions with the comparison with a deterministic approach.

The developed study firstly took into account the ICQ categories introduced by the European Standard EN 15251 and consider requirements of both ITC and IAQ. Variations of operative temperature and ventilation air change rates accordingly to the Standard have been applied. Results highlight significant influences of ICQ levels on the building energy demands and suggest that ICQ category should be considered in the design and in the operational stage. Secondly, by means of a monitoring carried out in 13 dwellings, the collected database has been elaborated and the relationship between users behaviours and the most influencing variables in adjusting heating set-points have been found. Even if the database refer to a quite short period (most of the data were collected during the fully winter), they were considered exhaustive for the characterization of real user profiles during the whole heating period. Based on the results, a probabilistic approach of occupants interactions with the heating controls is developed. The probability of switching up/down the set-point temperature on the TRV is predicted for three different users models named “active”, “medium” and “passive”. Moreover, probabilistic distributions of energy consumptions and ICQ category for different real user types have been determined. Even if consumptions in the analysed Danish dwellings do not significantly vary in between them, they are definitively higher compared with the simulations ran in accordance with the European Standard recommendations. Future field study should include other aspects of occupants control on building systems in order to enhance a more real representations by simulation tools.

Acknowledgments

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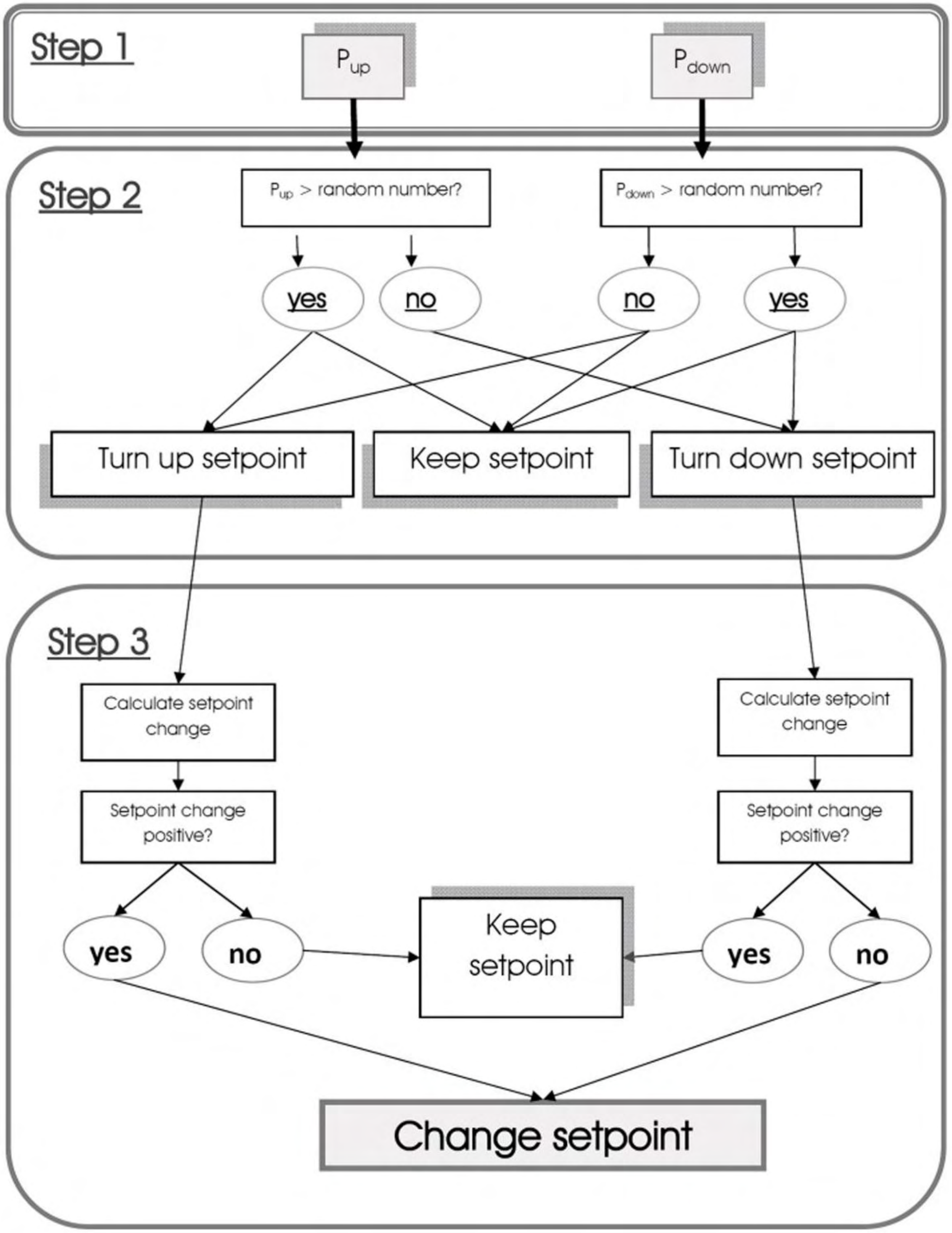

