SENSING

Oversimplified or ignored Adaptive and non-adaptive OB building operation process

How to study OB based on facts and not hypothesis?

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Advances in research and applications of energy-related occupant behavior in buildings☆

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ABSTRACT

Occupant behavior is one of the major factors influencing building energy consumption and contributing to uncertainty in building energy use prediction and simulation. Currently the understanding of occupant behavior is insufficient both in building design, operation and retrofit, leading to incorrect simplifications in modeling and analysis. This paper introduced the most recent advances and current obstacles in modeling occupant behavior and quantifying its impact on building energy use. The major themes include advancements in data collection techniques, analytical and modeling methods, and simulation applications which provide insights into behavior energy savings potential and impact. There has been growing research and applications in this field, but significant challenges and opportunities still lie ahead.

Contents

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1. Introduction

An occupant's interaction with building systems attributes to the sizeable variation in building energy use. Therefore it becomes paramount that solutions in both energy efficient behavior and technology robustness collectively contribute toward achieving low energy buildings [1,2,3•]. Social scientists have been scrutinizing occupant behavior for decades, particularly in the areas of user behavior, attitudes, individual or household consumption patterns etc. [4]. Recently, the need to integrate social science aspects into energy research has brought more awareness to the role of occupants in buildings [4,5]. Energy related occupant behavior, in its simplest form, includes adjusting thermostat settings, opening/closing windows, dimming/switching lights, pulling up/down blinds, turning on/off HVAC systems, and movement between spaces. In addition, behavioral adaptations, such as clothing adjustments, the consumption of drinks and changes in the human metabolic rate, all directly affect individual comfort which in turn influences building energy consumption. In fact, direct and indirect drivers, at the individual, local, whole-space or zonal level each impact the building energy consumption differently. Langevin et al. [6] demonstrated that the use of personal heating/cooling devices could allow for an increase in the thermostat set point enhancing thermal comfort, while reducing the total energy use. An occupant's interaction with building systems and the available systems, play a significant role in influencing the total energy use of buildings. A study by Danny Parker of Florida Solar Energy Center [7] (Fig. 1) showed that the total energy use of 10 identical homes varied by a factor of three, even though they had the same floor area (102 m^2), were on the same street, built in same year and with similar efficiencies. This variation is even larger at the energy end use level (e.g. up to 10.6 times in space heating energy use).

Due to the uncertainty associated with occupant behavior model inputs, simulation results often vary widely from actual building energy consumption [8]. Eguaras-Martínez et al. [9] suggested that the inclusion or exclusion of occupant behavior in simulations, resulted in differences of up to 30%. A comparison between the simulated energy consumption in the design phase and the measured energy use for LEED (Leadership in Energy and Environmental Design) certified buildings in the U.S., shows a significant error (root mean square error of 18%) in a group of 62 buildings [10]. The prediction error is even larger for low energy buildings which use passive designs, such as natural ventilation, relying more on occupant interactions. Therefore, occupant behavior is a leading source of uncertainty in predicting energy use [11].

ASHRAE 90.1 Standard [12] Appendix G states that there are large discrepancies between measured and building design energy consumption. This limits the application and potential impact of building performance simulation (BPS) in industry. Thus, having a better understanding of occupant-building interactions will help bridge-the-gap between actual and predicted energy consumption [13•]. However, quantifying the impact of these behaviors proves challenging. The International Energy Agency Energy in the Buildings and Communities Program (IEA EBC) Annex 53: Total Energy Use in Buildings, indicated that there are six driving factors of energy use in buildings: (1) climate, (2) building envelope, (3) building energy and services systems, (4) indoor design criteria, (5) building operation and maintenance, and (6) occupant behavior. While significant progress has been made in quantifying these primary drivers, there lacks scientific and robust methods to define and model energy related occupant behavior in buildings.

Recent advances, presented in journal articles from 2013 to 2015 (up to February), have shown significant improvements in the three thematic areas shown in the occupant-building interaction energy behavior loop (Fig. 2). On the *data collection* front, data driven techniques such as real-time remote sensing to investigate occupants' interaction with building technologies is at an all-time high, with more data on occupant actions collected than ever before. On the *analytical and modeling* front, advanced statistical, data mining, and stochastic modeling methods are being developed and applied to extract behavioral models from the experimental data. An ontology to standardize the representation of energy related occupant behavior in buildings has been proposed. The combination of observation and modeling aspects will subsequently help to improve *simulation* techniques to quantify the impacts of the energy-related occupant behavior and to provide insights toward energy saving behaviors and robust architectural design. The article is organized according to the three themes shown in Fig. 2. Additionally, this review covers both residential and commercial buildings at a higher level, with the understanding that specific differences exist between these unique building types. Some influential differences include: (i) behaviors in each building are usually different considering the different activities performed and who is responsible for paying the energy bill, (ii) negotiations and group behavior may be different between a commercial setting and home environment and, (iii) the system controls are often different [14]. These considerations, among others, are particularly important to keep in mind during the data collection and model input phases of occupant behavior research.

2. Advances in data collection techniques

Gathering data to change building operation and occupant behavior is the next frontier in sustainable design. Improvements to data collection techniques, the accuracy of individual sensors, and the information obtained, has led to progress in the areas of (i) occupant movement and presence, (ii) thermal comfort, (iii) windows, shades and blinds and, (iv) lighting and electrical equipment.

2.1. Occupant movement and presence

The use of sensors in wireless networks and wearable devices provides the unprecedented ability to easily capture occupant movement and presence, a preeminent factor that affects lighting, thermostat, plug loads, HVAC equipment, fresh air requirements and internal heat gains or losses within a building. Energy simulation programs often rely on homogenous and standardized occupant schedules, often unrepresentative of actual occupancy diversity. Data and analytics has enabled the active reforming of occupancy schedules to better capture the stochastic nature of occupants, with improved schedules demonstrating as much as 46% difference from the prescribed ASHRAE 90.1 Standard [12,15,16]. Individualized occupancy patterns facilitate more accurate modeling of occupant movement and presence and their implementation into BPS provides one method to assess the impact of occupant behavior on building energy consumption [17–19]. For example, Motuziene and Vilutiene [20] used four different occupancy profiles from homes in Lithuania in conjunction with BPS, to demonstrate up to 31% savings depending upon heating strategies. Moreover, excessive energy use during vacancy has proven to hold substantial energy savings potential [21,22]. For example, dormitories in South Korea use up to 31.5% of all energy while unoccupied [23].

2.2. Thermal comfort

Thermal comfort is defined as an occupant's gratification with their thermal environment [24]. Energy consumption can fluctuate subject to the HVAC control strategy, with the primary physical-behavioral forces including ventilation, thermostat set-point and indoor thermal environment [25,26]. Thermostat control is used by different users with varied privileges dependent upon the organizational policy of the building [17]. About 30% of programmable

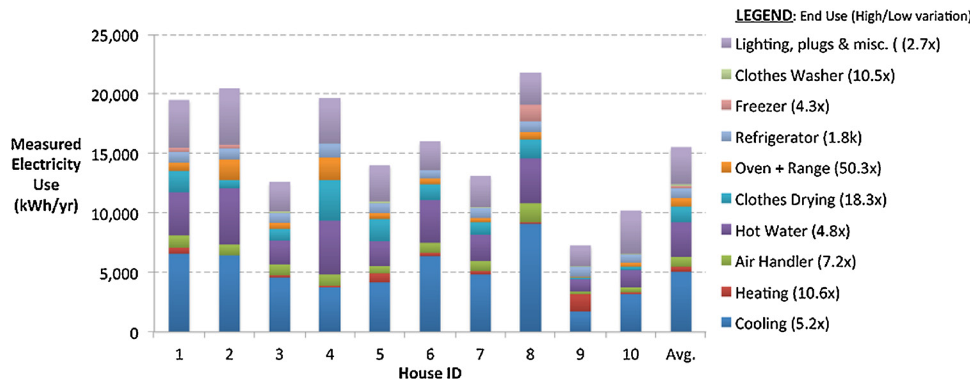

Fig. 1. The measured electricity use for ten nearly identical homes, showing considerable variations in energy use [7].

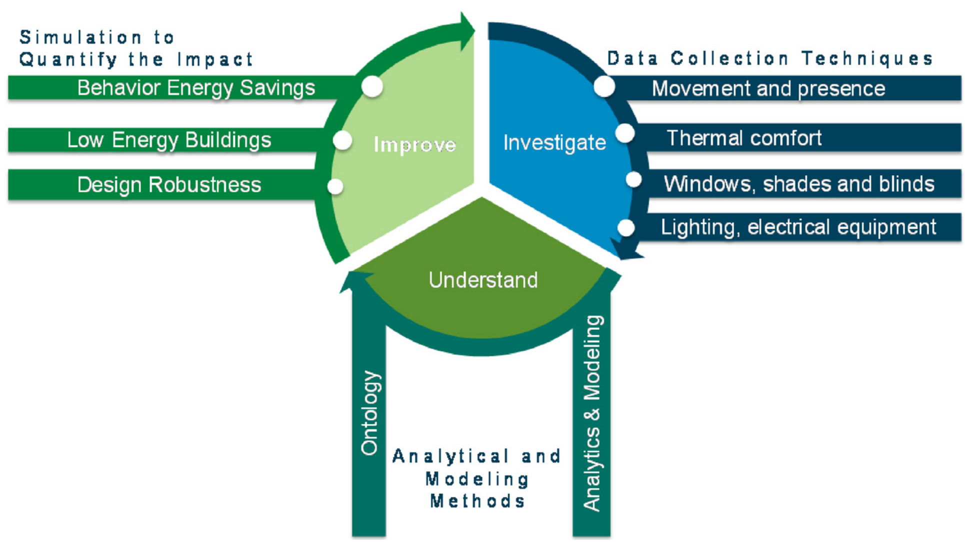

Fig. 2. Occupant-building interaction energy behavior loop.

thermostats are used as intended by the manufacturer, suggesting a large margin for improvement [27,28]. The drivers of space-heating behavior can be categorized as (i) environmental factors, (ii) building and system related factors, (iii) occupant related factors and, (iv) other factors (i.e. time of day, time of week) [29]. Some of the top influential factors impacting heating loads include occupant mode, thermostat set-point and heated area [30,31]. An alternative methodology is to classify the occupant, as an active, medium and passive user, linking occupant behavioral characteristics with heating set-point preferences which in turn impacts the indoor thermal environment and energy consumption [32,33]. Technical solutions which limit an occupants' interaction with technology may seemingly provide a robust solution to mitigate wasted energy. However, it is suggested that the perception of having thermal control results in greater occupant satisfaction, indicating a solution requiring occupant-building interactions [3•].

2.3. Windows, shades and blinds

Windows, shades and blinds allow building occupants to control and adjust thermal and visual comfort levels. Currently, there is great variability associated with the operation of windows, shades and blinds within buildings and these actions impact the thermal comfort, IAQ and building energy consumption [34•]. Studies have focused on the influence of opening combinations, open area [13•], seasonal transitions [35] or end-of-the-day positions [36]. Wei et al. [36] showed the end-of-the-day window position impacted the energy and thermal performance of the building, the following day. To better capture patterns within seemingly random data, advanced numerical methods, such as data mining, are being used [13•]. Using data mining, D'Oca and Hong [13•] classified the primary, behavioral-driven, categories for motivating window opening and closing, as (i) thermal driven patterns, (ii) time driven, opening duration patterns (iii) activity or inactivity patterns (iv) opening position patterns [13•]. Like windows, the position and the frequency of interaction with movable shading and blinds impacts the building energy use, peak loads, and visual and thermal comfort. O'Brien [34•] comprehensively reviewed advancements in the experimental practices and methodologies for manual shade operation. Proper activity with windows, shades and blinds offers an energy efficient strategy, but also easily lends the opportunity for misuse, leading to energy waste [8,35].

2.4. Lighting and electrical equipment

Lighting represents about 25.5% of the energy used in commercial buildings in the U.S., indicating an opportunity for more natural light and control systems [3•]. Control types such as occupancy detection techniques, passive infrared sensors and imaging occupancy detection allows for more consistent energy savings [37]. Traditionally, stochastic models are used to simulate lighting profiles and quantify and predict the impact of LEDs on lighting systems [37]. Models demonstrating future predictions indicate that a 65% reduction in energy consumption could be obtained with 80%

replacement of current lamps for LEDs, in Andalusia, Spain [38]. The use of real time monitoring of electrical equipment and providing occupants with systematic energy visualization, generated energy savings of more than 9% [39].

Plug loads generally refer to an equipment powered by an ordinary AC plug and excludes major end uses such as HVAC, lighting, electric car charging and water heating. Plug loads are generated by specific devises requiring power (e.g. computers, toasters, localized fans/heaters) and therefore are typically unique to the building. As the demand for charging technological devices becomes more prolific, the portion of demand associated with plug load draw also increases. User behavior is a major factor for the overall increase in plug load energy use. One of the simplest methods to reduce plug loads is to turn-off or unplug unused items. Webber et al. [40] observed, in offices in Washington DC and San Francisco, that only 44% of computers, 32% of monitors and 25% of printers were turned off at night. Presently, there is an opportunity to reduce the energy consumption from lighting and plug loads, especially during the design and operation phase of the building.

2.5. Data gathering

Gathering data to investigate (i) occupant movement and presence, (ii) thermal comfort, (iii) windows, shades and blinds and, (iv) lighting and electrical equipment, requires a host of information, from the utilization of custom sensors, weather stations, building, energy and lighting management systems (if applicable). Table 1 presents a general guideline highlighting the different variables within the building that need to be monitored to capture the necessary information to analyze different behavioral actions. The guideline uses a priority ranking of mandatory or optional dependent mostly upon the building type, experimental accessibility and experimental resources available. Generally, the more data collected for longer durations of time is preferred, however resource and time limitations often restrict data collection periods. Specific sensors for each variable are rapidly advancing with the opportunity to easily obtain the necessary information for monitoring. Generally, environmental, behavioral and personal data is collected and integrated across time to match particular drivers with actions.

3. Advances in analytical and modeling methods

3.1. Ontology and schema to represent occupant behavior

Advancements in the standardization of the quantitative descriptions and classification of occupant behavior on building performance has been initiated by programs such as the IEA EBC Annex 66: Definition and Simulation of Occupant Behavior in Buildings. An ontology to represent energy-related occupant behavior has been outlined in a DNAs (Drivers, Needs, Systems, Actions) framework, providing a systematic representation of energy-related occupant behavior in buildings [41••]. An XML (eXtensible Markup Language) schema is used for the exchange of occupant information modeling and to integrate with building simulation tools [41••] (Fig. 3).

3.2. Implicit and explicit behavioral models

Implicit models, based on a predictor variable, capture the driving forces behind occupant behavior or predict the state of a building system or the occurrence of an action [41••]. Simply, implicit models deal with rules associated with physical systems (e.g. windows, lights etc.) rather than the occupant directly. These models include linear and logistic regression [42], probability equations [43,44], statistical analysis of measured occupancy data [45], sub-hourly occupancy-based control models and Bayesian estimations [46].

Explicit models, based on monitored behavior, provide the state of a building system or the action of the occupant or agent [41••]. Simply, they deal with rules and logic associated directly with the occupant. The three major forms of stochastic occupant behavior models most commonly found are: (1) Markov chain [1,18,47,48] and agent-based modeling [49,50•], (2) the Bernoulli process [51] and, (3) survival analysis. The Bernoulli process, functions such that the probability of an event or state is independent (memoryless or not dependent on a previous state). Although simple and easily applied, it fails to capture individual comfort or to predict individual behaviors. In contrast, the discrete-time Markov chain depends on the previous state, becoming particularly useful for representing individual actions such as occupant movement. An extension of the Markovian model are agent-based modeling (ABM) that specify the interactions of occupants with their environment. ABM include individual attributes such as behavior rules, memory, resources and decision-making. One common framework used for ABM is Belief-Desire-Intention (BDI) model [52] that mimics the practical reasoning process of occupant decision making and gives structure to this process. Lastly, the survival process, a continuous time approach, is used to estimate the time duration until an event occurs (initially used to predict longevity). Other promising approaches include discrete event formulation, which only triggers when significant changes to model inputs occur [48].

3.3. Modeling challenges

A present challenge is dealing with the oversimplification of existing occupant behavior models [27]. Simply, the stochastic nature of the occupant is distilled into homogeneous and deterministic inputs, often ignoring the diversity and inter-dependency of various behavioral and seemingly stochastic actions. Model inputs are typically model specific, often selected based on the intent of the study and suffer from user input assumptions. The incorporation of qualitative models that can significantly improve the predictability of behavior, include: (1) clustering multiple contextual factors or inputs into a single equation or (2) treating the factors that influence model behavior independently [53]. At the most basic level, model inputs and model validation are based on real behaviors (actual data), using statistical methods (chi-square goodness-of-fit, R^2, variance) [46,54]. However no general scientific standard outlines appropriate model validation techniques, thus often model validation is not upheld.

Additionally, one greater challenge to model development is establishing common hierarchies of behavioral actions, such as how to deal with multiple decisions and multiple actions. When modeling sequences of behavior, the complexity of the model grows due to the necessity to capture all combined affects that influence different behaviors together [55]. Programming often uses a form of priority ranking or logic to represent multiple occupant decision making, with inherent error associated with this process. Perhaps future work will be able to determine behavioral action hierarchy from future data for advanced algorithm development.

4. Simulation to quantify the impact

4.1. Integration of occupant behavior models with building performance simulation programs

The integration of occupant behavior models with existing BPS programs enables researchers and practitioners to simulate energy-related occupant behavior in buildings, helping to match simulated results with the actual energy use. Observational

Table 1
A mapping of the data needed to complete basic occupant behavior studies in window opening/closing, occupancy, shading, lighting, thermal comfort, plug loads, and HVAC.

	Variables\behaviors	Units	Window opening	Occupancy	Shading	Lighting	Thermal comfort	Plug loads	HVAC	Occupancy survey	Device/system
Weather data	Outdoor air temperature	°C	√√				√√		√√		Weather station
	Outdoor air humidity	%	√√				√√		√√		Weather station
	Wind speed	m/s	√√				√√				Weather station
	Wind direction	N, E, S, W	√				√				Weather station
	Solar irradiance	W	√		√√	√√	√		√		Weather station
	Illuminance	Lux	√		√√	√√	√				LMS
	Rain (event)	Y, N	√				√		√		Weather station
Space data	Indoor air temperature	°C	√√		√√		√√	√	√√		BMS
	Indoor air humidity	%	√				√√	√	√√		BMS
	CO_2	ppm	√√	√√			√√		√√		BMS
	Occupancy	0–1	√√	√√	√√	√√	√√	√√	√√		BMS/custom sensor
	Light level	On-off, dimming		√	√√	√√	√	√			BMS/LMS
	Window state	Open, closed	√√	√	√		√√		√		BMS/LMS
	Shading state	Up-down, partial		√	√√	√√	√		√		EMS
	Plug loads	On-off		√		√		√√	√		EMS
	Thermostat settings (cooling & heating)	°C		√			√√	√	√√		BMS
	Heating/cooling state	On-off		√			√	√	√√		EMS
Energy data	Total energy use	kW h	√	√	√	√	√	√	√√	√√	EMS/survey
	Submetering (lighting, HVAC, plug-loads, etc)	kW h				√	√	√	√		EMS
	Energy production (renewable)	kW h				√	√	√	√		EMS
Occupants data	Age	Number	√	√	√	√	√	√	√	√√	Management/survey
	Gender	F, M	√	√	√	√	√	√	√	√√	Management/survey
	Working profiles	Working, non-working	√	√	√	√	√	√	√	√√	Management/survey
										BMS = building management system	
							√√	Mandatory		EMS = energy management system	
							√	Optional		LMS = lighting management system	

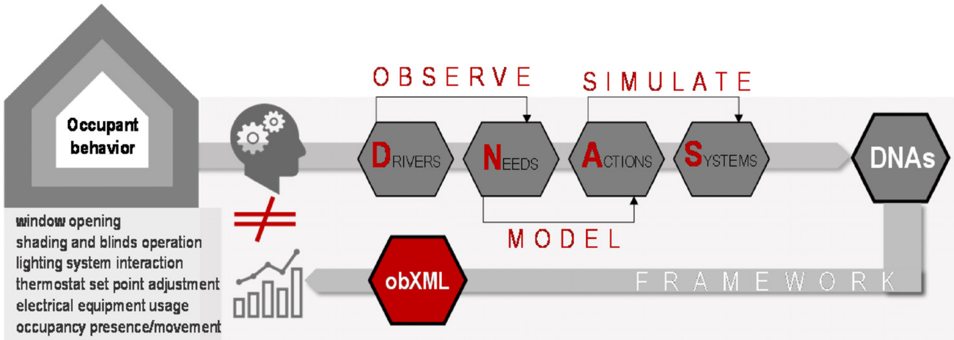

Fig. 3. A schematic showing the integration of advanced data collection techniques with the DNAs framework and integrated into the obXML for occupant information modeling [41••].

data, processed through derivative, descriptive or stochastic methods, can lead to predictive occupancy and activity models which can be integrated in BPS applications. Simulation engines allow researchers to assess the implications of different occupant behaviors within the context of the building environment and energy flow. The main approaches used to integrate occupant behavior into building simulation programs are shown in Table 2. There are on-going efforts to develop a stand-alone behavior module, as a functional mock-up unit, which can co-simulate with BPS programs. Such co-simulation approaches provide the maximum degree of flexibility in coupling behavior modeling with BPS program [56]. However work is needed for current BPS programs to fully support co-simulation features.

4.2. *Behavior influence on energy savings*

Quantifying the savings from occupant behavior remains a primary challenge. For behavior-related energy savings an estimated savings of 10% [57] to 20% [58] for residential and 5% to 30% [59] for commercial buildings (i.e. private offices) was achieved. More moderate savings was shown using a workplace behavior program, demonstrating only 5% in energy savings [60]. Hong et al. [59] compared work styles in a single story office building, suggesting an energy-saving work style consumed up to 50% less energy, while an energy-wasteful work style consumed up to 90% more energy, compared with a control. As can be demonstrated, the quantification of energy saving varies widely from study to study, retracting from the meaningfulness of such estimates and highlighting the fact that quantification of behavior energy savings is a current weakness in the field. Future work should strive to more clearly categorize behavior energy style and incorporate the associated uncertainties into simulated energy impacts.