Step 1
P up
P down
Step 2
P up > random number?
P down > random number?
yes
no
no
yes
Turn up setpoint
Keep setpoint
Turn down setpoint
Step 3
Calculate setpoint change
Calculate setpoint change
Setpoint change positive?
Setpoint change positive?
yes
no
Keep setpoint
yes
no
Change setpoint

Figure 1. The methodology used for the modelling and simulation of the occupant behaviour

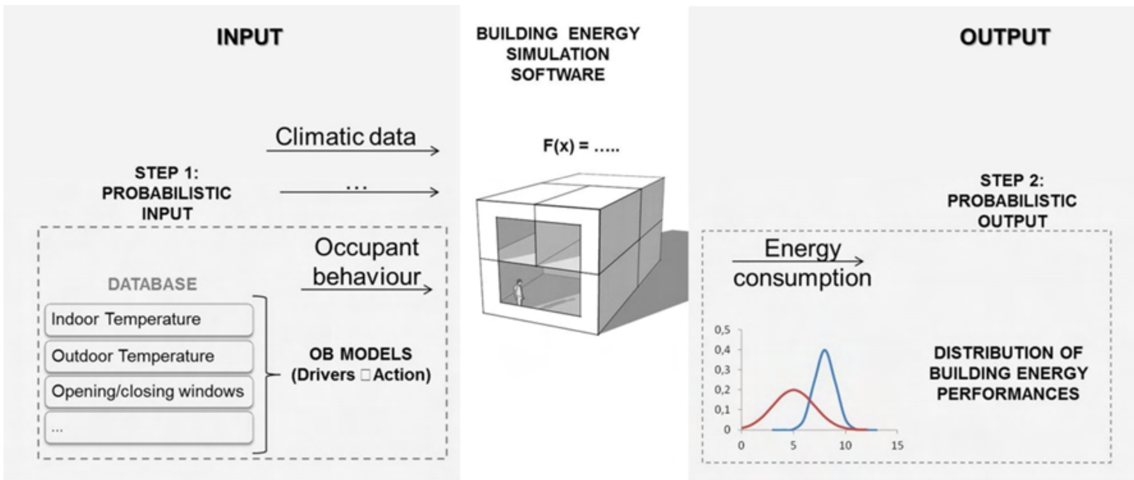

Figure 2. The two steps of the probabilistic modelling

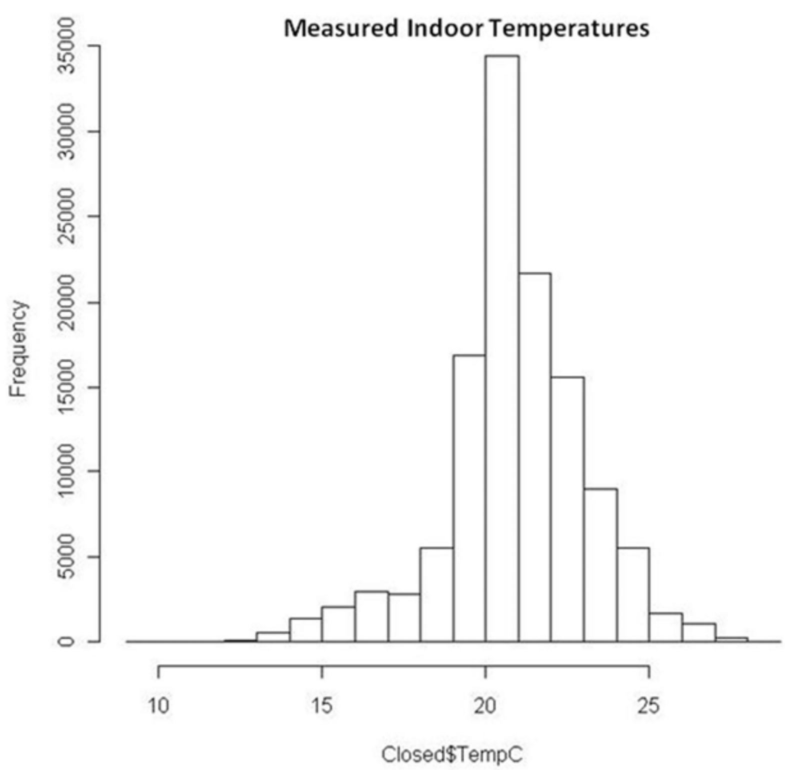

Figure 3. Histogram of the monitored values of indoor temperature.

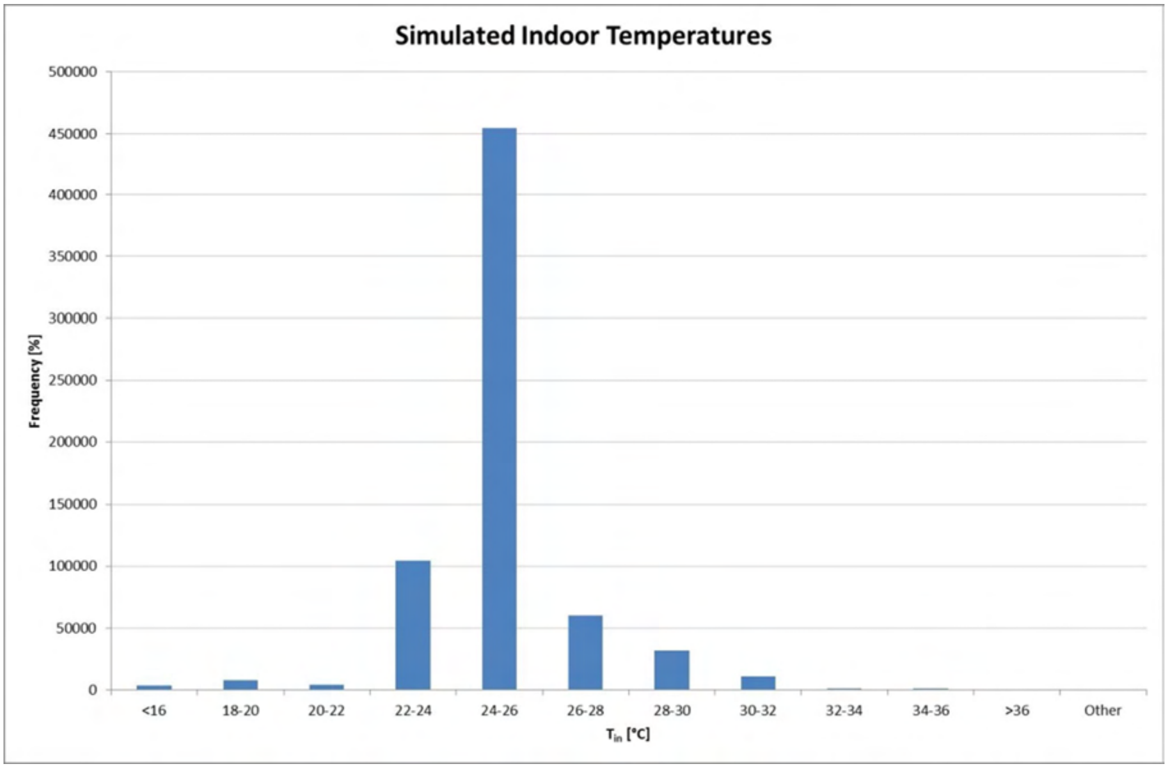

Figure 4. Histogram of the simulated values of indoor temperatures during the heating season.