4.3. *Behavior influence on non-energy savings*

A large portion of the energy spent in buildings is to maintain healthy and comfortable conditions, for the occupants' well-being and productivity. Therefore, occupant behavior also impacts

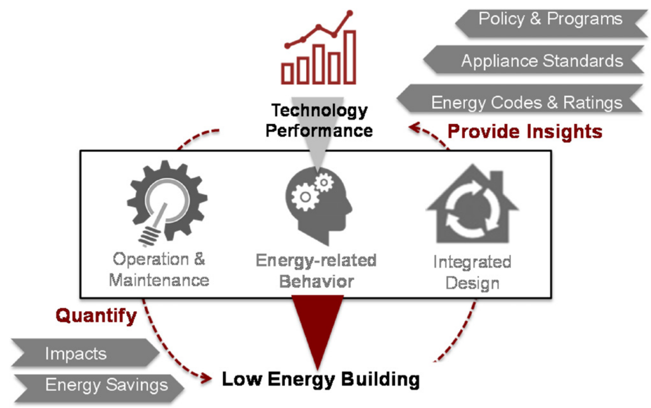

Fig. 4. Key strategies to low energy buildings.

comfort conditions, and indoor environmental quality (IEQ). Roughly 26% of the total primary energy consumed in the U.S. is used in an effort to maintain a healthy and comfortable indoor climate [61]. It has been shown that the utilization of technologies and designs, that strengthen the correlation between occupants' perceived control of building systems and thermal comfort, helps occupants to exhibit energy savings behavior without perceived loss of comfort [62]. In general, one of the greatest goals is to achieve indoor thermal comfort and premium indoor air quality, with the minimum possible energy cost and environmental impact.

4.4. *Low energy buildings and design robustness*

To satisfy comfort needs, occupants use technologies which impact the building energy performance [63,64]. It is commonplace that low energy buildings, with substantial dependence on passive design and intricate technologies, do not meet design goals, in part due to operational behavior [3•,65]. Quantifiable performance metrics and appliance standards go into the performance strategy for achieving low energy buildings (Fig. 4). This

Table 2
Current approaches to include occupant behavior into building simulation programs.

Approach	Description	BPS program
User defined profiles	Users define and input temperature set points, schedules of lighting use, plug-loads and HVAC system operations	EnergyPlus, DeST, DOE-2, TRNSYS, IDA-ICE, ESP-r
User customized code	Users can write custom code or overwrite existing or default values without re-compiling the simulation tools	EnergyPlus, DOE-2
Embedded occupant behavior modules	Users directly employ the occupant behavior module of the simulation tools	DeST, IDA-ICE, ESP-r
User modified source code	Users add new code or change existing code requiring re-compiling the simulation tools	EnergyPlus, DeST, TRNSYS, IDA-ICE, ESP-r
Co-simulation	Occupant behavior tools and the simulation tools run simultaneously and exchange information in real-time	EnergyPlus

combined with advanced building technologies, energy-related behavior, integrated design, and active operation and maintenance, complete the strategy (Fig. 4). Recent, proposed solutions for technological advancement to bridge-the-gap between building design and actual energy consumption include (i) occupant-based energy retrofits [66], (ii) building performance simulations that capture the occupant dimension and passive design [67••] and (iii) operational improvement technologies built on guiding occupants toward energy savings.

5. Discussion

Occupant behavior in buildings is a multidisciplinary research topic crossing social and behavior science, building science, sensing and control technologies, computing science, and data science. One of the biggest challenges associated with data collection is the lack of standardized data and the regulation of privacy issues. Uncertainties beyond physical and user behavior [68], occur due to situational awareness, when occupants alter behavior due to heightened awareness, making data collection challenging. The current challenges in modeling and simulation include the lack of standardization within models, with developers using diverse semantics, the lack of support for co-simulation, the inflexibility of behavior software modules, and the accuracy of input assumptions.

The applicability and lack of verification for occupant behavior models begs the question as to the limits of research findings. In a broader context, one can argue the usefulness of occupancy behavior categorization in capturing the stochastic nature of individual occupants. Such that many believe that each occupant is unique and can't be lumped into a general category such as 'wasteful' or 'austerity.' Despite these challenges, real opportunities exists where big real-time data from sensors and IcT (Information and Communications Technology), data analytics and modeling provide valuable actionable information to guide occupants, building designers and operators in reducing energy consumption in buildings [69]. From the analysis of measured data, building energy simulation or sensitivity analysis, it is generally concluded that occupant behavior greatly impacts building system operation and energy consumption [70]. It is projected that the evaluation of technologies, technological design and robustness of design, will be guided by occupant interaction studies [71]. Therefore solutions in both energy efficient behavior and technology robustness will collectively contribute in achieving low energy buildings.

6. Conclusions

A growing interest emerged from the most updated literature on the role of occupant behavior in bridging the gap toward more energy efficient buildings. This review covered a combination of methods to measure and collect data on occupant behavior, new occupant behavior models, and the integration of these models with building simulation programs. The review also highlights case studies demonstrating the use of these tools to solve real world problems to improve building design, operation and retrofit.

Current challenges are: (1) collection of good and adequate data for behavior understanding and modeling, (2) an ontology specific and broad enough to represent occupant behavior in buildings, (3) evaluation of applicability of behavior models, (4) quantifying the impact of energy-related occupant behavior on building energy performance, and (5) providing metrics and insights to integrate sustainable behaviors into robust buildings and smart communities. Despite these challenges, understanding occupant behavior poses a new opportunity to mold the evolution of building technology, to improve energy efficiency and occupant comfort in buildings.

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ANALYTICS

DEFICIENCY OF EFFECTIVE ANALYTIC TECHNIQUES PROVIDING USEFUL KNOWLEDGE ON OB IN BUILDINGS

HOW TO TRANSLATE BUILDING AND HUMAN INFORMATION INTO USEFUL KNOWLEDGE?

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A data-mining approach to discover patterns of window opening and closing behavior in offices

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A B S T R A C T

Understanding the relationship between occupant behaviors and building energy consumption is one of the most effective ways to bridge the gap between predicted and actual energy consumption in buildings. However effective methodologies to remove the impact of other variables on building energy consumption and isolate the leverage of the human factor precisely are still poorly investigated. Moreover, the effectiveness of statistical and data mining approaches in finding meaningful correlations in data is largely undiscussed in literature. This study develops a framework combining statistical analysis with two data-mining techniques, cluster analysis and association rules mining, to identify valid window operational patterns in measured data. Analyses are performed on a data set with measured indoor and outdoor physical parameters and human interaction with operable windows in 16 offices. Logistic regression was first used to identify factors influencing window opening and closing behavior. Clustering procedures were employed to obtain distinct behavioral patterns, including motivational, opening duration, interactivity and window position patterns. Finally the clustered patterns constituted a base for association rules segmenting the window opening behaviors into two archetypal office user profiles for which different natural ventilation strategies as well as robust building design recommendations that may be appropriate. Moreover, discerned working user profiles represent more accurate input to building energy modeling programs, to investigate the impacts of typical window opening behavior scenarios on energy use, thermal comfort and productivity in office buildings.

1. Introduction

To secure sustainable energy development in the building sector, occupant behavior needs to be modified towards a more efficient and conscious energy usage. The development of energy-conserving technologies is a necessary but incomplete step toward reduced energy consumption in buildings. Achieving energy conservation becomes a double challenge, partly technical and partly human, since energy consumption may vary largely due to how occupants interact with system controls and the building envelope. Currently, building simulation tools can only imitate some typical occupant activities in a rigid and pre-defined way (occupancy, use of windows, thermostat, shadings, and lighting). Nevertheless, occupant behavior and comfort is stochastic, complex, and multi-disciplinary therefore more realistic behavioral patterns need to be developed.

As a matter of fact, a deeper understanding of the relationship between occupant behavior and building energy consumption can be seen as one of the most effective ways to bridge the gap between predicted and actual energy consumption in buildings Several studies underlined that huge variability exists in terms of default settings and day-to-day use of control systems and appliances in buildings, where 'behavior' is central to consumption levels [1–3]. In this context, the 'dark side of occupant behavior on building energy use' was demonstrated by Masoso et al., in 2000 [4]. The work showed that more energy was used during non-working hours (56%) than during working hours (44%) in one office building. This arises largely from occupants' behavior of leaving lights and equipment on at the end of the day, and partly due to poor zoning and controls. In 2004 Bordass et al. [5] referred to this occurrence as the 'credibility gap', alluding to the loss of credibility when design expectations of energy efficiency and actual building consumption outcomes differ substantially. They suggest that credibility gaps arise not so much because occupants preform 'wrong', but because the assumptions often used are not well enough informed by what really happens in practice. In the last

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decades, a number of studies focused on overcoming this barrier, testing valid, applicable and robust methodologies and analysis techniques to predict building occupant behavior seriously [6–16]. Describing, predicting or influencing energy related individual behavior are challenging tasks that must start with the non-trivial understanding of the stochastic nature of human beings. In this view, the scientific community is addressing rising interest around the issue of energy efficient buildings and specifically toward the need of a more robust description of the motivations driving humans to interact with building envelope and control systems (fans, windows, thermostats, lights, etc.) in order to bring about desired comfort conditions [21].

The most important issue in between perceived indoor environmental quality and outdoors, in the built environment, is the building envelope [17]. As a consequence, window operation is one of the most relevant tools that allow occupants to bring about desired indoor thermal and air quality conditions, by moving air through the building. Further, since the building envelope is getting always more thermally efficient, ventilation and air infiltrations due to window opening are increasing their influence with respect to energy use, becoming the most dominant source of thermal loss of the heat balance mechanism. Fitting the Humphrey's adaptive principle that if a change occurs such as to produce discomfort, people react in a way which tend to restore their comfort [18] to the findings in literature [19,20], it is demonstrated that occupants in naturally ventilated buildings accepted and actually preferred a significant wider range of temperatures compared to users of mechanically ventilated buildings. As a matter of fact, naturally ventilated buildings allow occupants' a greater degree of control over indoor hydro-thermal conditions than air conditioned buildings that strongly influence their satisfaction with working spaces [19]. In 2004 de Dear and Brager [20] highlighted that the variation of indoor environmental conditions caused from a human operable control source such as windows lead occupants to a relaxation in expectations and higher tolerance of temperature excursions.

1.1. Statistical analysis of factors influencing occupant behavior in buildings

Statistical analysis techniques are extensively applied to discover associations and relationships among the various factors influencing building energy performance and occupant behavior in buildings. Different suitable user behavioral models were defined by means of statistical analysis (Markov Chain, Generalized Linear Models, etc …) [7–16,23–32]. An extensive review of these studies has been conducted in the context of Annex 53 – Total Energy Use in Buildings, under the International Energy Agency Energy in Buildings and Communities Program [21], in order to understand the correlation between window opening and the parameters, also called drivers, influencing users' interaction in buildings with natural ventilation. The parameters are divided into five categories of influencing factors:

- Physical (indoor and outdoor environment);
- Psychological (preferences, attitudes);
- Physiological (age, sex);
- Contextual (type of environment where the occupants are located);
- Social (income, lifestyle).

Specifically for window opening in office buildings, a literature review was carried out in 2012 by Fabi et al. [22] of more than 70 scientific papers, indicating that window operation was not only influenced by perceived thermal condition, but it was also seen as a response of sensed indoor air quality, external (outdoor temperature, solar radiation, wind speed, rain) and internal (indoor temperature) environmental conditions as well as contextual factors (window type, time of the day, season of the year) and personal and cultural preferences. In these studies, statistical analysis techniques were applied to identify the influential variables on user behavior in buildings. The strength of this methodology was the simplicity and widespread familiarity.

- Indoor and outdoor temperatures were found as paramount factors influencing window opening and closing by several studies [23–27]. For instance, Fabi et al. suggested that rising indoor temperatures might drive the opening of windows, but how long the window stayed open might depend more on outdoor temperature. More specifically, Andersen et al. [28] found that the CO_2 concentration was the most important driver for opening the windows, while the outdoor temperature was the most dominant driver for closing the windows.
- Solar radiation was found by Herkel et al. [29] to have little correlation with window openings. Solar radiation was a relatively small factor when compared with the correlation of indoor and outdoor temperatures
- Wind speed was reported by Roetzel et al. [30] as a driver for closing the windows when the sensation of draft was producing a predominant discomfort.
- Time of arrival and departure as well as the time of the day had been found having a strong correlation between window adjustments by several researches. [28,29,31]
- The season of the year was found by Herkel et al. [29] to have a strong correlation with window opening [6]. Usually, the interactivity with openings was higher in summer and during the midseason (autumn and spring) and lower in winter.
- The current state of the window was also underlined by several studies [30,32] as a key aspect to take into account when concerning user's willingness to open and close windows.

1.2. A data mining framework for behavioral pattern discovery

Currently, there is no comprehensive consensus about the way people interact with building controls or the motivating factors that influence their decisions. However, there is a substantial body of research that offers guidance on patterns of behaviors. Patterns are expressions describing typical behaviors or models applicable to a subset of the data to anticipate and replicate common actions. Moreover, patterns correlate repetitive behaviors and actions to user profiles. Guerra Santin [33] statistically determined behavioral patterns of HVAC system interactions and associated energy spent on heating. From this, household and building characteristics that could contribute to the development of energy-user profiles, were identified [33]. A study conducted by Van Den Wymelenberg [34] reviewed data from more than 50 buildings and identified patterns of occupant interaction with window blind controls. Moreover, Yun and Steemers [35,36] provided evidence of a statistically significant relationship between window-opening behavior patterns and clusters of indoor stimuli. In 1983 Van Raaij and Verhallen [37] carried out a study in 145 Dutch dwellings and defined five patterns of energy behavior (conservers, spenders, cool, warm and average) in relation to the use of heating systems and ventilation habits. Findings of this research showed that the energy uses of these five pattern groups differed considerably, up to 31% [37].

Data mining techniques to discover patterns of data are largely applied to research fields such as marketing, medicine, biology, engineering, medicine, and social sciences [38]. Even so, the application of data mining framework to building energy consumption and operational data is still under investigation and nevertheless could be potentially highly effective.

Data mining was defined in 2001 by Hand et al. [39] as: *"The analysis of large observation data sets to find unsuspected relationships and to summarize the data in novel ways so that owners can fully understand and make use of the data"*. Another definition was given in 1998 by Cabena et al. [40] as: "*An interdisciplinary field bringing together techniques from machine learning, pattern recognition, statistics, databases and visualization to address the issue of information extraction from large databases*".

Applying data mining techniques, with the scope to discern behavioral patterns, were tested by several studies both in residential and office buildings. Between 2011 and 2012 Yu et al. [41–43] tested several systematic data mining methodologies for identifying and improving occupant behavior in buildings. The results showed that this analysis methodology proved powerful in providing insights into energy pattern related to the occupant behavior, facilitating evaluations of building saving potential by improving users' energy profiles as well as driving building energy policy formulation.

2. Methodology

In this study, a methodology was proposed in order to identify valid, novel, potential useful and understandable patterns of window opening and closing behavior in offices.

Statistical analysis and data-mining techniques were applied to measured building energy and environmental data. Statistical analysis provided leverage in identifying the influencing factors on occupant energy-related behavior and removed the effects of other insignificant variables on building energy performance. In the literature, examples could be found of logistic regression analyses to discover the variables influencing energy-related behavior [21]. This technique was borrowed from the natural sciences literature, where several investigations focused on the relations between energy-related behavior and (mainly physical) drivers of this behavior [44,45]. According to Nicol [46], energy-related behavior was clearly affected by physical parameters, but the relationship tended to be stochastic. For example, there was no exact temperature at which every occupant would open a window, but for increasing temperatures, the probability of the occupant opening the window, increased.

However, associations among variables found to have little statistical correlation on isolated occupant behaviors or small data set may lead to the understanding of more general patterns of behavior in a large data set, helping direct future research. In this context, data mining techniques such as cluster analysis and association rules algorithms were applied in the proposed framework with the scope to discern typical office user profiles which may allow for more accurate assumptions on group behaviors, overcoming the lack of personalization of statistical patterns.

The proposed framework suggests an improvement of the notion of behavioral patterns not only as merely statistical relevant clusters, but also incorporating the driver-response conditioning dimension with typical window opening habits.

Fig. 1 shows the proposed framework in this study:

- In *step 1*, a statistical analysis technique (logistic regression) was applied to the given data set. The goal was to discover the factors (variables and coefficients) influencing window opening and closing behavior.

A two steps cluster-then-association rules mining approach was applied to the given data set.

- In *step 2*, clustering procedures were employed in order to obtain distinct behavioral patterns. The goal was to estimate the motivational, opening duration, interactivity, degree of opening and behavioral patterns. In this aim, the research was estimating why (*motivational* pattern), for how long (*opening duration* pattern), how often (*interactivity* pattern) and how much (*position* pattern) working users open and close windows in offices of the same building.
- In *step 3*, the clustered patterns constitute a base for association rules segmenting the building occupants into typical office *user profiles*.

2.1. Statistical analysis technique

Generalized linear models (GLMs) [47] are a class of statistical models for describing linear combination of predictor and dependent variables. The GLM allows the statistical model to be related to a dependent variable via a link function of its predicted values. In the specific case, logistic regression is a sigmoidal classification GLM able to predict the probability of an event having binary outcome (0–1) occurrences based upon predictor variables and coefficients. Logistic regression also allows to express the magnitude of the coefficients of each dependent variables as a function of the binary outcome.

Formula (1) describes the relationship:

$$\mathrm{Log}\left(\frac{P}{1-P}\right) = a + b_1 \cdot X_1 + \ldots + b_n \cdot X_n + \ldots \tag{1}$$

where:

- P is the probability
- a is the intercept
- b_{1-n} are coefficients
- x_{1-n} are variables

2.2. Data mining techniques

Two descriptive data mining approaches: 1) cluster analysis (k-means algorithm) and 2) association rules mining (Frequent Pattern FP-Growth Algorithm) were employed to discover patterns of windows opening and closing [38].

Cluster analysis is the process of merging data into different clusters, so that instances in the same cluster have high similarity and instances in different clusters have low similarity. The similarity between clusters was computed based on the distance between the clusters. The distance measure was described using the Euclidian distance Formula (2) where:

$$d(a,b) = d(b,a) = \sqrt{(b_1 - a_1)^2 + (b_2 - a_2)^2 + \ldots + (b_n - a_n)^2} \tag{2}$$

where:

- $a = (a_1, a_2,\ldots, a_n)$ and $b = (b_1, b_2,\ldots, b_n)$ are two points in an Euclidean n-space

The *k-means algorithm* is a method of vector quantization for cluster analysis in data mining. Given the simple nature of the algorithm, it is one of the widely used classification technique. Assumed a data set D, containing a number n of records (instances), the number of clusters K must be specified.

The performance of the cluster models was evaluated by means a Cluster Distance Performance operator. In this study, the

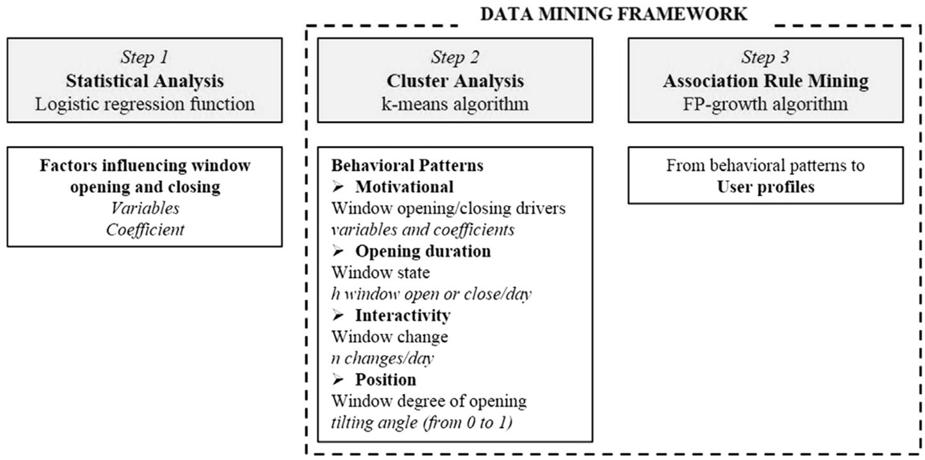

Fig. 1. Proposed framework of the research.

Davies–Bouldin index was used for performance evaluation. The $k = n$ algorithm that produces clusters with low intra-cluster distances (high intra-cluster similarity) and high inter-cluster distances (low inter-cluster similarity) will have a low Davies–Bouldin index, and will be considered the $k = n_{opt}$ cluster algorithm for the specific data set. Each cluster was associated with a centroid (center point), the mean of the points in the cluster and each point was assigned to the cluster with the closest centroid.

Association rule mining (ARM) is a classification technique used to identify associations and correlations between parameters (attributes). Main objective was to extract frequent correlations or patterns (association rules) from a database. Given a data set D, containing a number n of non-ordered records, the association rule was used and described by the Formula (3):

$$\mathrm{A,\ B} \Rightarrow \mathrm{C} \tag{3}$$

where:

- A, B = items in the rule body
- C = item in the rule head

The validity of the association rules was indicated by support, confidence and lift.

Support, represents the fraction of transactions (T) containing both A and B, shown in Formula (4).

$$\mathrm{Support} = \frac{\#(\mathrm{A,\ B})}{|T|} \tag{4}$$

Confidence (5) represents the conditional probability of finding B having found A, and gives strength to the “if, then” statement of the association rules. Mathematically, confidence can be calculated as the frequency of B in transactions containing A.

$$\mathrm{Confidence} = \frac{\mathrm{sup(A,\ B)}}{\mathrm{sup(A)}} \tag{5}$$

To discover reliable and valid rules in data set, minimum value for confidence and support must be pre-defined. Accordingly, in this study association rules that satisfy the minimum support of 0.3 and minimum confidence of 0.8 in the given data set, were used.

Lift (6) represents the ratio of the observed support to that expected, if A and B were independent. The *Lift* value must be different to 1, to avoid the occurrence of A being independent of the occurrence of B. The higher the lift value, the more likely that a correlation between A and B exists.

$$\mathrm{Lift} = \frac{\mathrm{sup(A,\ B)}}{\mathrm{sup(A)*sup(B)}} \tag{6}$$

The *frequent pattern growth algorithm* (FP growth), the most commonly used algorithm to discover patterns into a given data set, generated a classification tree (FP-tree) that exploited a memory compressed representation of the database. This dense data distribution was used to mine frequent patterns of the smaller subsets.

2.3. The data set

An office building based in Frankfurt am Main, Germany, was used as case study (Table 1). Frankfurt am Main has generally a temperate-oceanic climate, with relatively cold winters and warm summers. The building was naturally ventilated and cooled in summer and every office was equipped with an operable window that may be opened and shut to accommodate the occupant's ventilation needs. Moreover, the building showed very strict design criteria in terms of energy efficiency and energy optimization for heating, cooling, ventilation and lighting, having an average transparent and opaque envelope U-value of 0.54 W/m^2 K.

In this study, the following data set [21] (Figs. 2 and 3) was used and includes:

Table 1
Building characteristics.

Type of building	Multi-story office building
Dimension	17,402 m^2 (8585 m^2 heated)
No. of employee	~350 employees
Location	Frankfurt, Germany
Thermal characteristics	Low energy standard of building envelope (U-values walls 0.24–0.5 W/m^2 K, windows 1.5 W/m^2 K)
Annual primary energy consumption	Less than 100 Wh/m^2
Type of observed spaces	Office rooms
Year of construction	2002
No. of floors	2-level underground car park + 4 office floors + 1 floor apartments on top
Windows, orientation	Mostly E and W
Window opening	Tilt-and turn (automatic BMS + occupant driven mode)
Shading devices	External sun protection (automatic BMS + occupant driven mode)

Fig. 2. Two-part sun protection enables glare-free use of daylight.

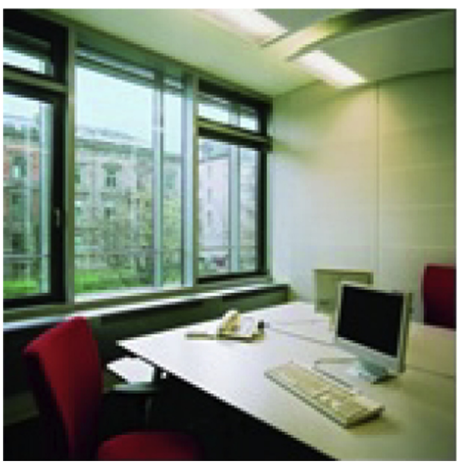

Fig. 3. Offices with operable windows and sun protection, allowing natural ventilation and natural lighting.

a) 16 private offices with single or dual occupancy (Table 2). E01–E11 are eleven offices facing the east while W01–W05 are five offices facing the west.
b) 10-min interval data over two complete years (Table 3)
c) measured indoor and outdoor physical parameters (Table 4)
d) measured behavior and energy use (Table 4)

2.4. Statistical analysis and data normalization

In this study, *logistic regression analysis* was performed to compare the leverage (b_{1-n} coefficient's impact factors) of the x_{1-n} variables influencing the window opening and closing probability.

Table 2
Database characteristics.

Number of offices	16
Period of measurement	2006 and 2007
Type of observed spaces with sensors	Standard offices
Dimension of observed spaces	20 m^2
Occupancy level of observed spaces	1 or 2 persons
Number of observed spaces with indoor CO_2-concentration	3
Orientation	East and West

Table 3
Data characteristics.

	Items	Interval
Climate	Outdoor air temperature, outdoor humidity, wind speed, solar radiance	10 min
Building envelope	Not in database	
Building service & Systems		10 min
Operation & Maintenance	Monitoring of heating, cooling, lighting and ventilation system, and related energy flows	10 min
Indoor environmental quality	Indoor (operative) temperature, humidity, (CO_2)	10 min
Occupants' activities and behavior	Window state (open/closed) Presence State of sun protection (open/closed) Usage of lighting equipment	Event
Social and economical aspects	None	

Table 4
Monitored parameters characteristics.

Outdoor	Indoor	Behavior
Solar radiation [W/m^2] Rain – amount [l/m^2] Rain – event [yes/no] Light intensity – horizontal [l×] Light intensity – South [l×] Light intensity – East [l×] Light intensity – North [l×] Light intensity – West [l×] Outdoor temperature [°C] Wind – velocity [m/s] Wind – direction [°] CO_2 content in air [ppm] Outdoor humidity [%rh]	Room air temperature [°C] Surface temperature [°C] Ceiling slab temperature [°C] CO_2 concentration [ppm]	Occupancy [0/1]* Window contact [0/1; reed contacts]* Top light control [0/1; reed contacts]* Sun protection [% of closure: 0% = open to 100% = closed] Electricity consumption [kWh]

Accordingly, the literature findings [22] suggested that the probability of opening and closing a window was calculated as function of 15 non-numerical and numerical variables for the 16 offices.

2.4.1. Non-numerical variables

1. Season (Summer, Spring, Autumn, Spring)
2. Day of the week (Monday to Sunday)
3. Time of the day (Early Morning 6–9 am, Morning 9 am–12 pm, Noon 12–3 pm, Afternoon 3–6 pm, Evening 6–9 pm, Night 9 pm–6 am)
4. Window State (0 = close, 1 = open)
5. Occupancy State (0 = vacant, 1 = present)
6. Window Change (if occupancy state $t_{n-1} = t_n$ then = no change, otherwise = change)
7. Occupancy Change (if occupancy state $t_{n-1} < t_n$ then = arriving time, if occupancy state $t_{n-1} > t_n$ then = leaving time, otherwise = no change)
8. Precipitation (event 0–1)

2.4.2. Numerical variables

9. Indoor air temperature
10. Outdoor air temperature
11. Outdoor relative humidity
12. Solar radiation horizontal
13. Illuminance level
14. Wind velocity
15. Wind direction.

In logistic regression modeling, it is normal practice in to undertake a process of parameter selection to identify the minimum number of variables required to predict observed behavior, based on their significance and usefulness. Nonetheless, cluster analysis was used in this study to group of variables influencing the window opening and closing behavior in the 16 offices. In this view, all the selected variables are potentially assumed equally significant and useful motivational stimuli driving occupants to satisfy their needs with respect to the natural ventilation of their offices.

Data normalization was applied to numerical variables in order to scale each coefficient within a comparable range and to normalize east-west office orientation. In order to determine the coefficient's impact factors, x_{max} and x_{min} were assumed as the original maximum and minimum coefficient values of the numerical variables selected for the statistical analysis. By rank normalization, a value x of the coefficient was transformed into x' in the new specific coefficient range for each of the numerical variables in the east and west orientations (Table 5).

$$x' = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})}$$

Logistic regression analysis was performed along the open source statistical analysis program R [48]. The east-west normalized coefficients' impact factor of every variable on the window opening (Table 6) and closing (Table 7) probability, was then calculated for the 16 offices.

The following key points could be observed from the statistical analysis results:

- Indoor air temperature, arrival time, occupant presence, time of the day (early morning) and outdoor temperature were the main factors influencing window opening behavior.
- Indoor air temperature, leaving time, occupant presence and time of the day (evening) were the main factors influencing window closing behavior.
- Window opening and closing occupant behavior was equally affected by common physical and non-physical drivers.
- Occupants in the building interact with windows principally driven by thermal discomfort (indoor air temperature) but also behave according to a daily routine (time of the day) and/or habits (arriving and leaving time).

2.5. Cluster analysis of behavioral patterns

The clusters in the present study disaggregate occupant behavior into patterns. Specifically, four patterns of behavior were mined in the given data set: *motivational*, *energy intensity*, *activity* and *position*.

- *Motivational patterns* clustered the factors which drive the users to open or close windows. Clusters were labeled according to the impact (b_{1-n} coefficient's impact factors) the x_{1-n} influencing variables had on the window opening and closing actions.
- *Opening duration patterns* cluster occupant behavior based on the number of hours the window state was recorded open every day.
- *Interactivity patterns* cluster occupant behavior based on the number of window position changes recorded every day.
- *Position patterns* cluster occupant behavior according to the most frequent window degree of opening every day.

Table 5
Coefficient range of the numerical variables for the East and West facing offices.

Numerical Variables	East offices	West offices
Indoor air temperature (C°)	23	18
Solar radiation horizontal	1092	1092
Illuminance level	98,824	97,646
Outdoor temperature	44	44
Wind velocity	13	13
Wind direction	360	360
Outdoor relative humidity	73	73

Four distinct data sets, based on different parameters, were used to mine window opening drivers, state, change and position (Table 8).

The k-means algorithm was employed along with the open source data mining program Rapid Miner 6.0 [49] to perform cluster analysis.

The value $2 > k < 10$ was adjusted in this study in order to find the k_{opt} by using Cluster Distance Performance operator. In this study, the Davies–Bouldin index was used for performance evaluation. The $k = n$ algorithm that produced clusters with low intra-cluster distances (high intra-cluster similarity) and high inter-cluster distances (low inter-cluster similarity) had a low Davies–Bouldin index, and were considered at the $k = n_{opt}$ cluster algorithm, for the specific data set.

2.5.1. Motivational behavioral patterns

Patterns of window opening and closing drivers in offices were clustered based on the impact that the influencing variables played on these actions. The optimal k-means algorithm, validated by means the Davies–Bouldin index, grouped $k_{opt} = 3$ clusters for factors influencing window opening and $k_{opt} = 2$ clusters for factors influencing window closing.

Each office was assigned to a cluster both considering window opening and closing actions.

- **Opening Cluster 1**: 31% offices assigned (E01, E03, E04, E11, W02)
- **Opening Cluster 2**: 31% offices assigned (E02, E05, E09, W04, W05)
- **Opening Cluster 3**: 38% offices assigned (E06, E07, E08, E10, W01, W03)
- **Closing Cluster 1**: 44% offices assigned (E01, E02, E03, E04, E09, E11, W02)
- **Closing Cluster 2** 56% offices assigned (E05, E06, E07, E08, E10, W01, W03, W04, W05)

The cluster centroids of the k = opt means algorithms were plotted to provide a visualization of the emerged occupancy patterns. Among the 15 numerical and non-numerical variables, Tables 9 and 10 highlight the top five influencing variables and coefficients for window opening and window closing, respectively. The results from Table 9 suggest the top five drivers for window opening were indoor air temperature, outdoor air temperature, time of the day (office arriving time and early morning) and occupancy presence. From Table 10, the top five drivers for window closing were indoor air temperature, time of the day (office leaving time and evening), occupancy presence and outdoor air temperature.

Fig. 4 shows the impacts (absolute value) that the driving forces have on the window opening and closing, towards the pursuit of occupant comfort. The key findings are as follows:

- Opening Cluster 1 appeared to be significantly more influenced by physical parameters such as indoor (6.49) and outdoor (2.25) air temperature than the other two clusters. Hence, offices

Table 6
Calculated variables and coefficients' impact factors for window opening probability.

	E01	E02	E03	E04	E05	E06	E07	E08	E09	E10	E11	W01	W02	W03	W04	W05
Intercept	−2.86	−0.44	0.24	1.59	3.33	−10.77	−2.38	1.04	1.81	−22.97	−19.97	2.97	1.99	7.49	−0.62	2.51
Occupancy presence	−1.13	−0.65	−1.7	−1.79	−1.66	−0.12	−1.24	−1.45	−2.78	16.67	14.85	−1.84	−1.61	−1.29	−1.15	−1.80
Air temperature	−2.92	0.40	−9.08	−7.49	−4.47	4.66	1.37	−5.31	−4.32	−0.58	−2.35	−6.81	−21.35	−8.16	−0.20	−5.04
Arriving time	−1.10	−1.69	−14.23	−2.25	−2.13	−2.61	−3.15	−2.53	−3.35	−0.83	−0.22	−2.47	0.34	−14.92	−19.18	−2.67
Season spring	0.74	−1.38	−1.80	0.17	0.15	−0.35	−0.68	−0.49	−0.59	1.32	−0.09	−0.69	−0.50	2.54	0.37	−0.03
Season summer	0.55	−1.54	0.05	−0.81	0.52	0.15	−0.73	−0.72	−0.32	−14.86	−1.91	−0.70	−14.20	1.08	−15.42	−0.20
Early morning	−2.76	−2.46	0.47	−0.88	−16.34	−0.22	−0.03	0.01	−1.91	−17.10	−1.46	−1.87	0.98	−2.73	−1.07	−0.98
Outdoor temperature	1.77	−0.17	3.99	2.99	−0.95	2.94	1.66	1.11	0.98	5.00	1.33	2.46	13.61	2.07	1.02	2.46
Outdoor RH	−0.80	−2.17	−4.54	−0.59	−1.65	1.06	−1.60	−0.34	−1.02	−0.31	−2.41	−0.60	−0.31	−2.15	−3.12	−0.32
Noon	−0.69	−0.11	1.06	0.00	−0.47	0.30	−0.31	0.30	−0.55	−17.48	0.57	−0.20	17.06	−0.28	−0.28	0.44
Solar radiation horizon	−2.03	−0.79	−2.64	−0.81	−0.29	0.06	−1.55	0.27	−1.44	−2.40	−1.56	−0.56	−3.31	−0.57	0.44	−2.03
Season winter	0.41	−0.28	0.05	0.09	−0.10	−0.38	−1.24	0.12	0.33	0.42	−0.52	−0.21	1.48	2.88	0.47	−0.05
Morning	−0.27	0.13	2.78	0.07	−1.08	−0.26	0.00	0.00	0.74	−16.95	−0.50	0.04	19.03	0.45	0.54	0.35
Illuminance level	1.01	0.24	−0.29	0.24	−1.56	1.50	0.74	0.21	0.43	−2.55	1.29	0.36	−4.77	−0.38	0.17	−1.04
Wind velocity	2.14	0.97	1.54	0.58	−0.08	0.42	0.34	1.52	1.43	2.97	−0.40	0.16	−1.20	−2.44	−0.30	−0.28
Wind direction	−0.38	−0.60	0.82	0.02	0.07	−0.19	−0.29	−0.50	−0.05	1.86	0.37	0.05	0.40	−0.11	0.61	0.36

assigned to this cluster were associated to a *thermal-driven* window opening behavior.

- Opening Cluster 3 appeared to be more influenced by time-dependent parameters such as office arrival time (2.65) and time of the day (2.1) than physical parameters. This cluster of behavior tend to open windows as a response to preference and attitudes which were psychological (preference and attitudes) and contextual more than physical drivers. Offices assigned to this cluster were therefore associated to a *time-driven* window opening behavior.
- Opening Cluster 2 was mainly driven by a combination of a physical parameter such as indoor air temperature (3.51) and psychological and contextual factors such as office arriving time (2.53). Offices assigned to this cluster were therefore associated to a *thermal-time driven* window opening behavior.
- Closing Cluster 1 was mainly influenced by indoor air temperature (4.93) and outdoor air temperature (3.87) when closing windows and time-dependent parameters were significant but secondary driving forces. Hence, offices assigned to this cluster were associated to a *thermal-driven* window closing behavior.
- Closing Cluster 2 was mainly influenced by time-dependent parameters such as time of the day (3.34) and office leaving time (3.23) than physical parameters. Offices assigned to this cluster were therefore associated to a *time-driven* window closing behavior.

Occupancy presence clearly emerged as one of the top five influencing factors for both window opening and closing actions.

2.5.2. Window opening duration behavioral patterns

The two-year data set was organized based on the number of hours the window state was recorded to be open in one day in each of the 16 monitored offices. The optimal k-means algorithm, validated by means the Davies–Bouldin index, grouped $k_{opt} = 4$ clusters of window opening duration during the four seasons of the year. Hence, three window opening *duration patterns* were clustered in the data set (Fig. 5):

- Long Openings: 19% offices assigned (E10, E04, W05)
- Medium Openings: 31% offices assigned (E07, W01, E08, E05, E09)
- Short Openings: 50% offices assigned (W04, E02, W03, E06, E01, E11, W02, E03)

Generally, window is kept open for longer periods during summer months and for shorter periods during winter months. Even following this tendency, office E10 was labeled as isolated cluster with respect to the average window opening duration in the data set records. Office E10 presented extreme window opening *duration patterns* where the window position was recorded (i) open almost all day long during summer months, (ii) around 16 h per day during autumn and spring and, (iii) around 12 h per day during the winter season. For simplicity to further consideration, this cluster was incorporated to the closest cluster and associated to the long openings behavioral pattern.

The variation of the average duration for which the window was kept open in every office ranged from 0.04 h/day (office E04) to 6 h/day (office E03) and not considering the extreme case (office E10, in which window state is recorded open on average for more than 17.2 h/day).

- Long Openings: windows stay open for an average of 6–17.2 h per day
- Medium Openings: windows stay open for an average of 1–2.2 h per day
- Short Openings: windows stay open for an average of less than 0.7 h per day

2.5.3. Window interactivity behavioral patterns

The same two-year data was reorganized based upon the average number of window state changes in one day, for each of the 16 offices. The optimal k-means algorithm, validated by means the Davies–Bouldin index, grouped $k_{opt} = 3$ clusters of window interactivity behavioral patterns during the four seasons of the year. Great variation among the number of daily window interaction was found among seasons of the year even in a same office. For these reasons, the number of daily window position changes during winter, summer, spring and autumn was used as indicators of the office user interactivity with the natural ventilation system.

Three *interactivity* behavioral patterns were clustered in the data set (Fig. 6):

- Active Operation: 31% offices assigned (E02, E04, E07, E08, W01)
- Neutral Operation: 25% offices assigned (E05, E06, E09, W05)
- Passive Operation: 44% offices assigned (E01, E03, E10, E11, W02, W03, W04)

The average number of changes varies from 0.04 to 3.8 changes per day.

Table 7
Calculated variables and coefficients' impact factors for window closing probability.

	E01	E02	E03	E04	E05	E06	E07	E08	E09	E10	E11	W01	W02	W03	W04	W05
Intercept	−15.9	−4.52	−12.55	−4.74	−3.93	−11.52	−5.69	−4.60	−4.54	−23.80	−7.71	−5.47	−11.48	1.34	−1.70	−5.53
Occupancy presence	−1.74	−1.52	−2.28	−2.31	−2.19	−1.98	−2.99	−2.05	−1.83	−3.23	−1.78	−2.40	−1.33	−2.91	−3.18	−2.41
Leaving time	−2.05	−2.68	−19.01	−5.13	−4.12	−3.17	−3.04	−3.35	−2.24	−20.52	−1.76	−3.46	−18.35	−16.08	−4.53	−4.68
Evening	−3.62	−3.57	−15.25	−2.72	−3.16	−4.96	−2.47	−5.03	−2.79	−1.94	−1.39	−17.20	1.24	−2.54	−3.00	−17.19
Season spring	0.72	−1.53	−2.25	−0.34	−0.33	−0.45	−0.79	−0.65	−1.25	16.90	−1.21	−0.71	−1.03	2.46	0.24	−0.38
Early Morning	0.04	−1.61	0.06	0.84	−1.95	0.30	0.88	0.69	0.77	1.10	0.42	0.45	4.09	1.00	1.16	1.34
Illuminance. level	0.36	0.70	0.09	1.12	1.57	1.07	1.54	0.20	1.53	−0.02	2.77	−1.29	5.14	−0.01	0.30	0.69
Season winter	0.31	−1.69	−0.02	−1.18	0.26	0.12	−1.00	−0.97	−0.59	−0.63	−2.31	−0.96	−14.60	0.92	−15.39	−0.84
Season summer	0.17	−0.32	−0.68	−0.56	−0.49	−0.52	−1.30	−0.21	−0.37	17.78	−1.43	−0.55	1.01	2.73	0.22	−0.50
Noon	0.21	0.15	0.77	0.41	0.28	0.42	0.18	0.52	−0.72	−0.50	1.41	0.64	3.70	0.28	0.62	0.94
Air temperature	8.65	2.78	1.54	0.77	1.41	5.78	3.20	0.76	1.24	0.99	2.72	2.75	−8.56	−1.31	2.33	2.42
Morning	0.12	0.03	1.80	−0.09	0.27	−0.43	0.18	0.32	−0.26	−0.03	1.26	0.83	4.38	1.48	1.43	0.93
Outdoor temperature	−0.37	−1.01	1.74	−0.38	−1.85	3.12	0.53	−0.24	−1.16	−2.84	−0.78	−1.12	11.02	−0.86	0.39	−1.11
Solar radiation horizon	0.00	1.05	3.43	−0.04	−0.41	0.73	0.12	0.69	0.17	1.48	−1.00	0.82	−1.51	−0.21	0.45	−0.20
Wind velocity	0.63	0.21	3.07	1.55	0.63	−0.09	−0.06	0.80	1.29	0.89	−1.90	−0.98	0.70	−2.04	−1.18	0.17
Outdoor RH	0.19	−0.47	1.42	0.23	0.19	1.37	0.67	0.01	0.12	−2.20	−2.23	0.36	−1.21	−2.21	−2.66	0.33
Wind direction	−0.15	−0.34	0.35	−0.15	0.17	−0.46	0.11	−0.23	0.07	0.01	1.47	−0.10	1.55	−0.66	0.25	−0.17

Table 8
Discerned behavioral patterns.

Patterns of behavior	Data mining	Parameters
Motivational	Window opening/closing drivers	Coefficients and variables (statistical analysis)
Opening duration	Window state	*h* window open or close/day
Interactivity	Window changes	*n* changes/day
Position	Window degree of opening	Tilting angle (from 0 to 1)

Table 9
Clustered top five influencing variables and coefficients for window opening probability.

Opening Cluster_1		Opening Cluster_2		Opening Cluster_3	
Variables	Coeff.	Variables	Coeff.	Variables	Coeff.
Indoor air temperature	−6.49	Indoor air temperature	−3.51	Arriving time	−2.65
Outdoor air temperature	−2.25	Arriving time	−2.53	Early morning	−2.1
Arriving time	−2.01	Early morning	−2.21	Air temperature	−1.64
Occupancy presence	−1.6	Occupancy presence	−1.82	Outdoor air temperature	1.57
Early morning	−1.09	Evening	−1.41	Occupancy presence	−1.48

- Active Operation: window position changes on the average from 2.1 to 3.8 times per day
- Neutral Operation: window position changes on the average from 1 to 1.7 times per day
- Passive Operation: window position changes on the average from 0 to 0.7 times per day

Table 10
Clustered top five influencing variables and coefficients for window closing probability.

Closing Cluster_1		Closing Cluster_2	
Variables	Coeff.	Variables	Coeff.
Air temperature	−4.93	Evening	−3.34
Outdoor air temperature	−3.87	Occupancy leaving	−3.23
Evening	−2.81	Occupancy presence	−2.31
Occupancy presence	−1.93	Indoor air temperature	1.19
Occupancy leaving	1.45	Outdoor air temperature	0.75

2.5.4. Window position behavioral patterns

The sole parameter of the number of window changes or the duration of the window state, was not indicative of the user preference regarding natural ventilation in indoor environment. Accordingly, the same two-year data was organized based on the most frequent window tilting angle position (where 0 indicates window totally closed and 1 window totally opened) recorded for each of the 16 offices. Hence, the most frequent window tilting angles were clustered into three *window position* behavioral patterns, named as small, intermediate and big opening (Fig. 7). Outlier behavioral patterns (uncommon window opening position) were isolated and associated to the most extreme behavioral pattern for further considerations (big openings).