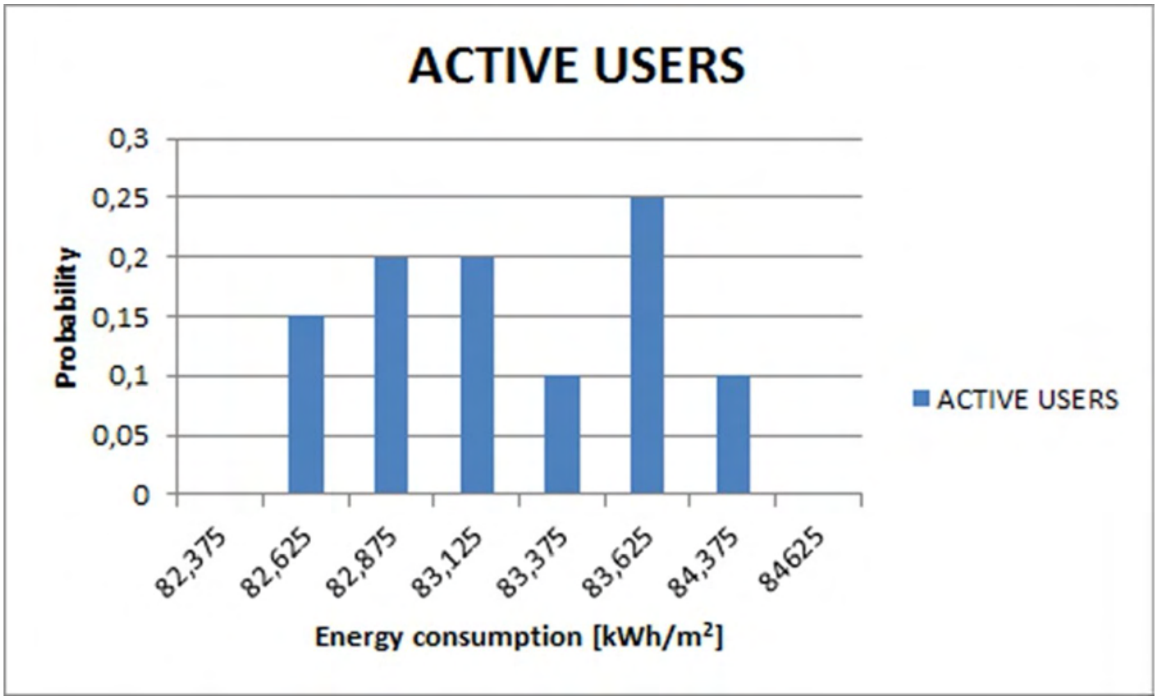

Figure 5. Distribution of primary energy consumptions for active user type.