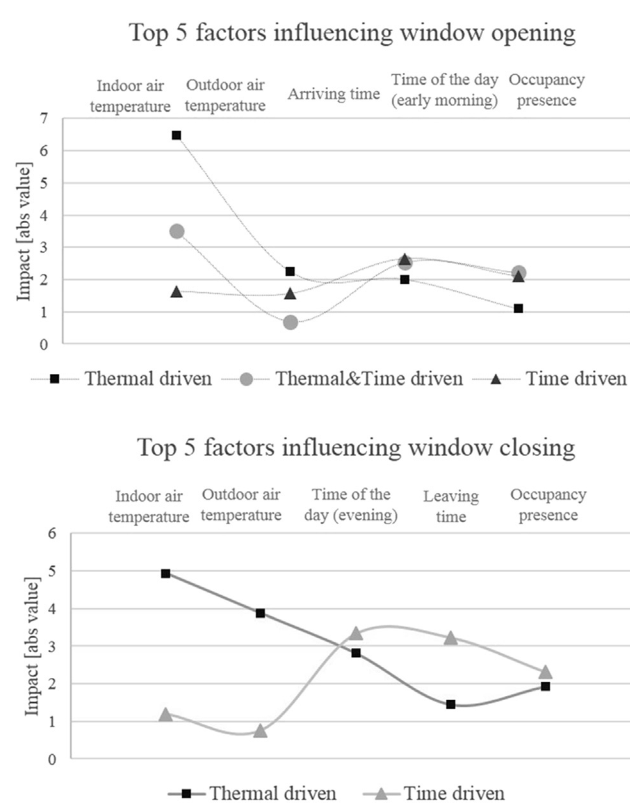

Fig. 4. Top 5 influencing factors for window opening and closing.

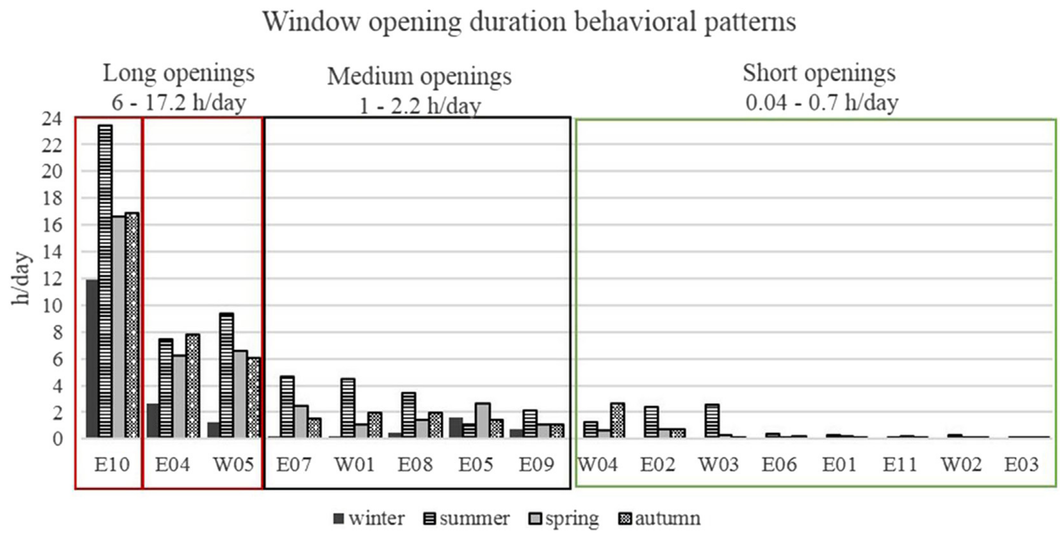

Fig. 5. Window opening duration behavioral patterns in 16 offices.

- Small Openings: 50% offices assigned (E01, E02, E03, E06, E09, E11, W02, W03)
- Intermediate Openings: 25% offices assigned (E05, E07, E08, W01, W04)
- Big Openings: 25% offices assigned (E04, E10, W05)

The average recorded window tilting angle varied based upon the hour of the day.

- Big Openings: window tilting angle position varied on the average from 0.8° around noon to 0.1 during night time.
- Intermediate Openings: window tilting angle position varied on the average from 0.6° around noon to a total close position during night time.
- Small Openings: window tilting angle position varied on the average from 0.3° around noon to a total close position during night time.

Interestingly, the typical window tilting angle of single offices varied broadly, when the data set was broken down into seasons. For these reasons, the window tilting angle recorded during winter, summer, spring and autumn was used to draw schedules of the window opening positions (values from 0 = totally closed to 1 = totally open) over the 24 h of the day, for the four season of the year (Fig. 8).

The findings presented in Fig. 7 allow for the patterns of window tilting angle preferences on energy use and design of natural ventilation in office buildings, to be considered in future building energy modeling programs. The discerned schedules, sorted by season, day of the week and time of the day, represent more robust inputs for building energy modeling programs, like EnergyPlus [50] or IDA-ICE [51].

2.6. Association rules mining among behavioral patterns

Based on the information gained from the cluster analysis conducted in this study, each office was associated to a *motivational, duration, interactivity* and *position* behavioral pattern concerning window use (Table 11).

Association rules were mined with the objective to extract frequent and meaningful correlations among the four window behavioral patterns. The *frequent pattern growth algorithm* (FP growth) was the most commonly used algorithm to discover patterns into a given data set. The FP-growth algorithm was employed along with the open source data mining program Rapid Miner to mine the association rule mining (ARM) analysis.

In order to obtain significant results from the ARM analysis, support of 30%, confidence of 80% and a lift of 1, were set as the minimum thresholds. Such criteria indicated that for each association rule mined, at least 30% of all the data records in the given data set contained both premise and conclusion, with the probability that a specific premise lead to a specific conclusion was more than 80%. Moreover, all of the rules mined had positive correlations (lift > 1). Such mining generated 12 rules which provided useful information for the demonstration purposes in this study (Table 12).

From the information gained by the 12 rules mined, two typical working user profiles can be drawn:

- *User* α was a working user type (rules 1, 2, 3, 4, 5, 6, 10, 11) which tended to open the window for short periods of time (0.04–0.7 h/day), interacting on the average in between 0.7 and 0.04 times per day (passive operation) and usually preferred small openings (<0.3° of tilting angle). Moreover, users α was mainly influenced by thermal parameters both when opening and closing windows (rule 9).
- User β was a working user type (rule 8, 12) whom tended to open the window on the average from 1 to 2.2 h per day (medium openings), interacting on the average in between 1.0 and 1.7 times per day (neutral operation) and usually preferred intermediate openings (<0.6° of tilting angle). Moreover, user β was mainly influenced by time-dependent parameters both when opening and closing window (rule 7).

3. Discussion

In a view of the complexity of human behavior, distinguishing singular diversity in big office building becomes a challenging task. Parameter selection methods such as regression and correlation analysis are commonly utilized to identify the factors influencing occupant behavior in buildings and to cluster driver-response conditioning behavioral patterns. The strength of these statistical analysis techniques is their widespread familiarity among researcher and data analysts. Nonetheless, their outcomes are

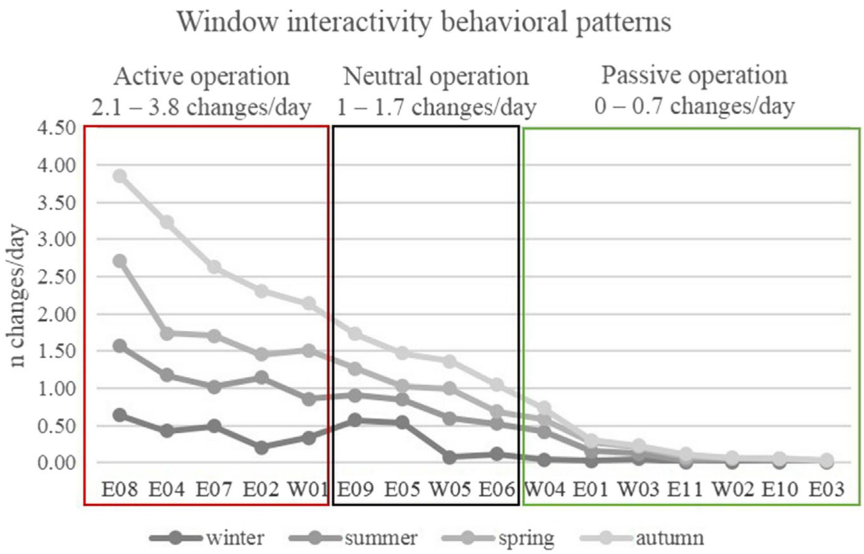

Fig. 6. Window interactivity behavioral patterns in 16 offices.

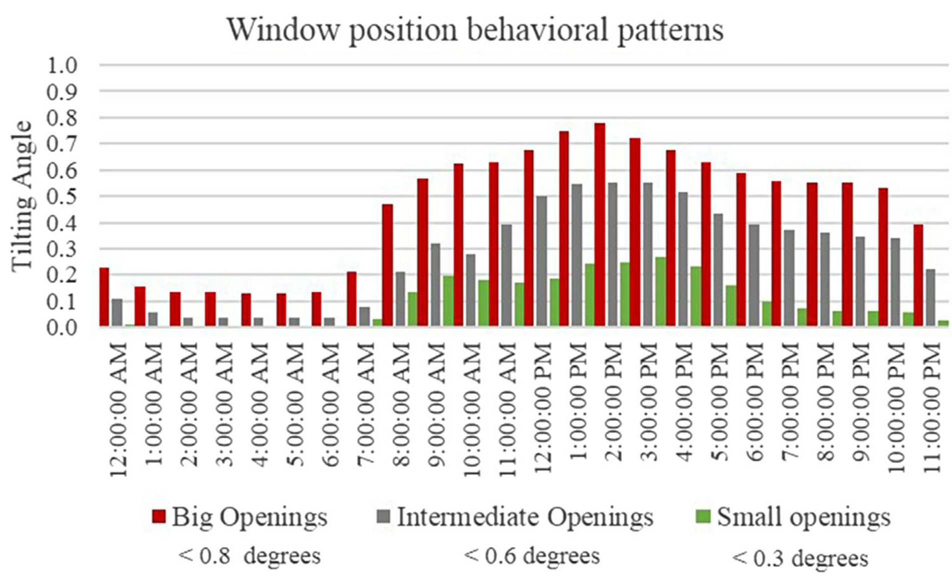

Fig. 7. Window position behavioral patterns in 16 monitored offices.

usually complex equations which may not be easily understandable and interpreted especially for non-expert users without advanced statistical knowledge (i.e. building operators and managers, building designers, energy modelers). Statistical analysis helps to identity repetitive behaviors, which may or may not be significant in terms of schedules of operation incorporated into energy models. Moreover, "standard" behavior does not exist in the real world, and the concept of pattern encompass much more than what is normally defined as expressions describing the most frequent behaviors in a building.

In a view of these facts, our data mining framework suggests an improvement of the notion of behavioral patterns not only as statistical relevant driver-response conditioning clusters, but also incorporating the motivational dimension with typical window opening habits. In this context, cluster analysis gain information from key determinants for individual behavior by revealing a set of rules which may allow more accurate assumption on group behaviors overcoming the lack of personalization of statistical methods. In a view of these facts, nevertheless the mined patterns of ventilation behavior are circumstantial to the given data set, the proposed framework was conceived generic enough to provide solutions to represent the diversity of typical office user profiles in real buildings. The further implementation of the discerned user profiles into building energy simulation tools provides an opportunity to establish an experience base for the assessment of real obtainable energy savings in buildings, equally in the design, retrofit and operation and maintenance contexts as well as for driving future energy policies (Fig. 9).

3.1. From driving factors to motivational patterns of behavior

Factors influencing window opening and closing, which could be named under the general term "drivers", are the stimuli leading to a reaction in the building occupants in ways to restore their comfort with respect to natural ventilation.

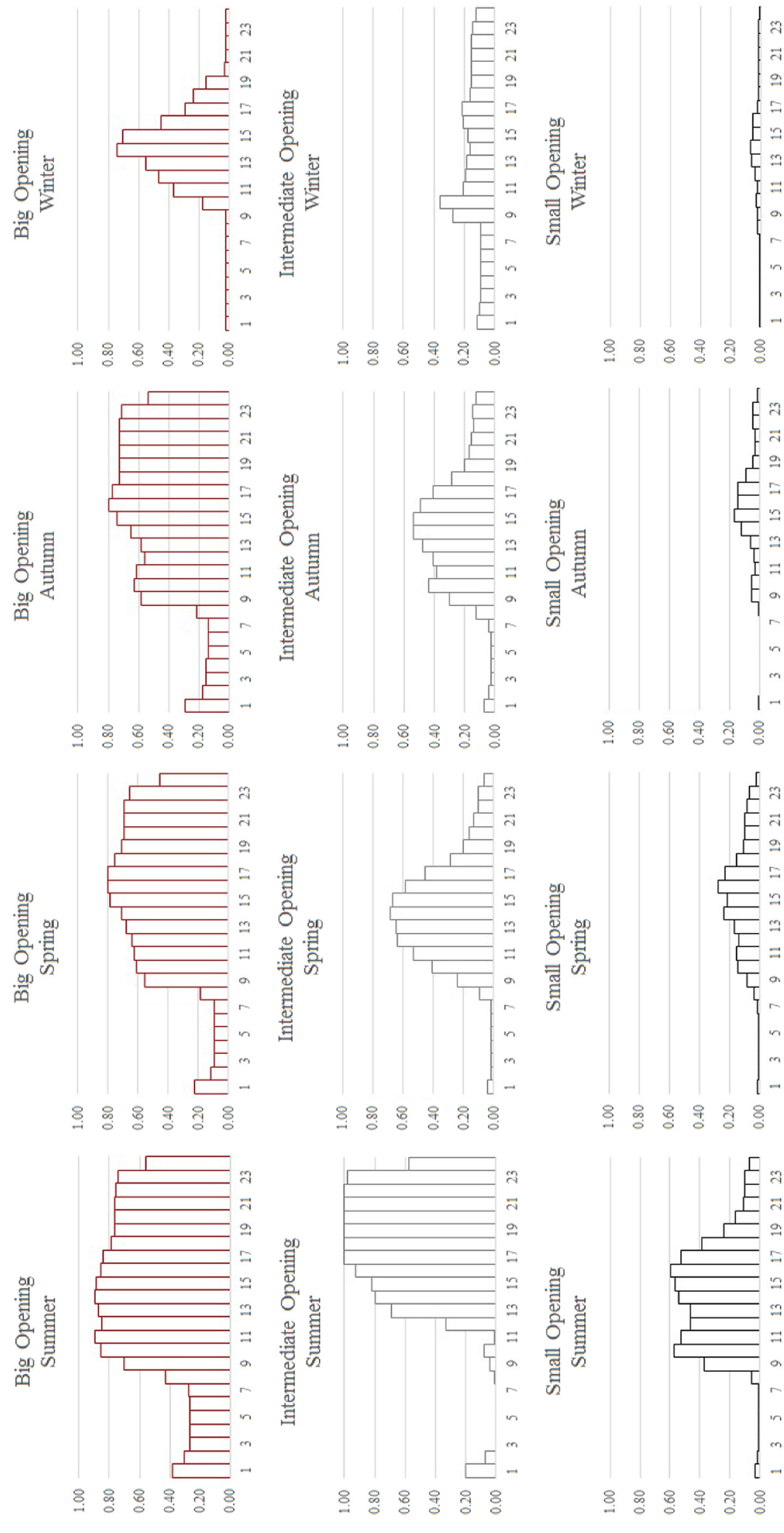

Fig. 8. Behavioral pattern schedules for window tilting angle.

Table 11
Clustered behavioral patterns in 16 offices.

Office	Motivational		Duration	Interactivity	Position
	Window opening	Window closing	Window state	Window change	Window tilting angle
E01	Thermal driven	Thermal driven	Short openings	Passive operation	Small openings
E02	Thermal/time driven	Thermal driven	Short openings	Active operation	Small openings
E03	Thermal driven	Thermal driven	Short openings	Passive operation	Small openings
E04	Thermal driven	Thermal driven	Long openings	Active operation	Big openings
E05	Thermal/time driven	Time driven	Medium openings	Neutral operation	Intermediate openings
E06	Time driven	Time driven	Short openings	Neutral operation	Small openings
E07	Time driven	Time driven	Medium openings	Active operation	Intermediate openings
E08	Time driven	Time driven	Medium openings	Active operation	Intermediate openings
E09	Thermal/time driven	Thermal driven	Medium openings	Neutral operation	Small openings
E10	Time driven	Time driven	Long openings[a]	Passive operation	Big openings[a]
E11	Thermal driven	Thermal driven	Short openings	Passive operation	Small openings
W01	Time driven	Time driven	Medium openings	Active operation	Intermediate openings
W02	Thermal driven	Thermal driven	Short openings	Passive operation	Small openings
W03	Time driven	Time driven	Short openings	Passive operation	Small openings
W04	Thermal/time driven	Time driven	Short openings	Passive operation	Intermediate openings
W05	Thermal/time driven	Time driven	Long openings	Neutral operation	Big openings

[a] Outlier.

Window operation is not only influenced by perceived thermal condition, but it is also seen as a response of sensed indoor air quality, external (outdoor temperature, solar radiation, wind speed, rain) and internal (indoor temperature) environmental conditions as well as contextual factors (window type, time of the day, season of the year) and personal and cultural preferences.

Different time scales of time dependent parameters such as 1) season of the year time 2) day of the week and 3) time of the day, were included in the statistical analysis as predictor of the window opening and closing probability. Moreover, window and occupancy were expressed in terms of 4) window state (open/closed) 5) occupancy state (present/vacant) and 6) window and 7) occupancy change of state. These predictors, even if closely related to the same parameters, were not surrogates of the others and were not duplicative of the same action. Instead, they were indicators of time dependence, occupant presence and movement respectively. Altogether they describe the intricate dynamics of different occupant behaviors in buildings. In our view, this overlap provides clarity in describing the complexity of occupant behavior and addresses the inadequacy of current practices based upon simplistic standardized schedules and input.

From the analysis it emerged that top drivers for window opening and closing were physical thermal (indoor air temperature, outdoor air temperature) and time-dependent contextual (time of arriving and leaving the office) parameters, apart from occupancy presence. These results strengthen the belief that not only physical factors, such as indoor and outdoor environmental parameters, influence human energy behavior, but also non-physical drivers, such as personal preference, habit, context and attitude, play an important role in understanding occupant behavior.

The results demonstrated that, in the specific office buildings, three motivational patterns of window opening (*thermal-driven*, *time-driven*, *thermal-time driven*) and two motivational patterns of window closing (*thermal-driven*, *time-driven*) stimulated an occupant to open a window.

3.2. From occupant behavior to user profiles

Clustering procedures were employed in order to analyze different aspects of the window opening and closing behavior. The goal was to estimate why, for how long, how often and how much similar patterns of occupant open and close windows in offices of the same building. In this aim, the research was clustering 1) *motivational*, 2) *opening duration*, 3) *interactivity* and 4) degree of opening *position* behavioral patterns which would further constitute a base for association rules segmenting the building occupants into attitudinal typical working user profiles. From the information gained by the 12 rules mined, two typical working user profiles were drawn. *User* α was a mainly *physical environmental driven* working user type which tends to open the window for short periods of time (0.04–0.7 h/day), interacting infrequently (on the average in between 0.7 and 0.04 times per day and usually preferred small openings (<0.3° of tilting angle). On the other side, *user* β was mainly *contextual driven* working user type which

Table 12
Association rules mining of behavioral patterns.

Rules	Premise	Conclusion	Support	Confidence	Lift
1	Window tilting angle_small openings, window closing_thermal driven	Window state_short openings	0.31	0.83	1.67
2	Window state_short openings, window change_passive operation	Window tilting angle_small openings	0.31	0.83	1.67
3	Window closing_thermal driven	Window tilting angle_small openings	0.38	0.86	1.71
4	Window change_passive operation	Window state_short openings	0.38	0.86	1.71
5	Window tilting angle_small openings	Window state_short openings	0.44	0.88	1.75
6	Window state_short openings	Window tilting angle_small openings	0.44	0.88	1.75
7	Window opening_time driven	Window closing_time driven	0.38	1	1.78
8	Window tilting angle_ intermediate openings	Window closing_time driven	0.31	1	1.78
9	Window opening_thermal driven	Window closing_thermal driven	0.31	1	2.29
10	Window state_short openings, window closing_thermal driven	Window tilting angle_small openings	0.31	1	2
11	Window tilting angle_small openings, window change_passive operation	Window state_short openings	0.31	1	2

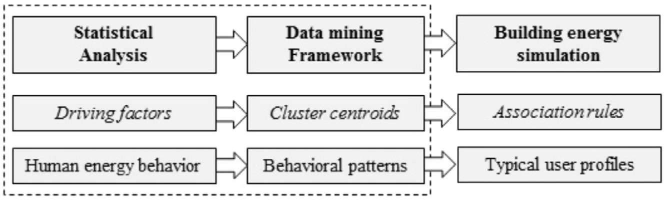

Fig. 9. Schema explaining actual and further steps of the proposed methodology.

tended to open the window for longer periods (on the average from 1.0 to 2.2 h per day), interacting more frequently (on the average in between 1 and 1.7 times per day) and usually preferred intermediate openings (<0.6° of tilting angle).

4. Conclusions

A framework combining statistical analysis with two data-mining techniques, clustering and association rules, was employed to identify occupant behavior patterns of window opening and closing in a natural ventilated office building in Germany, using detailed time-interval measured building data.

Goal of the research was to identify 1) *motivational*, 2) *opening duration*, 3) *interactivity* and 4) degree of opening *position* behavioral patterns. In this aim, four aspects of window operations were clustered:

1. three (*thermal-driven*, *thermal/time-driven*, *time-driven*) motivational patterns clustering the factors driving window opening and closing behavior according to the impact that the factors play on the two actions
2. three (*long*, *medium*, *short*) opening duration patterns clustering occupant behavior based on the number of hours the window state was recorded open every day
3. three (*active*, *neutral*, *passive*) interactivity patterns clustering occupant behavior based on the number of window position changes recorded every day
4. three (*small*, *intermediate*, *big*) opening position patterns clustering occupant behavior according to the most frequent window degree of opening every day.

Analysis of the results indicated indoor air temperature, outdoor air temperature, time of the day (office arriving time and early morning) and occupancy presence are the top drivers for window opening. On the other hand, indoor air temperature, time of the day (office leaving time and evening), occupancy presence and outdoor air temperature emerged as top drivers for window closing.

The four behavioral patterns were further mined using association rules to produce two typical window opening office user profiles, one mainly *physical environmental driven* and one mainly *contextual driven*. The results indicated that office users interact with windows principally driven by thermal discomfort (indoor air temperature) but also behave accordingly to daily routine (time of the day) and habits (arriving and leaving time). The implications of these findings suggest that occupant behavior was somewhat predictive and subject to the constraints or motivating factors of thermal comfort and time management.

From the association rule, it emerged that when interacting with windows to restore the indoor environmental quality, users mainly driven by *physical environmental parameters* had less impact on natural ventilation than users driven by *contextual factors and habits*, opening windows for shorter periods of time, interacting less frequently and usually preferring smaller openings.