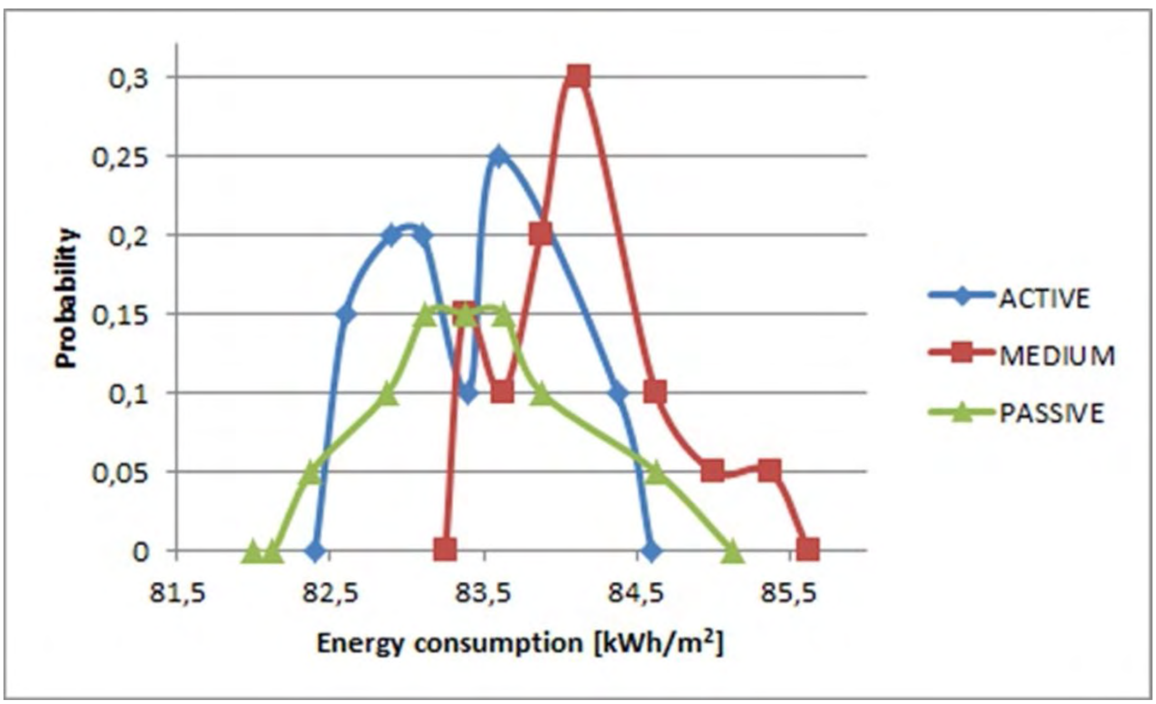

Figure 6. Distributions of primary energy consumptions for different user types.

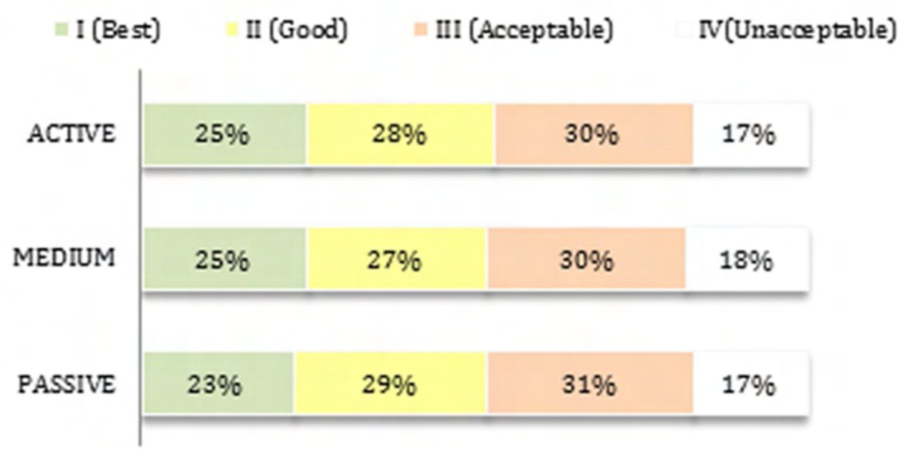

Figure 7. Distribution of thermal comfort categories for different user's types with II comfort category setting in the year.

Table 1. Driving forces for occupant behaviour regarding the heating set- point adjustments.

biological	**Psychological**	**Social**	**physical environment**	**building/equipment properties**
Age	Indoor environmental preferences in terms of	Annual income	Outdoor temperature	Dwelling type

	temperature			
Gender	Thermal background	User presence	Indoor temperature	Dwelling size
	Behavioural background		Wind speed	Room type
			Solar radiation	Temperature control Type
				Ownership

Table 2. Classification of users' types based on the users' interactions frequency with TRVs.

User types	**Number of interactions with heating controls in six months (March-August)**
Passive users	0-2
Medium users	9-22

Active users	70-106

Table 3. Results of the models of the TRVs set-point for different user's type.

User type		Variable	Time	Coefficient	Magnitude[a]
Active users[b]	Model up	Intercept	Night	-4.286	
			Morning	-0.6264	
			Day	-0.839	
			Afternoon	-0.8663	
			Evening	-2.1435	
		Indoor relative humidity	-	-0.085	4.2654
		Outdoor temperature	-	-0.1441	5.2337
	Model down	Intercept	-	-3.514	-
		Solar radiation	-	-0.0194	16.5181
Medium users[c]	Model up	Intercept	-	-7.6356	-
		Outdoor temperature	-	-0.2284	8.2916
		Wind speed	-	0.3699	3.9581
	Model down	Intercept	Night	-22.8446	-
			Morning	-5.1599	17.6847
			Day	-6.0973	16.7473
			Afternoon	-6.5805	16.2641

			Evening	-6.6572	16.1874
Passive users[d]	Model up	Intercept	-	-9.716	-
	Model down	Intercept	-	-14.2779	-
		Wind speed	-	1.0077	10.7824

[a] The magnitude of the variable is a measure of the maximum impact of the variable on the probability of turning up/down the heat.

[b] The AIC value for model up is: 1120.5. The AIC value for model down is 925.01.

[c] The AIC value for model up is 723.59: The AIC value for model down is 625.53

[d] The AIC value for model up is: 87.72. The AIC value for model down is 36.28

Table 4. Results of the linear model that quantitatively describes size of the set-point change, when the models described in table 3 predict that a set-point change occurs.

Model Change	**Variable**		**Coefficient**
	Intercept	Night	31.3
		Morning	32.1
		Day	31.5
		Afternoon	31.3
		Evening	27.8
	SetptTemp		-1.28
	Outdoor relative humidity		-0.0390

Indoor relative humidity	-0.124
Solar timer	-0.217

R^2 of the model was 0.76

Table 5. Thermo physical properties of the opaque components

	Material	U-value (W/m2)	Thickness (cm)	Thermal conductivity (W/(m K))	Density (kg/m3)	Specific heat capacity (J/(kg·K))
External wall	Brick	0.129	10	0.58	1500	840
	Gap		5	0.17	1.2	1006
	Mineral wool		25	0.036	55	840
	Brick		10	0.58	1500	840
Internal wall	Gypsum plaster	0.618	0.2	0.22	970	1090
	Gap		3	0.17	1.2	1006
	Insulating layer		3	0.036	55	840
	Gap		3	0.17	1.2	1006
	Gypsum plaster		0.2	0.22	970	1090

External ceiling	Waterproof barrier Hard insulation Mineral wool Concrete	0.070	1 13 40 23	0.052 0.036 1.7	92 55 2300	982 840 880
External floor	Plastic covering Concrete Hard insulation Gravel	0.057	5 15 10 -	0.18 1.7 0.036 2	1100 2003 20 2000	920 880 1200 1000

Table 6. Primary energy for space heating for different comfort categories (operative temperature and ventilation rates)

Comfort category	**Ventilation rate ($l/(s \cdot m^2)$)**	**Temperature for heating (°C)**	**Heating, PE (kWh/m^2)**	**AHU, PE (kWh/m^2)**
I	0.49	21	22	22
II	0.42	20	14	19
III	0.35	18	5	16

Table 7. Results for simulation I –II for primary energy consumptions [kWh/m^{2}year].

	STANDARD	ACTIVE	MEDIUM	PASSIVE	Factor*
Category I	84	93	93	86	1.10
Category II	73	83	83	77.0	1.14
Category III	60	74	77	74	1.30

** The factor is the ratio between the higher energy consumption and the deterministic one.*

PAPER V

Validation of models of users' window opening behaviour

in residential buildings"

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Fabi V., Andersen RV., Corgnati SP.