In the bigger picture this implies that behavioral patterns are not only statistical relevant driver-response conditioning clusters, but also incorporate the motivational dimension with typical window opening habits. In a view of these facts, any improvement of the notion of behavioral patterns associating the driver-response conditioning motivational dimension with typical window opening habits data mining, overcoming the lack of personalization of statistical methods, is strongly required in order to bridge the gap between predicted and actual building energy performance.

Occupants in naturally ventilated buildings are demonstrated to accept and actually prefer a significant wider range of temperatures compared to users of mechanically ventilated buildings, positively influencing their satisfaction with working spaces and leading them to higher productivity. However, while providing manual ventilation opportunities seems to be beneficial, in doing so the behavior of the occupants gained a larger degree of influence on the indoor environment and energy performance, especially when a robust variation of motivations leading to window opening and closing, duration and number of opening and typical degree of opening was demonstrated. In this view, the persistent patterns of operation and non-homogeneous working user profiles drawn by this study could be broadly applied in further studies to:

1) provide more accurate assumption of actual natural ventilation scenarios in big office buildings that may allow building designers and operating manager to tailor more efficient and robust control strategies and system and envelope design;
2) quantify the energy and economic impacts of diverse ventilation office user profiles in a block of buildings, as well as the sensitivity of physical-environment and contextual time-dependent influencing factors on occupancy, space optimization, thermal comfort and productivity in offices;
3) deliver a set of behavioral rules at the office level to direct specific operation and maintenance and ventilation energy saving strategies with a high replication potential and low capital investment, as well as future energy saving policy in the commercial building sector.

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ANALYTICS

DEFICIENCY OF EFFECTIVE ANALYTIC TECHNIQUES PROVIDING USEFUL KNOWLEDGE ON OB IN BUILDINGS

HOW TO TRANSLATE BUILDING AND HUMAN INFORMATION INTO USEFUL KNOWLEDGE?

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A data-mining approach to discover patterns of the window opening and closing behavior in offices.
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Occupancy schedules learning process through a data mining framework

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ABSTRACT

Building occupancy is a paramount factor in building energy simulations. Specifically, lighting, plug loads, HVAC equipment utilization, fresh air requirements and internal heat gain or loss greatly depends on the level of occupancy within a building. Developing the appropriate methodologies to describe and reproduce the intricate network responsible for human-building interactions are needed. Extrapolation of patterns from big data streams is a powerful analysis technique which will allow for a better understanding of energy usage in buildings. A three-step data mining framework is applied to discover occupancy patterns in office spaces. First, a data set of 16 offices with 10 min interval occupancy data, over a two year period is mined through a decision tree model which predicts the occupancy presence. Then a rule induction algorithm is used to learn a pruned set of rules on the results from the decision tree model. Finally, a cluster analysis is employed in order to obtain consistent patterns of occupancy schedules. The identified occupancy rules and schedules are representative as four archetypal working profiles that can be used as input to current building energy modeling programs, such as EnergyPlus or IDA-ICE, to investigate impact of occupant presence on design, operation and energy use in office buildings.

1. Introduction

One of the paramount efforts engineers, architects and policy-makers are currently facing is the need to deliver highly efficient buildings. In the roadmap toward net-zero energy buildings, office buildings play an important role as they represent approximately 17% of the energy used in the U.S. commercial building sector [1].

Several efforts have been made to accelerate the uptake of energy efficiency technologies in office buildings. While the driving factors of building energy performance such as climate, building envelope and building equipment are well recognized, the description of factors such as operation and maintenance, occupant behavior, and indoor environmental conditions are still over-simplified. Often building occupancy schedules are based upon generalized assumptions that hinge on standards, energy codes or rely on the experience of energy modelers. The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 90.1-2004 [2] provides standardized occupancy factors for different building types which can be used to design occupancy when actual schedules are unknown (Fig. 1). A daily profile, handled differently for weekend and weekdays, is composed of hourly values, each of which corresponds to a fraction of the occupancy peak load.

Nevertheless the stochastic nature of occupant behavior, the number of people that occupy a space and the duration occupied, is a non-trivial aspect to characterize. Literature studies have focused on the impact of occupancy presence scenarios on energy use in office buildings, with Burak Gunay et al. [3] providing a comprehensive and up-to-date critical review of observation studies, modeling, and simulation of adaptive occupant behaviors in offices. In 2013 a study conducted by Duarte et al. [4] analyzed the occupancy sensors of a large commercial multi-tenant office building and showed up to 46% variation in occupancy patterns for the time of day, day of the week, holidays and months, when compared with the standardized occupancy schedules in ASHRAE Standard 90.1-2004 [2]. The discrepancy presented by Duarte et al. [4] may lead to the incorrect design of office building equipment and to system inefficiencies. Chang and Hong [5] demonstrated the stochastic nature of occupancy profiles was one of the driving factors behind the discrepancy between the measured and simulated energy consumption in buildings. Based on statistical analysis of measured lighting-switch data, Chang and Hong [5] proved the frequencies of occupants leaving their cubicles and the corresponding durations of absence had significant impact on the total energy use and

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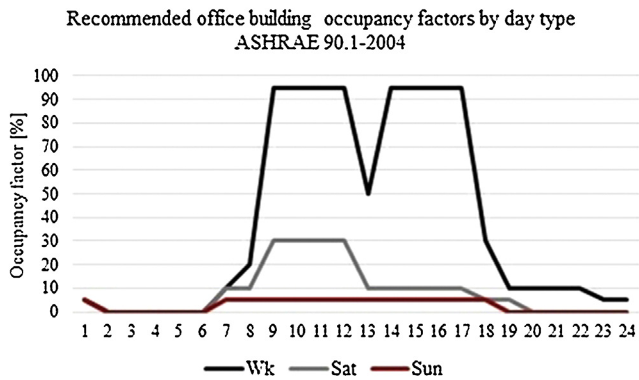

Fig. 1. Recommended office building occupancy factors [%] by day type, ASHRAE Standard 90.1-2004.

operational controls of the office building. Results from EnergyPlus simulations to evaluate the impact of occupant behavior on energy use of private offices with single occupancy [6], demonstrated that occupants with wasteful work-style consumed up to 90% more energy than standard users, while austerity work-style occupants used half of the energy of the standard occupants. Moreover, real-time estimation of occupancy in commercial buildings is largely treated with the aim to achieve better dynamic modeling results. However, it is a challenging task to develop reliable mathematical models of occupant presence due to the *stochastic* nature of human behavior [7].

Some stochastic models of the occupancy level of single offices have been proposed in the last decade within the scientific community [8–10]. Wang et al. [8] examined the statistical properties of occupancy in single person offices of a large office building in San Francisco and found that, while vacancy intervals could be treated as a constant over the day, occupancy intervals were more complex due to their varied distribution in time. Tabak and de Vries [9] proposed a model to predict the occurrence and the frequency of intermediate break activities during an office working day (i.e. walking to a printer/mailbox or using the bathroom). For each intermediate activity, a probabilistic formula was presented for use in office occupancy schedule designs. More recently, Sun et al. [10] developed a stochastic model, using a binomial distribution to represent the total number of occupants working overtime and an exponential distribution to represent the duration of overtime periods. Moreover, Stoppel and Leite [11] presented a probabilistic occupancy model simulating annual building occupancy rates based on frequency, duration and seasonality of occupants' long vacancy activities that can be further implemented into a building simulation model.

Additionally, there has been a gowning interest in agent-based models (ABM) to simulate patterns of human individual action and presence at the building level. Most notably, the Markov Chain method, provides a simulation approach to capture the movement process per occupant in the time and space dimensions of building models. The earliest ABM of occupant presence using a Markov Chain was proposed in 2005 by Yamaguchi et al. [12] in the development of a district energy system simulation model. The working state of each occupant of a group of commercial was simulated based on appliances energy consumption data, where the times of arrival, lunch break and departure were selected on a 5 min interval with a random distribution by using the inverse function method (IFM).

One of the first agent-based models of occupancy in single office was provided in 2008 by Page et al. [13]. The model predictions used a Markov Chain to create random occupancy profiles (i.e. time of arrival and departure, periods of intermediate absence and presence, as well as periods of long absence from the space) based on and validated by sensor data, and were later used as an input to occupant behavior models within building simulation tools [13]. Wang et al. [14] handled occupancy as the straightforward result of occupant movement processes which occurred among the spaces inside and outside a building. By using the Markov Chain method, the model generated the location for each occupant and the zone-level occupancy for a whole office building type. Additionally, Virote and Neves-Silva [15] used the Markov Chain method to relate behavior in an office space catalogued by data logger measurements to occupant presence in the office building.

More recently in 2014, Dong and Lam [16] developed a real-time predictive control model for building heating and cooling systems based upon the occupancy behavior pattern detection in coordination with local weather forecasting, using advanced machine learning methods including Adaptive Gaussian Process, Hidden Markov Model, Episode Discovery and Semi-Markov Model.

Currently, more granular real-time measurements of the occupant presence, movement and interaction with system controls (thermostats, lighting) and building envelope action (windows, shades) are streamed. Sensor networks enable multidisciplinary and integrated layers of big data source collection, providing reliable information on occupancy recognition and scheduling, in addition to building performance and operation.

State-of-the-art data mining methods provide a powerful analysis technique to extrapolate useful and understandable occupancy patterns from big data streams.

For clarity, data mining is defined in 2001 by Hand et al. [17] as: "The analysis of large observation datasets to find unsuspected relationships and to summarize the data in novel ways so that owners can fully understand and make use of the data." Cabena et al. [18] provided another definition as: "An interdisciplinary field bringing together techniques from machine learning, pattern recognition, statistics, databases and visualization to address the issue of information extraction from large databases." In many applications, it is difficult to extrapolate useful information from monitored building data due to large data scattering. Instead patterns of data discovered through data mining techniques may present applicable solutions at high levels of abstraction. Data mining of frequent patterns has been a focused theme in data mining research for over a decade with a comprehensive review provided by Han et al. [19]. Although, data mining techniques are largely applied to research fields such as marketing, medicine, biology, engineering, medicine, and social sciences, the application of a data mining framework to building energy consumption and operational data, is still in elementary phases. One highly effective technique of data mining for obtaining information on human-building interaction is the use of patterns correlating repetitive behaviors and actions to typical user profiles [20–22]. In this context, between 2011 and 2012 Yu et al. [23–26] tested several systematic data mining methodologies for identifying and improving occupant behavior in buildings. The results showed that the analysis methodology was powerful in providing insights into energy patterns related to the occupant behavior, facilitating evaluation of building saving potential by improving users' energy profiles as well as driving building energy policy formulation [23–26].

2. Methodology

Traditional methods of turning data into useful knowledge require data cleaning, analysis and interpretation. However, such manual data analysis often becomes impractical, slow and expensive as data volume grows exponentially. In view of these facts, researchers in the field of machine learning, pattern recognition, databases, statistics, artificial intelligence, knowledge acquisition and data visualization, have focused their attention on the

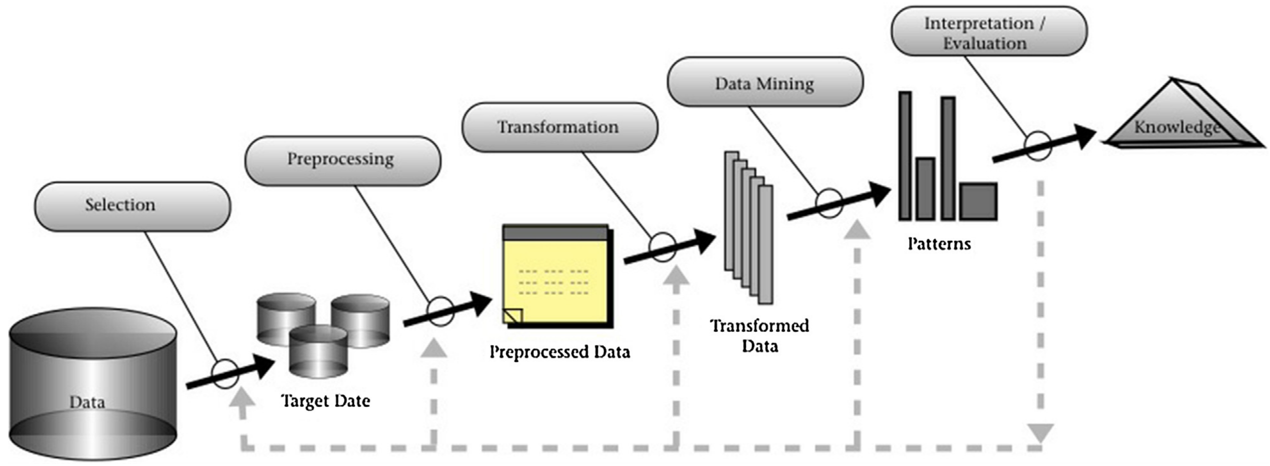

Fig. 2. Graphical representation of the Knowledge Discovery in Databases (KDD) process.

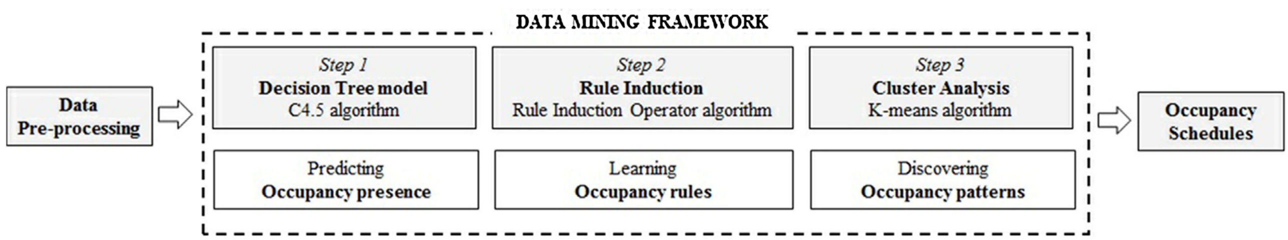

Fig. 3. Proposed occupancy schedule learning framework.

Knowledge Discovery in Databases (KDD), advancing beyond traditional methods [27]. KDD is the broad process of knowledge extraction in big data streams and involves the application of the following six steps (Fig. 2):

1. *Data selection: Creating a target data set: selecting a* data set, or focusing on a subset of variables, or data samples, on which discovery is to be performed.
2. *Data cleaning and preprocessing:* Removal of noise or outliers, strategies for handling missing data fields.
3. *Data transformation:* Finding useful features to represent the data depending on the goal of the task.
4. *Data mining:* Matching a particular data mining method for searching patterns in the data.
5. *Data interpretation and evaluation:* Deciding which parameters may be appropriate and interpreting mined patterns.
6. *Knowledge extraction:* Consolidating discovered knowledge that can be used for further analysis.

This study uses the KDD data mining process to extrapolate information on occupancy schedule patterns from measured building big data streams (Fig. 3). A three-step data mining schedule method is applied to a data set to provide insight into patterns of occupancy in office buildings. In step 1, a data set of 16 offices with 10 min interval occupancy data over a 2 year period is mined though a decision tree model that predicts the occupancy presence. In step 2, a rule induction algorithm is used to mine a pruned set of rules on the results from the decision tree model. In step 3, cluster analysis is employed to obtain consistent patterns of occupancy schedules representative of typical single office working user profiles.

The data mining algorithms are employed along with the open source data mining program Rapid Miner 6 [28] to perform the analysis. Rapid Miner is a free open source visual environment for predictive analytics and data mining. Rapid Miner is based on an XML internal process structure, it has an intuitive graphical user interface and no programming is required. For these reasons, it one of the best open source data mining tools both in terms of technology and applicability.

Table 1
Building characteristics.

Type of building	Multi-story office building
Dimension	17,402 m^2 (8585 m^2 heated)
No. of employee	~350 Employees
Location	Frankfurt, Germany
Thermal characteristics	(*U*-values walls 0.24 to 0.5 W/(m^2 K), windows 1.5 W/(m^2 K))
Annual primary energy consumption	Less than 100 kWh/m^2
Type of observed spaces	Office rooms
Year of construction	2002
No. of floors	2-Level underground car park + 4 office floors + 1 floor apartments on top

2.1. The data set

An office building located in Frankfurt am Main [29] is used as the case study (Table 1).

Frankfurt is located in central Germany with a temperate-oceanic climate with relatively cold winters and warm summers. The building combines a high energy standard with high occupant comfort. The building is naturally ventilated and cooled in summer and equipped with a night-time mechanical ventilation. Moreover, the monitored office building shows very strict design criteria in terms of energy efficiency and energy optimization for heating, cooling, ventilation and lighting. With an average *U*-value of 0.54 W/(m^2K) (façade including windows), the building exceeds the requirements of the German 2002 Energy Saving Standards by approximately 30%.

Fig. 4. Two-part sun protection enables glare-free use of daylight.

Fig. 5. Offices with operable windows and sun protection, allowing natural ventilation and lighting.

In this study, we use the following dataset (Figs. 4 and 5) with:

(a) 16 private offices with single or dual occupancy (Table 2). E01 to E11 are eleven offices facing the east while W01 to W05 are five offices facing the west.
(b) 10-min occupancy interval data over two complete years.

Table 2
Dataset characteristics.

Number of offices	16
Period of measurement	2006 and 2007
Type of observed spaces with sensors	Standard offices
Dimension of observed spaces	20 m^2
Occupancy level of observed spaces	1 Person
Orientation	East and West

2.2. Decision tree model

A decision tree is a branched flowchart graphical classification model. This representation of the data has the advantage of being easy to interpret. Decision tree models segregate a set of data into various predefined classes and provide description, categorization and generalization of a given dataset. The goal of a decision tree is to create a classification model (Fig. 6) that predicts the value of a target attribute (*label attribute*) based on several input attributes (*predictor attribute*). Each interior node (*leaf node*) of tree corresponds to one of the predictor attributes. The number of edges (*branches*) of a nominal interior node is equal to the number of possible values of the corresponding predictor attribute. Each leaf node represents a value of the label attribute represented by the path from the root tree (*root node*) to the final leaf (*possible answers*).

Decision tree model generation is a two-step process, namely learning and classification, as shown in Fig. 7.

In the *learning process*, records in the dataset are automatically and randomly divided into two subsets: a *training* dataset and a *test* dataset. Then, a decision tree algorithm *generates* a decision tree. In this study, we employ the C4.5 algorithm, along with the open-source data mining software RapidMiner.

The C4.5 algorithm was first introduced by Quinlan [30] for inducing decision trees classification models from data. In building a decision tree, the C4.5 algorithm deals with training sets that have records with unknown attribute values by evaluating the "Gain" (also called "Gain-ratio"), for an attribute by considering only the records where that attribute is defined. Gain is defined in the following equation:

$$\text{Gain}\left(\vec{y}, j\right) = \text{Entropy}\left(\vec{y} - \text{Entropy}\left(j|\vec{y}\right)\right) \quad (1)$$

where Entropy $(y) = -\sum_{j=1}^{n}\left(y_j/y\right)\log\left(y_j/y\right)$ and Entropy $\left(j/y\right) = \left(y_j/y\right)\log\left(y_j/y\right)$

This process uses entropy as a measure of the disorder of the data. The final aim is to maximize the Gain by dividing by the overall Entropy due to split argument y by value j. In the *classification process*, the accuracy of the obtained decision tree is *validated* by cross-validation in order to estimate the statistical performance of a learning process. In the cross-validation process, the data set is partitioned into k subsets of equal size. Of the k subsets, a single subset is retained as the testing data set and the remaining $k-1$ subsets are used as training data set. The cross-validation process is then repeated k times, with each of the k subsets used exactly once as the testing data. The k results from the k iterations then can be averaged (or otherwise combined) to produce a single estimation. The value k is adjusted in this study using a $k = 10$ number of validations. If the accuracy is considered acceptable, the decision tree can be applied to new datasets for classification and prediction.

2.3. Rule induction

The rule induction is a classification data mining technique which generates sets of rules in big data sets. Rules have the advantage of being easy to understand, representable in first order logic and prior knowledge can be easily added. A variety of rule-induction algorithms are applied in the field of machine learning and applied data mining literature [30,31]. Such algorithms are likelihood-based model evaluation methods, which are typically used for predictive modeling, both for classification and regression, although they can also be applied to descriptive modeling in big data [32]. Pruning in decision trees is a technique in which leaf nodes that do not add useful information to the classification of the decision tree are removed. This is done by converting an over-specific or over-fitted tree to a more general form in order to enhance its predictive power on unseen datasets. In the prune

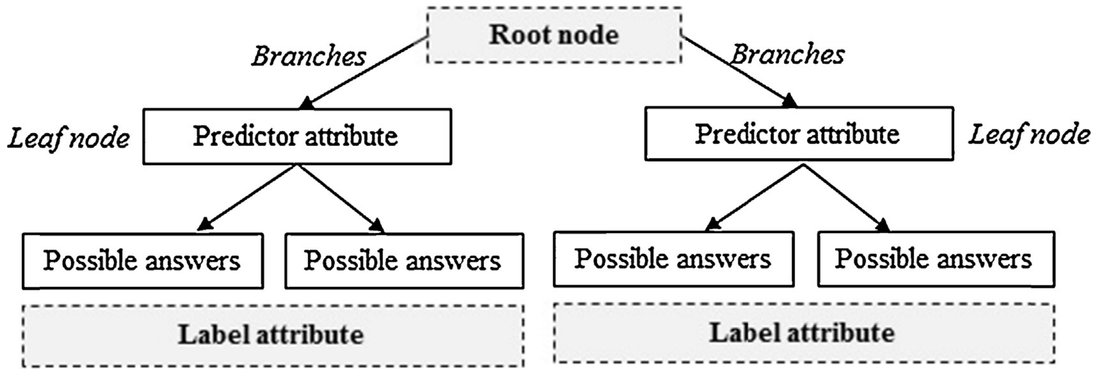

Fig. 6. Graphical representation of the flowchart tree-like graph decision tree model.

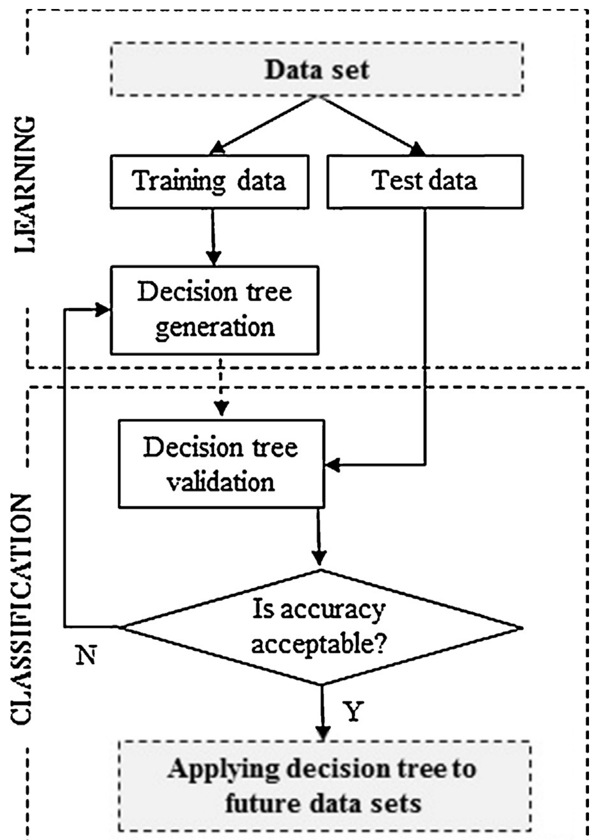

Fig. 7. The decision tree model generation process.

phase, for each rule any final sequences of the antecedents is pruned with the pruning metric $p/(p+n)$.

In this study, *information gain* has been used as criterion parameter for selecting attributes and numerical splits of the rule induction. Similarly for the decision tree model, the entropy (Eq. (1)) of all the attributes is calculated, and the attribute with minimum entropy is selected for split. Accordingly, the Rule Induction operator algorithm is applied to the given data set to iteratively grow and prune rules until there are no positive examples left or the error rate is greater than 50%.

2.4. Cluster analysis

Cluster analysis is the process of merging data into different clusters, so that (i) instances in the same cluster have high similarity and, (ii) instances in different clusters have low similarity (Fig. 7). The similarity between clusters is normally computed based on the distance between the clusters. The most popular distance measure is described by the Euclidian distance shown in the following equation:

$$d(a,b) = d(b,a) = \sqrt{(b_1-a_1)^2 + (b_2-a_2)^2 + \cdots + (b_n-a_n)^2} \quad (2)$$

where $a=(a_1, a_2, \ldots, a_n)$ and $b=(b_1, b_2, \ldots, b_n)$ are two points in an Euclidean n-space.

The k-means algorithm is a method of vector quantization for cluster analysis in data mining. Given the simple nature of the algorithm, it is one of the widely used classification technique. Assumed a data set D, containing a number n of records (instances), the number of clusters k must be specified. Each cluster is associated with a centroid (center point) representing the mean of the points in the cluster and each point is assigned to the cluster with the closest centroid.

The performance of the cluster models is evaluated by means a Cluster Distance Performance operator. In this study, the Davies–Bouldin index (DBI) is used for performance evaluation. This index is defined in Eq. (3) as "the ratio of the sum of average distance inside clusters to distance between clusters" [33].

$$E = \frac{1}{n}\sum_{i=1}^{n} \max_{i \neq j} \left[\frac{R_i + R_j}{M_{i,j}}\right] \quad (3)$$

where n is the number of clusters, R_i; R_j are the average distance inside cluster i and cluster j by averaging the distance between each cluster object and the cluster center; and M_{ij} is the distance between the cluster centers.

Consequently, a smaller DBI indicates a better performance of the clustering algorithm. The $k=n$ algorithm that produces clusters with low intra-cluster distances (high intra-cluster similarity) and high inter-cluster distances (low inter-cluster similarity) will have a low Davies–Bouldin index, and will be considered the $k=n_{opt}$ cluster algorithm for the specific data set (Fig. 8).

3. Results

In this study, a data mining learning framework was applied in an effort to extrapolate valid and understandable occupancy schedules patterns from the given measured building data set. The main outcomes are summarized as follows:

3.1. Data transformation

Transformation methods are applied to the given data set with the aim of finding useful predictor attributes to classify the data depending on the office occupancy rates. Raw data at each 10 min time step are transformed into more significant pre-processed data

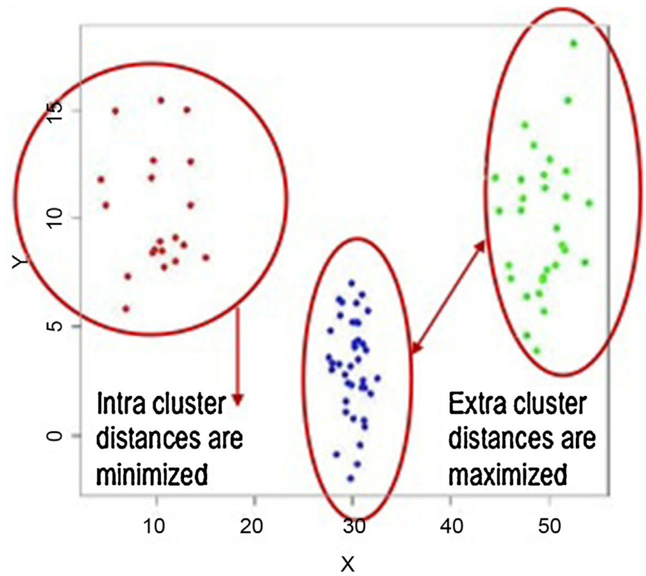

Fig. 8. Graphical representation of data clusters.

representing invariant *predictor and label attributes* of the data set, as follows:

1. *Season* (Summer, Spring, Autumn, Spring)
2. *Day of the week* (Monday to Sunday)
3. *Time of the day* (Early Morning 6–9am, Morning 9am–12pm, Noon 12–3pm, Afternoon 3–6pm, Evening 6–9pm, Night 9pm–6am)
4. *Window change* (if occupancy state $t_{n-1} = t_n$ then = 0, otherwise = 1)
5. *Office occupancy state* (0 = vacant, 1 = occupied)

Table 3
Multiclass classification performance of the decision tree model.

Accuracy 90.53%	True vacant	True occupied	Class precision
pred. vacant	74,995	2045	97.35%
pred. occupied	7905	20,175	71.85%
class recall	90.46%	90.80%	

The pre-processed data set is then used for the three-step schedule learning via data mining.

3.2. Step 1: Decision tree induction

The goal of this step is to create a decision tree model that predicts the value of a label attribute (occupancy) based on several input attributes (predictor attribute) of the data set.

In this study, we employ the C4.5 algorithm, along with the open-source data mining software RapidMiner to generate a decision tree. Gain ratio is the criterion on which attributes (occupied/vacant) are selected for splitting. Gain ratio calculates the entropy of all the attributes and selects for the split the attribute with minimum entropy. According to the gain ratio criterion, the range and uniformity of the attribute splits is assured with a minimum confidence of 50%. Fig. 9 shows the decision tree for the classification of the 16 offices occupancy state. The classification model predicts the value of the label attribute (*Office Occupancy State vacant/occupied*) based on the predictor attributes (*Time of the day, day of the week, season of the year, Window Change*). The tree-like graph presented above must be read from top to bottom. The predicted answers of the model represent the probability of the office being vacant/occupied based upon the path from the root-to-final leaf of the tree.

The decision tree is validated by cross-validation along with the open-source data mining software RapidMiner to estimate statistical performance of the learning process. As shown in Table 3, 90.53% of all the training records are correctly classified as vacant or occupied. This indicates a good accuracy of the decision tree model

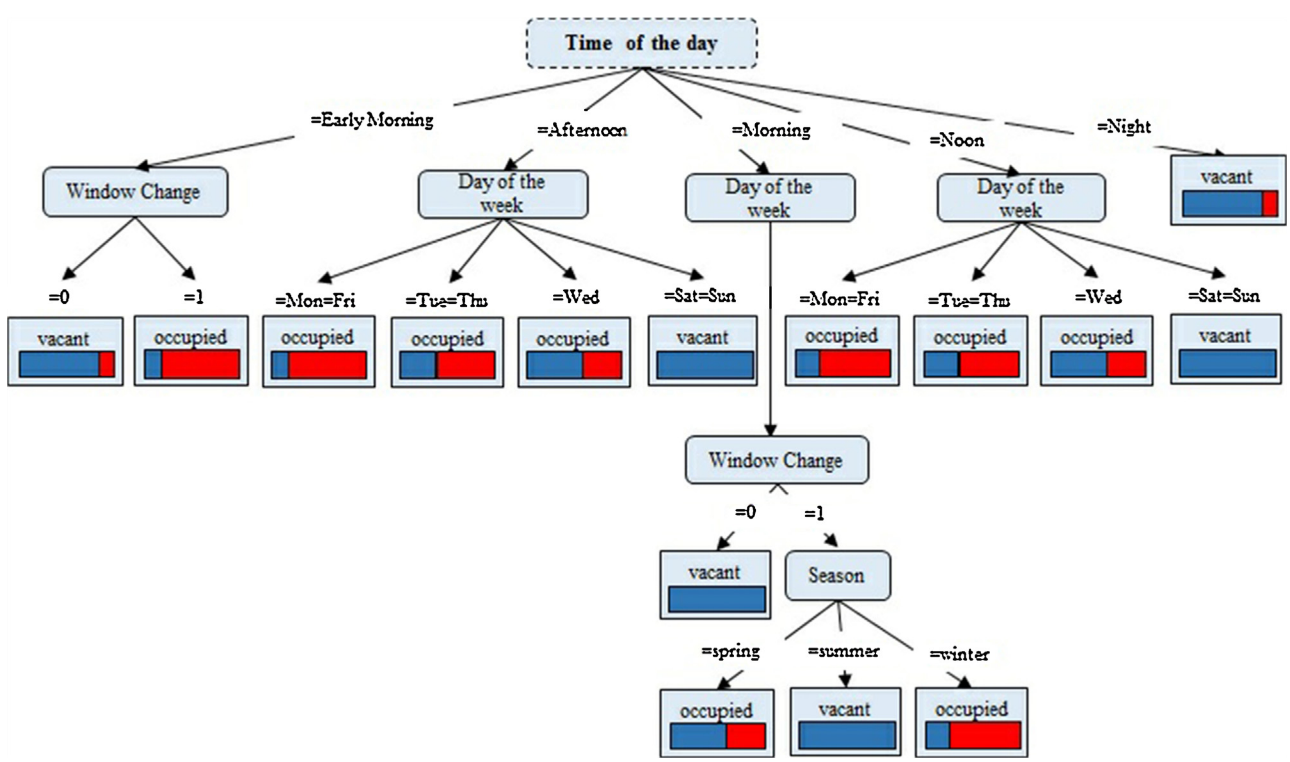

Fig. 9. Decision tree for the classification of the 16 offices occupancy state.

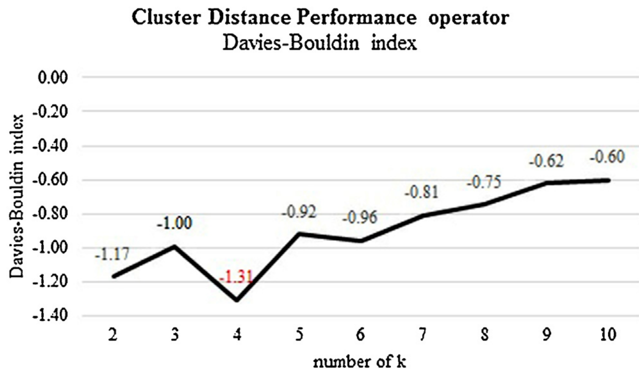

Fig. 10. Cluster Distance Performance Analysis with the Davies–Bouldin index.

which can be further applied to new datasets for classification and prediction.

3.3. Step 2: Rule induction

Based on the decision tree, decision rules are induced by traversing the tree model from the root node to a leaf node. Since each leaf node produces a decision rule, the complete set of decision rules, which is equivalent to the decision tree, is derived. Accordingly, generated decision tree is converted to a set of decision rules, as show in Table 4. For example, a decision rule can be generated from root node to node 4 in above decision tree as follows: if Time of the day = Morning and Window Change = 1 then the office is OCCUPIED with a probability equal to 26% (1058 records over 4118 assigned).

3.4. Step 3: Cluster analysis

The goal of this step is to disaggregate the occupant presence during working days into valid working user profile schedules. The k-means algorithm is employed, along with the open-source data mining software RapidMiner, to generate clusters of occupancy patterns in 16 single occupancy offices of the same building. The value $2 > k < 10$ is adjusted in this study in order to find the k_{opt} by using Cluster Distance Performance operator. In this study, the Davies–Bouldin index is used for performance evaluation. As shown in Fig. 10, the $k = 4$ algorithm has the lowest Davies–Bouldin index (-1.31). For this reason, a $k = 4$ is chosen as the k_{opt} cluster algorithm for the specific data set.

The cluster centroids of the $k_{opt} = 4$ algorithm are plotted in order to provide a visualization of the emerged occupancy patterns. Significantly, the algorithm highlights four different office occupancy patterns, as A, B, C, and D (Fig. 11). A variation up to 60% occurred in the hourly occupancy rate, among the four patterns of occupancy, with noticeable variation happening during times of arriving (8am) and leaving (5pm) the office.

Patterns of occupancy presence clustered in the data set are leading to four typical working occupancy rates, from Monday to Friday (Fig. 12).

- Pattern A presents the highest occupancy rate Monday through Friday.
- Pattern B presents a medium occupancy rate Monday through Friday.
- Pattern C characterizes the most variable occupancy rate. This pattern presents a medium occupancy rate on Monday, Tuesday and Thursday and medium-high occupancy on Friday (before-after the lunch vacancy). On Wednesday, user's vacancy/presence state in the office space varies with high frequency.

Table 4
Decision rules derived by rule induction from the obtained decision tree.

1. If Time of the day = Night then vacant (257,979/4821)
2. If Day of the week = Sunday then vacant (37,795/5)
3. If Day of the week = Saturday then vacant (37,703/97)
4. If Time of the day = Morning and Window Change = 1 then occupied (1058/4118)
5. If Time of the day = Morning and Season = Autumn then occupied (3142/7592)
6. If Time of the day = Noon and Window Change = 1 then occupied (1792/5123)
7. If Time of the day = Early morning and Window Change = 0 then vacant (36,317/6618)
8. If Window Change = 1 and Time of the day = Early morning then occupied (707/3158)
9. If Time of the day = Morning and Season = Summer then occupied (2936/6442)
10. If Time of the day = Noon and Season = Autumn then occupied (3216/6956)
11. If Season = Winter and Time of the day = Morning then occupied (3458/7456)
12. If Day of the week = Wednesday and Time of the day = Noon then occupied (1805/4092)
13. If Window Change = 1 and Season = Spring then occupied (295/1008)
14. If Season = Winter and Time of the day = Noon then occupied (2866/5707)
15. If Day of the week = Wednesday and Window Change = 1 then occupied (239/672)
16. If Day of the week = Wednesday and Time of the day = Morning then occupied (661/1387)
17. If Day of the week = Thursday and Season = Autumn then occupied (729/1611)
18. If Day of the week = Wednesday and Season = Winter then occupied (797/1333)
19. If Window Change = 1 and Day of the week = Monday then occupied (217/588)
20. If Time of the day = Morning and Day of the week = Tuesday then occupied (788/1389)
21. If Day of the week = Thursday and Season = Winter then occupied (762/1578)
22. If Season = Summer and Time of the day = Noon then occupied (2757/4421)
23. If Day of the week = Wednesday and Season = Spring then occupied (764/1249)
24. If Season = Autumn and Day of the week = Monday then occupied (794/1349)
25. If Time of the day = Morning and Day of the week = Thursday then occupied (838/1254)
26. If Window Change = 1 and Season = Summer then occupied (462/954)
27. If Day of the week = Wednesday and Season = Summer then occupied (736/1137)
28. If Day of the week = Tuesday and Season = Autumn then occupied (948/1392)
29. If Time of the day = Morning and Day of the week = Friday then occupied (872/1257)
30. If Day of the week = Monday and Season = Winter then occupied (846/1302)
31. If Time of the day = Noon and Day of the week = Tuesday then occupied (903/1150)
32. If Day of the week = Friday and Time of the day = Afternoon then vacant (5028/3805)
33. If Season = Summer and Day of the week = Monday then occupied (757/1077)
34. If Season = Autumn and Day of the week = Wednesday then occupied (889/1217)
35. If Season = Winter and Window Change = 1 then occupied (24/41)
36. If Season = Winter and Day of the week = Tuesday then occupied (929/1166)
37. If Day of the week = Thursday and Time of the day = Noon then occupied (879/1027)
38. If Season = Summer and Day of the week = Tuesday then occupied (880/1020)
39. If Time of the day = Afternoon and Day of the week = Monday then vacant (1243/907)
40. If Day of the week = Friday and Season = Spring then occupied (961/1125)
41. If Time of the day = Morning and Season = Spring then occupied (985/1167)
42. If Day of the week = Tuesday and Season = Spring then vacant (1198/1008)
43. If Day of the week = Thursday and Season = Summer then occupied (870/949)
44. If Day of the week = Thursday and Season = Spring then occupied (993/1037)
45. If Season = Spring then vacant (1025/995)

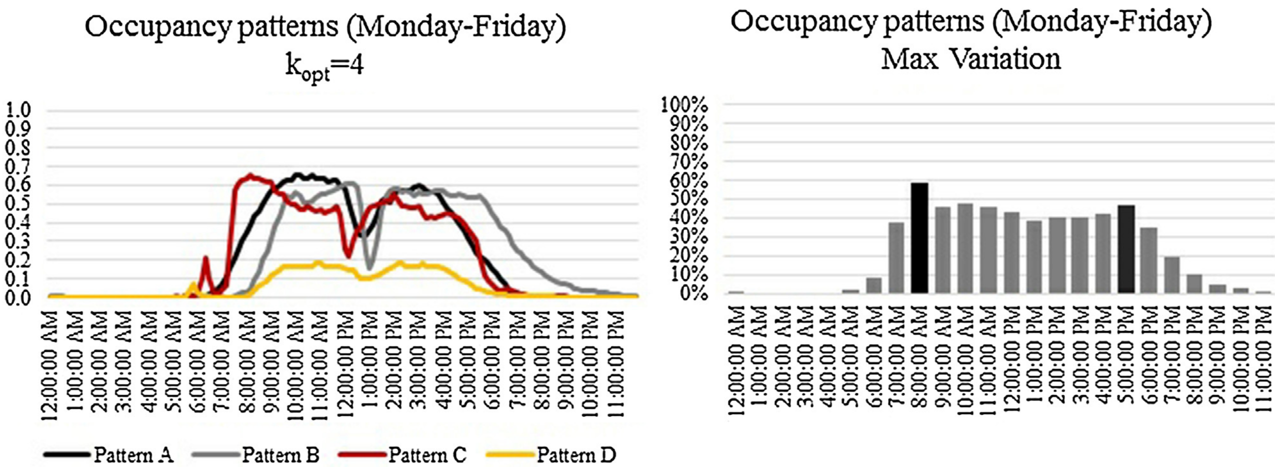

Fig. 11. Occupancy patterns (Monday–Friday) emerged by applying the $k_{opt} = 4$ cluster algorithm.

- Pattern D characterizes the lowest occupancy rate Monday through Friday.

Each of the 16 offices is assigned to an occupancy behavioral cluster for every day of the working week. Results in Fig. 13 demonstrate single occupancy offices are characterized by dissimilar patterns of occupancy during working weekdays. This means that the working profile of a singular office may vary broadly on different working days. The distribution of the office working profiles over the working days (Monday-Friday) is presented in

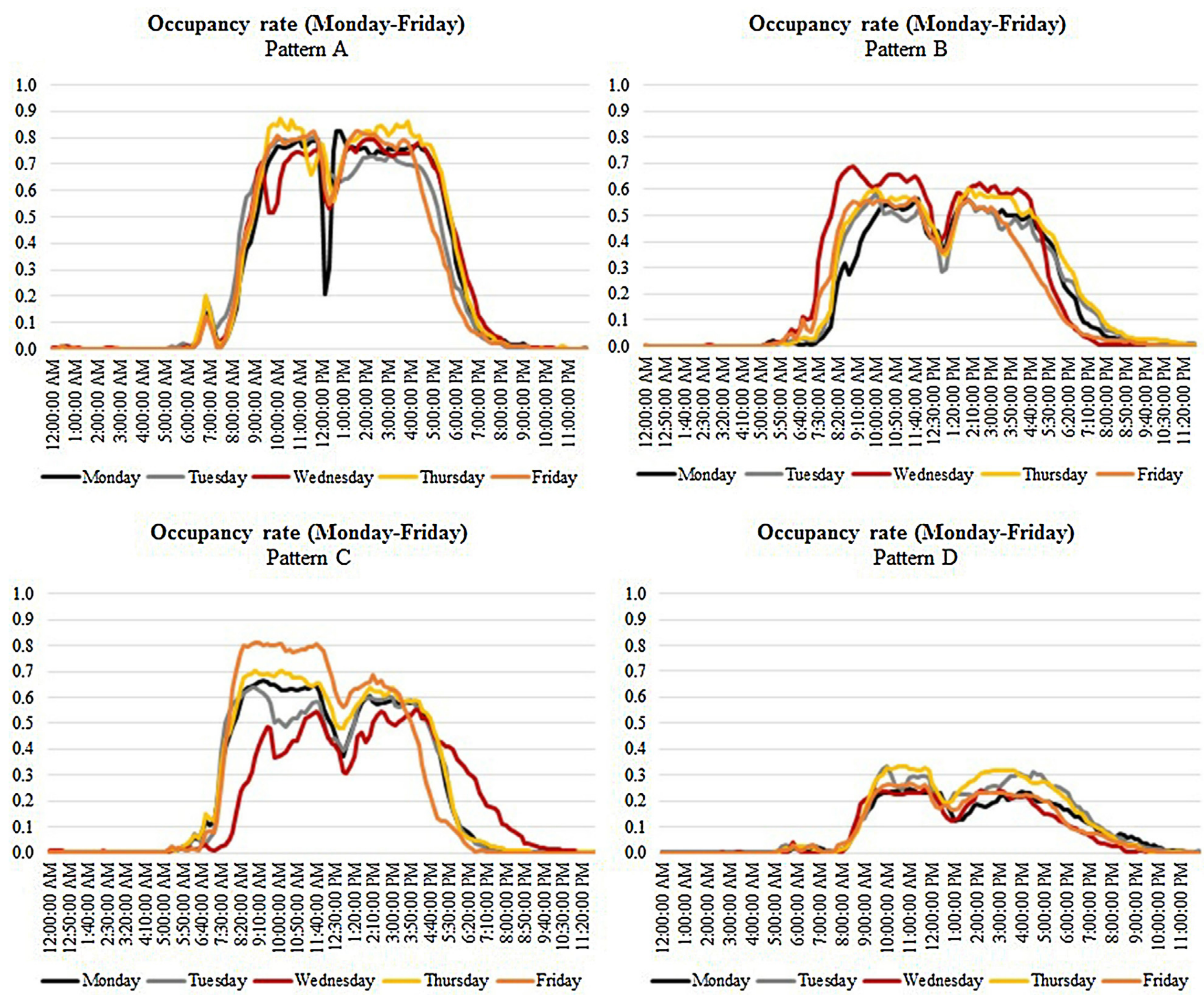

Fig. 12. Occupancy rate patterns (Monday–Friday) emerged by applying the $k_{opt} = 4$ cluster algorithm.