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
b) Group 2 (G2, MechOw): Owner-occupied, mechanical ventilation
c) Group 3 (G3, NatRent): Rented-occupied, natural ventilation
d) Group 4 (G4MechRent): rented-occupied, mechanical ventilation

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, CO_2 concentration etc.). Moreover, this equation takes into account the interactions between variables by adding interaction terms to the model.

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

Models 1 (G1, NatOw), 2 (G2, MechOw) 3 (G3, NatRent) and 4 (G4, MechRent) were infered from merged data from several dwellings (Andersen et al. 2013).

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 infering models from data from each appartment (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 cathegorized 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.

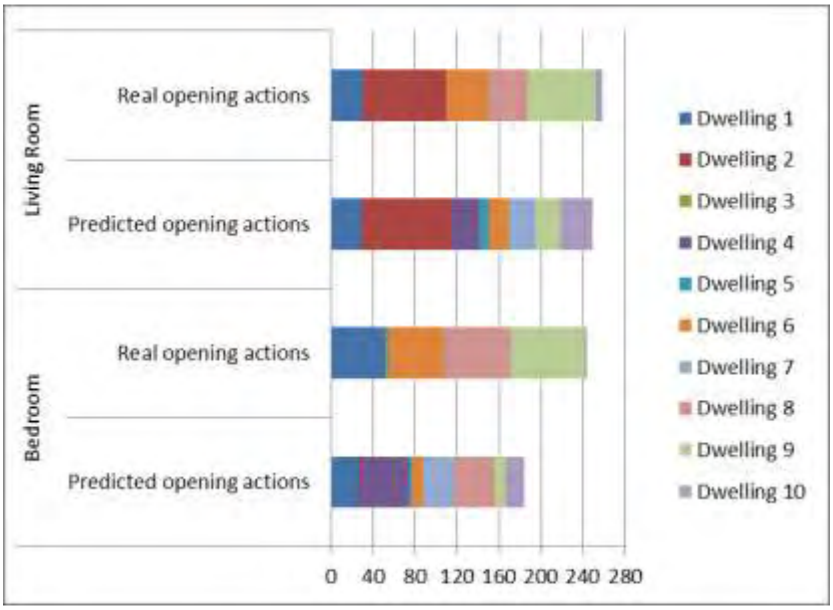

Figure 1. Comparison between predicted and observed number of actions on windows for each dwelling tested with the G2 model.

The results of the the validation of the models derived from data from the single dwllings 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**	**Bedroo m**	**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 CO_2 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 CO_2 concentration and illumination values (Group 2 and dwelling 16 models) and a negative correlation with sun hours and illumination level for closing windows.

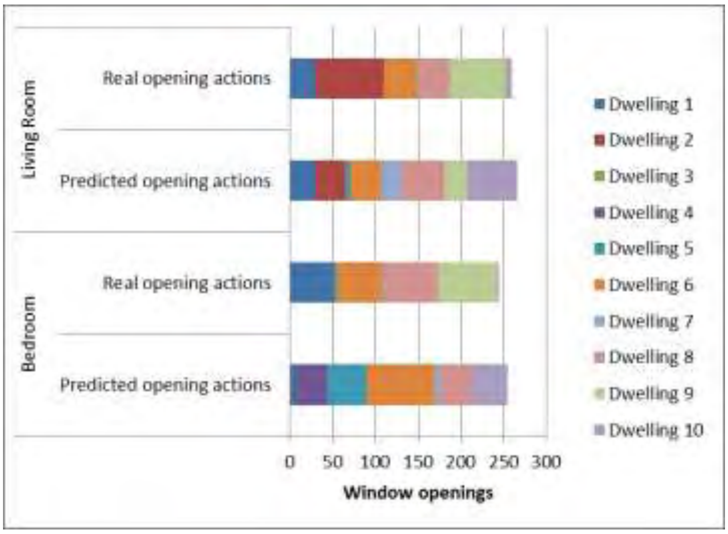

Figure 2. Comparison between predicted and observed number of actions on windows for each dwelling tested with the d16 model.

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 CO_2 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 approapriate 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 CO_2 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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