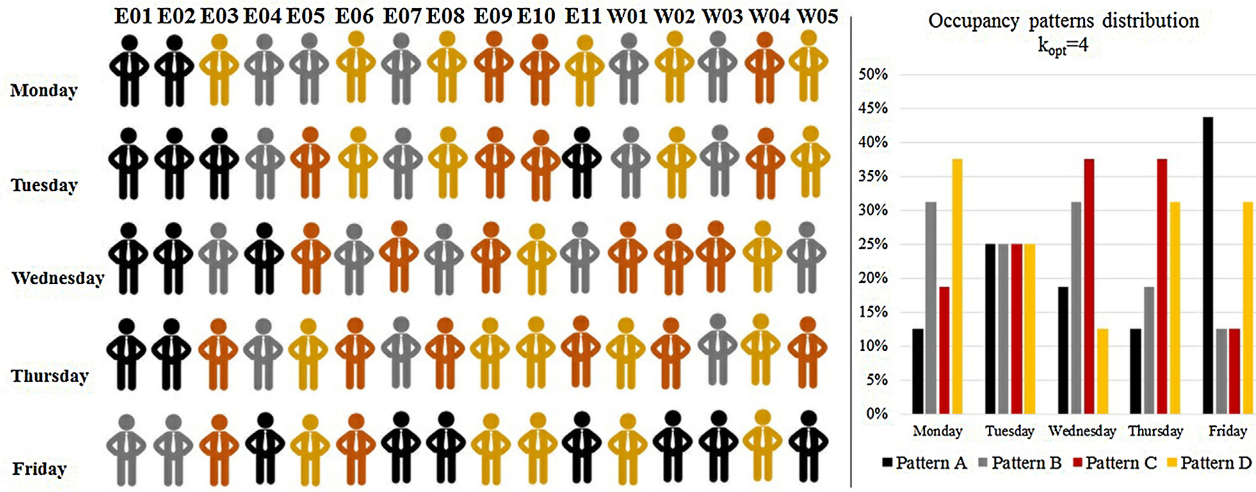

Fig. 13. Distribution of the occupancy patterns in 16 offices (Monday–Friday).

Fig. 13, showing a predominance of occupancy Pattern A on Friday (44% offices), Pattern D on Monday (38% offices) and Pattern C on Wednesday and Thursday (38% offices). Occupancy patterns are distributed uniformly over the 16 offices on Tuesday.

In order to understand the implication of the occurrence and the frequency of a single occupancy office being occupied/vacant over the 24 h period, analysis of the correlation among occupancy patterns during the same days of the week, is conducted (Fig. 14). Fig. 15 illustrates a scatter plot matrix of the four occupancy patterns, sorted by day of the week, from Monday to Friday. *R*-values of the linear correlation of occupancy patterns coupled two by two (Pattern A–Pattern B, Pattern A–Pattern C, Pattern A–Pattern D, Pattern B–Pattern C, Pattern B–Pattern D, Pattern C–Pattern D) show a good correlation of occupancy patterns during the same days of the week (*R*-value > 0.8). This means office users tend to occupy the office space with a similar pattern over the working hours but that occupancy may vary based on the frequency an occurring event (i.e. arriving or leaving the office space). On the contrary, a small correlation is found in between occupancy Pattern C and Pattern D (*R*-value < 0.7), indicating that the event the office user arriving or leaving the office space occurs with dissimilar frequency and is also strongly shifted in the 24 h time schedule.

3.4.1. *From occupancy patterns to working profiles*

The Knowledge Discovery in Database (KDD) process, patterns extraction from the data base and cannot be considered the final step of the data mining occupancy learning process. In order to extrapolate useful, valid and further applicable knowledge on the occupancy of the case study office building, the mined

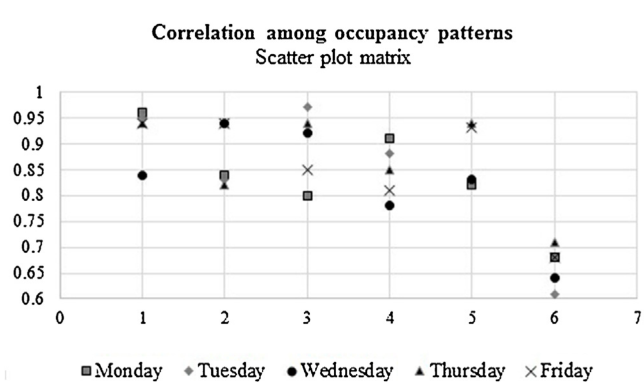

Fig. 14. Correlation among occupancy patterns in the scatter plot matrix.

24 h occupancy patterns must be transformed into working user profiles. For this, time dependent description of typical working activity, presence and intermediate absence in a singular office space is required. Fig. 16 provides a graphical visualization of main typical working activities for the four mined patterns:

- going to work: increase in global occupancy curve;
- working: stable global occupancy curve;
- lunch/breakfast: one valley decrease/increase in global occupancy curve; and
- going off work: decrease in global occupancy curve.

The patterns of occurrence of repetitive, typical activities occurring during a working day in a single occupancy office, in the 24 h time schedule, include: (i) time of arriving/leaving the office, (ii) period of stable work from the office and (iii) period of intermediate absences. These activities are characterized in four emerging working-user profiles, as shown in Fig. 17 and described as follows:

- Pattern A working-user profile arrives at work around 6–9am, works stable from the office in the morning from 9am to 12pm and in the afternoon from 1:30 to 4pm, going for lunch around 12–1:30pm, leaves work around 4–7pm.
- Pattern B working-user profile arrives at work around 8–9:30am, works stable from the office in the morning from 9:30am to 12:30pm and in the afternoon from 2 to 5:30pm, going for lunch around 12:30–2pm, leaves work around 5:30–10:30pm.
- Pattern C working-user profile arrives at work around 5:30–6:30am, leaves office in between 6:30 and 7am, works stable from the office in the morning from 7 to 11:45am and in the afternoon from 1 to 5pm, going for lunch around 12–1pm, leaves work around 5–7pm.
- Pattern D working-user profile arrives at work around 5:30–6am, leaves office in between 6 and 8am, returns to office around 8–9:30am, works stable from the office in the morning from 9:30am to 12pm and in the afternoon from 2 to 4pm, going for lunch around 12–2pm, leaves work around 4–6:30pm.

Pattern B working-user profile tends to arrive later in the office and typically works beyond normal working hours (Fig. 17). Fig. 18 shows the average total breakdown of hours spent at work during the work week, with the following breakdown of occurrence for Pattern B working-user: (i) working stable from the office (26%), (ii) moving from the office (26%) and, (iii) taking breaks (7%). Therefore,

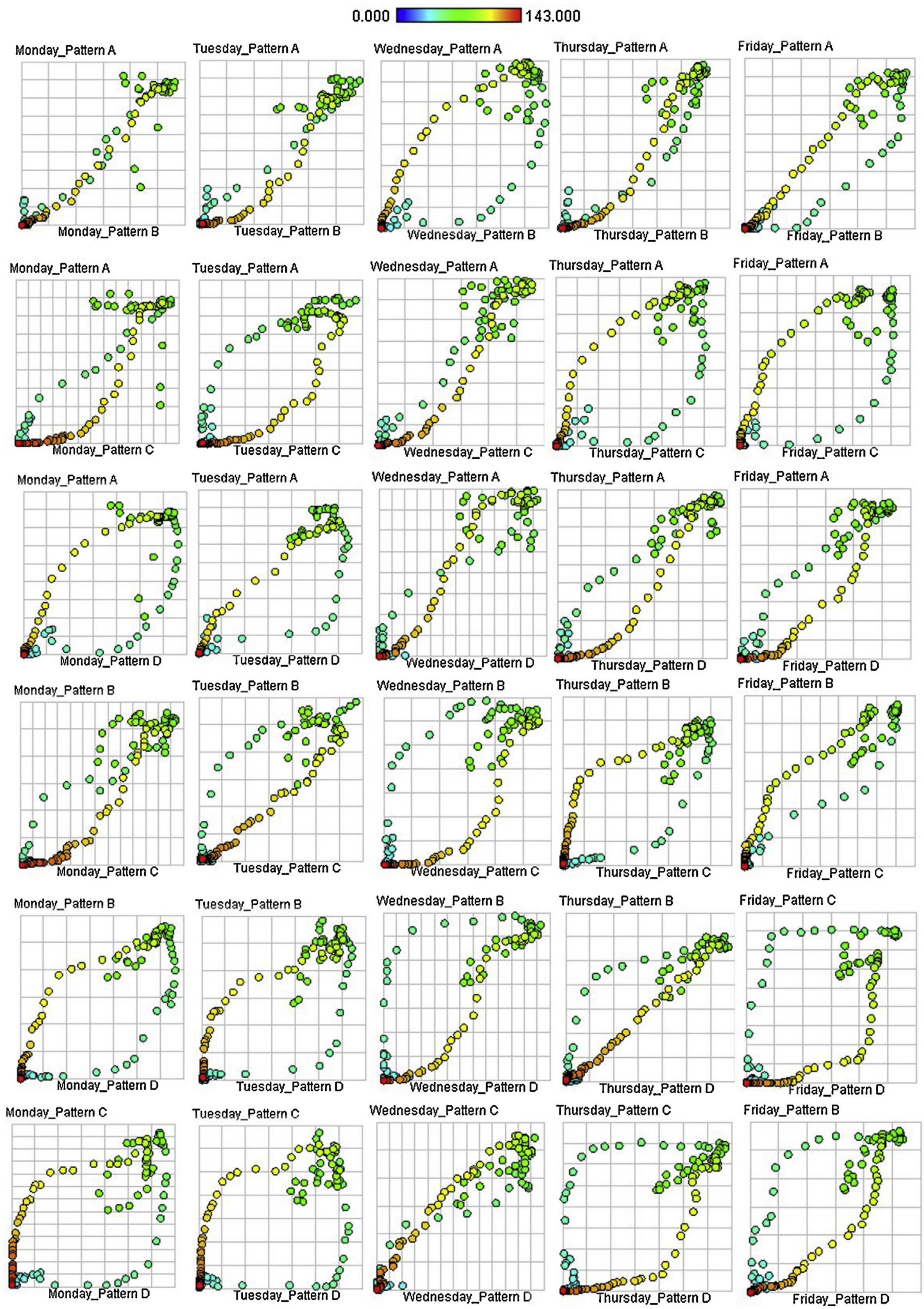

Fig. 15. Scatter plot matrix of the four occupancy patterns during same day of the week.

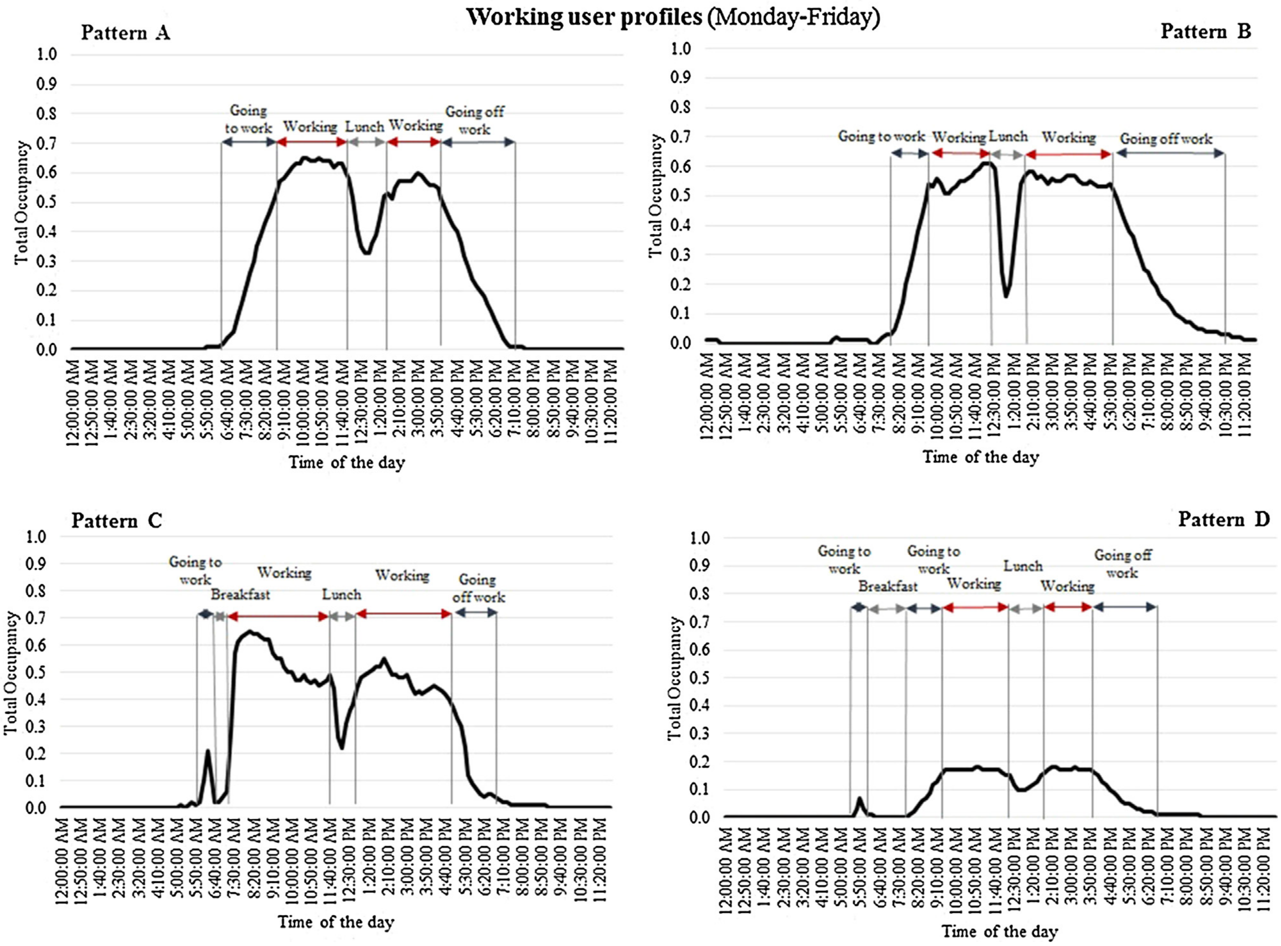

Fig. 16. Graphical visualization of main working typical activities for the four mined patterns.

Pattern B working-user is just slightly above (60%), whereas the breakdown for the other working profiles is less (49% Pattern A, 48% Pattern C and 38% Pattern D).

Pattern C is characterized for a more stable working-user profile, whom tends to spend more time working from office (35%) than moving from the office (13%).

Pattern D working-user profile tends to spend less time in the working space, with an average of about 20% considered working stable and an almost equivalent amount (18%) arriving/leaving the working position. Additionally, more work day time (17%) is spent away from the office.

3.5. Occupancy schedule

Final goal of the proposed method is to identify archetypal user profiles for which different energy conservation strategies, as well

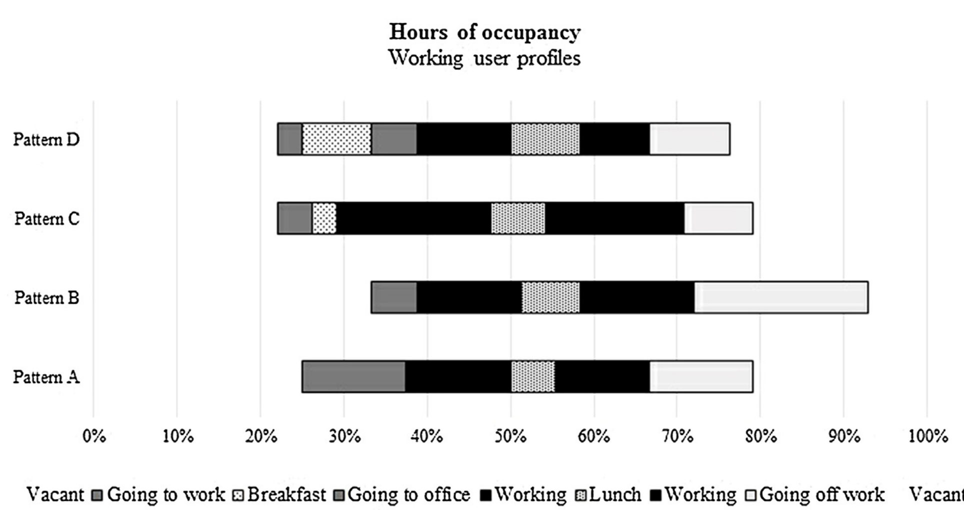

Fig. 17. 24-h typical office activities for Patterns A, B, C and D working user profiles.

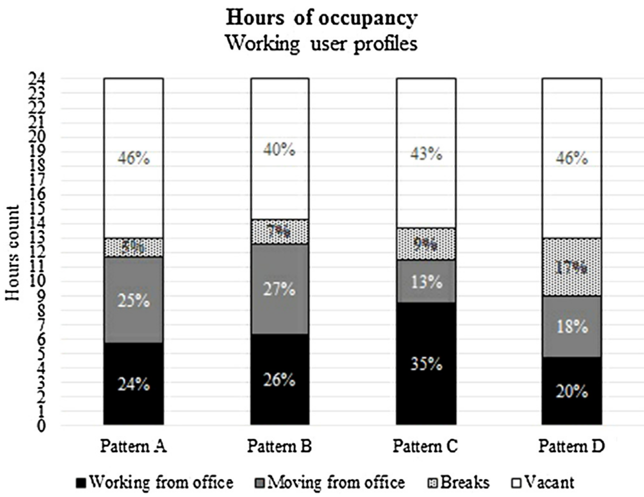

Fig. 18. Breakdown of occupancy hours for Patterns A, B, C and D working user profiles.

as building design recommendations, may be appropriate. For this aim, the identified occupancy patterns are transformed into four typical working profile schedules of occupancy (Fig. 19).

Such schedules characterize the probability of an office being occupied at a specific time of the day and day of the week (Monday–Friday). Schedules do not represent the percentage of full occupancy as represented by traditional occupant schedules. Fig. 19 shows the occupancy level in similar offices of the same building may vary largely, based on different working-user profiles. This finding greatly impacts appliance, lighting, plug-load, system controls and therefore on total energy consumption of the building.

4. Discussion

In the last decades, the evolution to more granular measurements of the occupancy presence, movement and interaction with system controls (thermostats, lighting) and building envelope (windows, shades) have transpired into building development.

Sensor networks make available multidisciplinary and integrated layers of big data source, providing reliable information on occupancy recognition and scheduling besides of actual building performance and operation. The aim of researchers to improve the accuracy of occupant presence in simulation models and some stochastic models and the topic of real-time estimation of occupancy treated largely in commercial buildings, all feeds into the larger objective of building better dynamic modeling for design, daily energy management and energy conservation measures assessments.

Nonetheless, previous research has highlighted due to the stochastic nature of human behavior, evolving randomly with time as one of the major shortcomings in obtaining reliable mathematical models.

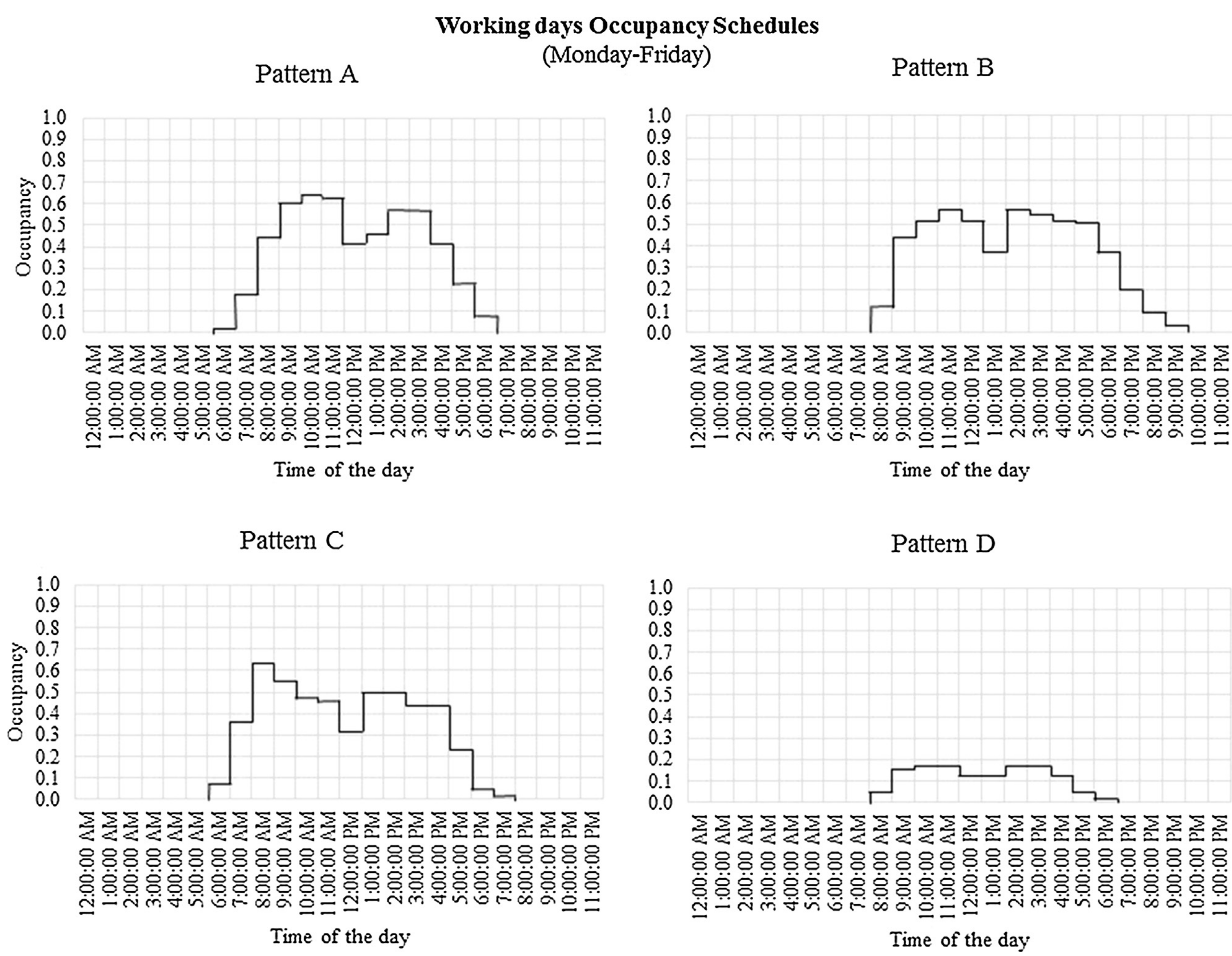

Fig. 19. Example of 24 h schedules of occupancy for Patterns A, B, C and D.

Moreover in many applications it is difficult to extrapolate useful information on the occupant movement and presence from monitored building data due to the data scattering at this level. Instead patterns of data discovered through data mining techniques may highlight commonsense knowledge applicable to solutions at high levels of abstraction.

In this context, data mining techniques have been shown as able to automatically extrapolate valid, novel, potential useful and understandable occupancy patterns from big data streams, highlighting expressions describing typical and repetitive working user profiles in office spaces or in office buildings.

Useful information can be extracted from the proposed data mining occupancy schedules learning process to improve energy building simulations. The decision tree model can help understand repetitive rules in occupancy patterns in order to optimize appliances, plug loads, lighting use, HVAC control systems, fresh air requirements, internal heat gain and building design plans in office buildings.

One of the limitation of this study is that the mined working user profiles and patterns of occupancy are circumstantial to the given data set.

The application of the proposed data mining framework on different data sets will enhance the robustness of individual as well as group energy related behavioral patterns description and prediction in office buildings.

The implementation of the emerged occupancy rules and schedules into current building energy modelling programs, would support the implementation of more efficient energy measures through more accurate investigation on the impact of typical working user profiles on appliances, plug loads, lighting use, HVAC control systems, fresh air requirements and components heat gain, both at the single office and at the office building level.

Moreover, it has to be underlined that the proposed methodology is not intended to substitute or contrast the agent-based stochastic models already developed for the integration of occupants' presence into building energy simulations.

More likely, the knowledge discovered related to occupancy rules and working user profiles schedules aims to support operators, building designers, auditors and managers decision making by providing solutions with fast legibility, high replication potential and low capital investment to direct specific operation and maintenance strategies at a building level as well as future energy-saving policy in the commercial building sector.

Scalability of solutions is probably one of the most critical point in pattern mining. The mined schedules and occupancy rules are circumstantial to the case study building and do not represent the complete set of patterns that can be derived within a comprehensive dataset of 10-min data in two full years. Nevertheless, they characterize the most compact, physical meaningful and high quality set of patterns that can be derived with satisfactory performance. Interesting results may emerge from further analysis, by applying the proposed data mining framework to a seasonal or one year behavioral data set, providing solutions to direct specific operation and maintenance strategies at a building level that may be appropriate for each of the distinct working user profiles in different periods of time. Moreover, is generic enough to be possibly

5. Conclusion

Using the Knowledge Discovery in Database (KDD) process, a data mining learning process was proposed to extrapolate office occupancy patterns and working user profiles from big data streams. A three-step data mining schedule learning method was applied to a data set along with the open source data mining program RapidMiner to provide insights into patterns of occupancy in 16 offices located in Frankfurt, Germany.

The transformation methods were applied to a given data set with 10-min interval occupancy data over two complete year periods. Raw data were transformed into more significant pre-processed data representing invariant attributes of the data set. The pre-processed data were mined though a decision tree model with the goal to predict the value of a label attribute (occupancy) based on several predictor attributes (Season, Day of the week, Time of the day, Occupancy State and Window Change) of the data set. The results demonstrated that the C4.5 is a suitable algorithm for learning the occupancy presence in offices. This was verified with a 90.3% accuracy rate of all training records correctly classified as vacant or occupied. The predicted answers of the tree-like graph model are probabilities of the office being vacant/occupied based on the condition defined by the path from the root tree to the final leaf.

Second, by traversing the tree model from the root node to a leaf node, a complete set of 45 rules was derived. The proposed tree and rule models can be used to understand repetitive occupancy patterns in order to optimize operation, maintenance and energy performance both at the single office and at the office building level.

Third, a cluster analysis was performed in order to disaggregate the occupancy presence into valid working user profile schedules for every working day (Monday–Friday) and for the whole working week. In this study, we employed the k-means algorithm, to generate an optimal $k = 4$ number of clusters. The results showed the occupancy patterns in single offices were not assigned to the same behavioral cluster every day, meaning that working profiles may vary broadly during different working days. A conspicuous variation up to 60% in the hourly occupancy rate was noticeable among patterns of occupancy especially during office arriving or leaving time (8am to 5pm). Furthermore, the clustering of typical office working activities such as working stable from the office, moving (arriving or leaving) from the office and taking breaks, such as having breakfast or lunch, highlighted that the average breakdown of hours spent every day by the monitored users in the single office space may differ broadly, as well as a significant shifting in the time the occupancy pattern activity/presence/intermediate absence was occurring. Also, the occurrence occupants arrive early in the morning before 5.30am and depart after 10.30pm (overtime work) emerged as phenomenon occurring frequently, nonetheless such patterns are omitted by using fixed deterministic occupancy schedules.

Finally, the proposed methods in this study identified rules of occupancy and archetypal user profiles for which different energy conservation strategies, as well as building design recommendations, may be appropriate. Characterization of the probability of an office being occupied at a specific season of the year, day of the week and time of the day will enable the more accurate development of building energy models. The results supported the assumption that occupant stochastic behavior and presence cannot easily described by means deterministic 24 h schedules. Instead more accurate profiles having the same patterns of occupancy of real building users are required to close the gap between predicted and actual building performance. The future applications of the proposed method to discern occupancy schedules and their implementation into a building energy modelling programs, like EnergyPlus or IDA-ICE, would strongly support the investigation of the impact of typical working occupancy patterns on design and operation of office appliances and control systems. In this context, further investigations are suggested to uncover cost-effective, applicable and reliable best practices and solutions supporting energy efficiency policies and decision makers on how to incorporate patterns of human movement and actions into behavioral models, with the aim of bridging the gap between actual and predicted energy performance in buildings.

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ANALYTICS

DEFICIENCY OF EFFECTIVE ANALYTIC TECHNIQUES PROVIDING USEFUL KNOWLEDGE ON OB IN BUILDINGS

HOW TO TRANSLATE BUILDING AND HUMAN INFORMATION INTO USEFUL KNOWLEDGE?

PAPER 2 **S. D'Oca**, T. Hong.
A data-mining approach to discover patterns of the window opening and closing behavior in offices.
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PAPER 3 **S. D'Oca**, T. Hong.
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PAPER 4 **S. D'Oca,** C. Delmastro, V. Fabi, S.P. Corgnati
Testing Socio-Economic Demographic Variables on building energy consumption scenarios at the urban scale in Italy. Proceedings of ClimaMed– 2015, Juan-les-Pins, pp. 1-8

ID 19 - Testing Socio-Economic Demographic Variables on building energy consumption scenarios at the urban scale in Italy

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SUMMARY

In order to meet EU 2020 energy efficiency aggressive goals, there is a need to scale up the achievement of real energy consumption savings of current high performing building to the urban level. However, current low-energy, zero carbon, and net zero energy buildings are not performing as designed. Within the building sector industry there is an increasing concern about the mismatch between expected and actual performance, typically addressed as the 'credibility gap'. The reasons for this discrepancy vary, but are mostly rooted in oversimplifying or ignoring occupant behavior in the building operation process. In this view, the presented study is testing the magnitude of socio-economic demographic variables on building energy consumption energy scenarios at the urban scale. Measured thermal energy consumption data for a block of building in Torino, Italy are coupled with Geographical System Information (GIS) public census socio-economic data related to building occupants and analyzed through data mining techniques. Hence, energy model scenarios will be drawn to represent the impact of different building occupant profiles over mid-long term building energy consumption at the urban scale.

Interpretation of the energy scenarios may allow energy designers and modelers, building operator and manager to develop energy efficiency measures and standards taking into account the leverage of socio-economic factors related to building occupants. Results may also support energy and urban planners to the release of energy policies and the development of robust energy urban planning tools aiming to bridge the "credibility gap" of targeted energy efficiency in building.

INTRODUCTION

Building occupants interact with the indoor environments in purposive and significant ways that contribute to both energy consumption and Indoor Environmental Quality (IEQ), and thus warrant significant attention in the building design and operation processes. For example, occupants' thermally adaptive behaviors (i.e. turning on fans/heaters, opening windows) are strongly tied to space heating and cooling loads, which make up 27% and 13% of global primary energy consumed in residential and office buildings in the Europe, respectively (Energy Efficiency trends in buildings in the EU, Enerdata). These behaviors also modify key thermal comfort determinants like air temperature, air speed and clothing insulation level [1]. Recent studies have begun to quantify the magnitude of occupant behavior's influence on energy use and comfort, reporting significant impacts that have intensified the focus on behavior as a key topic of built environment research [2, 3].

If the general importance of the human-building interaction is well established, however, the mechanisms behind this interaction are still being explored. Increasingly, this effort has involved the collection of longitudinal data, which allow one to observe occupant comfort and adaptive behavior as they evolve together across the day and season. Nevertheless, longitudinal studies are time-consuming and expensive to carry out, and existing comfort and behavior data are accordingly limited in their coverage of certain adaptive actions, building types and climates. In recent years, data mining has been used more and more in the building science area, to investigate occupant behavior patterns or to analyze building automation systems and building energy performance. In this context, data mining is a useful technique to elaborate huge samples of data extrapolating significant information. Data mining techniques lead the way to

automatically analyzing huge amounts of data. They can be used to extract interesting, useful, and previously unknown knowledge from data. The increasing usage and technology development of IT, large amounts of data will be available in the building sector. This presents an excellent opportunity for data mining applications to discover new science. The research has demonstrated the data mining method is capable of predicting occupancy patterns [4] and operations of both window opening and heating set point adjustment [5, 6] for energy scheduling purpose. Even if lot of work is done to better represent the occupant behavior patterns in building science research, further fields of studies still remain. For example, with only few exceptions, the role of occupant behavior at urban level is not yet investigated.
Sustainable urban development requires a long-term sector-integrative approach. Scenario-based analysis with respect to development paths determines the energy consumption of different city occupancy configurations. Long-term strategies are crucial especially with regard to the development of key projects, sites and locations, as the short-term realization of supposedly appropriate projects on specific locations might prohibit the future viability of sustainable projects in these locations.
This paper proposes a method of system analysis and partial simulation for urban structures for this purpose. The aim of this paper is to provide a methodology to develop strategies for complex situations while sustainable planning of urban settlements, based on modeling of urban energy and accounting for occupants' behavior defined by cluster analysis of an urban neighborhoods. The main purpose of this development is to derive a method to set up a systems model that supports decision processes in planning and designing the built environment and is tailored specifically for this purpose.

METHODS

Assessment of the reference blocks of buildings

The analysis is focused on 21 buildings sited in the municipality of Turin, Italy, that is located in the climatic E zone (temperate continental) (Fig.1). In this session, reference buildings characteristics and thermal performances are assessed in order to be able to investigate the refurbishment potential of the area.

Figure 1 – Reference Block of Buildings

Thanks to the availability of statistical information and supported by a Geographic Information Systems (GIS), physical characteristics have been associated to each building. It results that the stock is characterized by two construction periods – from 1971 to 1980 and 1881-1990 - and by three building types – multi family apartment buildings, towers and low rise buildings. According to the analysis performed by [7], space heating energy consumption of the 21 buildings has been evaluated by matching real consumption data provided by local utilities and the results of the thermal model described in [8]. This thermal model was built by analyzing 300 residential buildings and it depends on degree-days, on the envelope's thermal insulation (related to the period of construction) and on the shape factors of buildings. Depending on the relative difference between real consumption data and the thermal model results it is possible to evaluate if some buildings have been already refurbished.

Table 1. Assessment of building space heating energy consumption [7]

Building ID	Calc. consumptions ($kWh/m^2/y$)	Real consumption ($kWh/m^2/y$)
1	111.67	116.88
2	113.69	110.96
3	118.88	107.84
4	118.88	114.66
5	119.02	128.3
6	118.58	116.99
7	116.73	130.08
8	115.73	110.05
9	115.58	113.73
10	115.63	109.5
11	145.04	162.79
12	115.11	115.92
13	114.26	117.58
14	113.56	119.61
15	113.71	119.83
16	118.94	108.65
17	108.47	113.86
18	109.46	111.68
19	116.45	112.32
20	118.63	114.98
21	169.11	189.82

From Table 1 results that none of the buildings have been previously refurbished and that energy consumption are comprised in a range varying from about 105 and 190 $kWh/m^2/y$. For allowing the analysis proposed in the next sessions, buildings have been grouped into four main reference building blocks (RBBs accordingly to their census area). It results:

- RBB-A: census area 2745, composed by 2 buildings (ID: 1 and 2);
- RBB-B: census area 2746, composed by 9 buildings (ID: 3, 4, 5, 6, 12, 13, 14, 15 and 20);
- RBB-C: census area 2999, composed by 8 buildings (ID: 7, 8, 9, 10, 16, 17, 18 and 19);
- RBB-D: census area 3698, composed by 2 buildings (ID: 11 and 21).

Assessment of the Socio-Economic Demographic Variables

A preliminary methodological approach for including behavioral variables into the energy service demand analysis at an urban/district scale was introduced by Delmastro et al, 2015 [8]. Similarly, this study is incorporating socio-economic behavioral variables into energy model scenarios representing the impact of archetypal building occupant profiles over mid-long term building energy consumption at the district level. Socio- economic conditions of inhabitants such as education level, income and employment, as well as demographic variables, such as household composition and dwelling ownership affect their lifestyle and consequently the energy demand at the household level [9]. In Italy, socio-economic data related to population and building census are provided by the National Institute of Statistics [10]. Programs such as the IEA – Annex 66 "Definition and Simulation of Occupant Behavior in Buildings" [11] – have initiated advancements in the standardization of the quantitative descriptions and classification of archetypal occupant behavior profiles on building performance. Specifically Sub-Task C is investigating the most effective methodologies to represent population diversity – e.g., clustering, combining all data to make a model, combining data just from each occupant to make a model, etc. – when implanting the behavioral variables in building energy performance simulations and forecasts. Aim of the project is to address the simulation user towards

the choice of the best fit-for-purpose user type diversity profiles (stochastic profiles, agent/action-based model, standard schedules, archetypal user profiles) to be applied to different levels of modeling applications (building, block of building), aims of simulation (design, optimization, forecast, energy planning), building typologies (destination of use) as well as building related factors (envelope, location, etc.).
Considering the case of energy planning at the urban context, diversity profiles must be general enough to be valid and applicable to the huge variety of energy-related behaviors and user socio-demographic characteristics. In this view, archetypal user profiles should be particularly useful in areas in which statistics on census data is quite detailed. For instance, the city of Turin, Italy, allows via a statistic database (DB) to know extrapolate information on the socio-demographic variables for each census area. This permits to identify, for each of this census area, the probability distribution of the archetypes user profiles, which could be associated with the RBC distribution.
The KDD (Knowledge Discovery in Database) methodology [12] is employed in order to extrapolate valid, potential useful and understandable knowledge from the information related to population and building census of an urban district located in Torino, Italy.

RESULTS

Clustering archetypal user profiles based on Socio-Economic Demographic Variables

In this study, data on socio-economic and demographic variables such as education level, employment, ownership type and age (Table 2) are clustered by means a k-means algorithm, in order to find homogeneous archetypal user profiles among the four reference blocks of buildings (here named RBB-A, RBB-B, RBB-C, RBB-D).

Table 2. Socio-economic and demographic variables such as education level, employment, ownership type and age provided by the [10] regarding census statistical data collected among 2012 and 2013 over the population of four census areas corresponding to the reference blocks of buildings

Education level	**Employment level**	**Ownership type**	**Population Age**
Bachelor/master degree	Employed	Private dwellings	0-24 years
High school diploma	Unemployed	Rented dwellings	25-49 years
Middle school certificate			50-69 years
Primary school certificate			>74 years

Cluster analysis is the process of merging data into different clusters, so that instances in the same cluster have high similarity and instances in different clusters have low similarity [13]. The similarity between clusters was computed based on the k-means algorithm, given the simple but powerful nature of the algorithm, it is one of the widely used classification technique.
The performance of the cluster models was assessed by means the Davies–Bouldin index. The k=n algorithm that produced clusters with low intra-cluster distances (high intra-cluster similarity) and high inter-cluster distances (low inter-cluster similarity) had a low Davies–Bouldin index, and was considered the $k=n_{opt}$ cluster algorithm for the specific data set. An example of the cluster analysis performance index assessment is provided in Table 3, whereas a number of 3<k<8 clusters of "population Age" among the census data was computed. A k=4 number of clusters was selected to assure the highest accuracy of the algorithm as follow: 1) 0-24 years; 2) 25-49 years; 3) 50-69 years; and 4) >74 years.

Table 3. Performance evaluation of the k-means algorithm for the "Population Age" Cluster Distribution, by using the Davis Bouldin Index

k- number of clusters	3	**4**	5	6	7	8

Davis Bouldin Index	-1.038	**-1.136**	-0.792	-0.604	-0.525	-0.415

Results of the cluster analysis showed a homogeneous distribution of the “Population Age” socio-demographic clusters, the four reference blocks of buildings. Specifically, the analyzed district emerged mainly populated by users aged 50-69 years old (Figure 2).
A consistent pattern also emerged among the socio-demographic clusters for “Education Level” and “Employment Level”, while a wide dispersion arose with reference to the “Ownership type” (private owned or rented) of the dwellings located in the reference blocks of buildings (Figure 3).

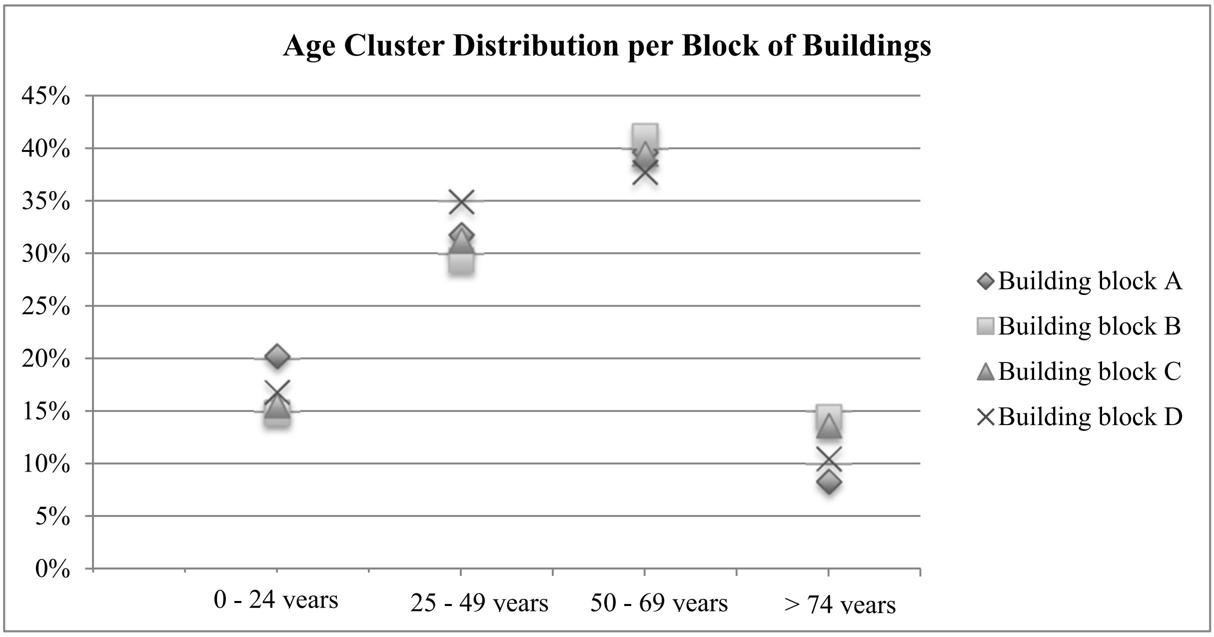

Figure 2. Age Cluster Distribution for each of the four case studies blocks of buildings

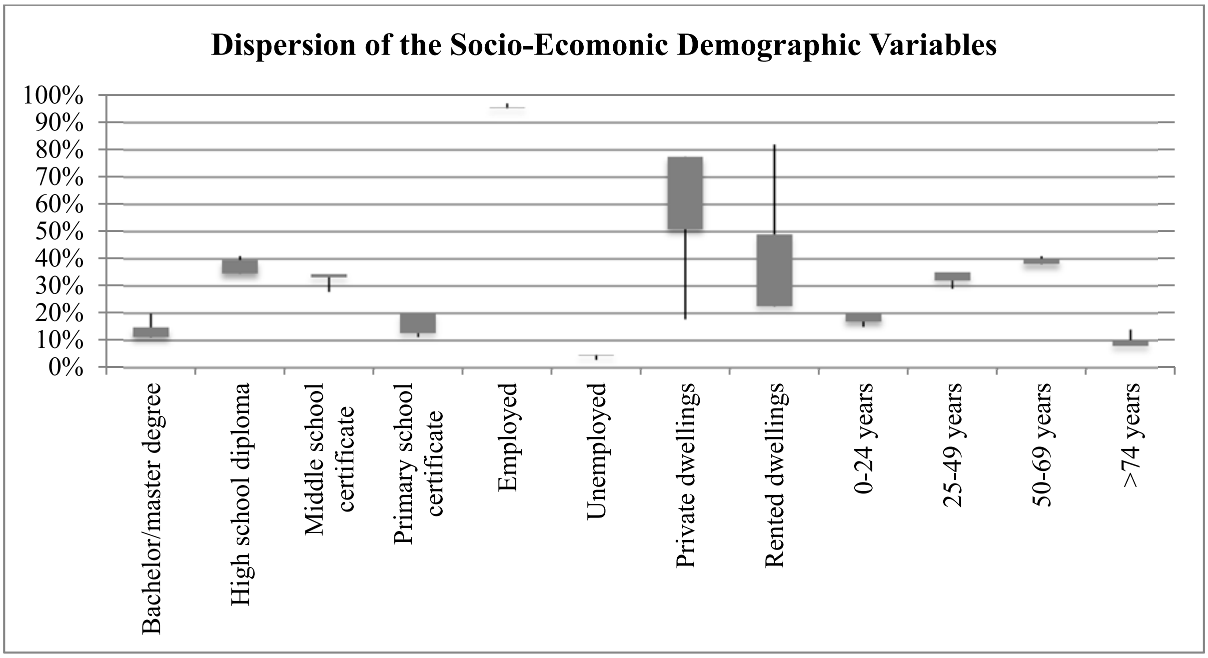

Figure 3. Dispersion of the socio-economic demographic variables regarding: education level, employment, ownership type and age among the 4 blocks of buildings.

Figure 4 illustrates the socio-economic demographic variables characterizing the archetypal user profiles emerged among the 4 blocks of buildings. Residents of the 4 blocks of buildings are pooled according to a similar and homogeneous: education level - high school diploma -, employment level

– occupied - and population age – from 50 to 69 years old. Hence, 3 different scenarios of ownership type – prevalence private owned dwellings, prevalence rented dwellings, balanced private owned/rented dwellings – are clustered respectively to the Building Block A, Building Block B, C and the Building Block D.

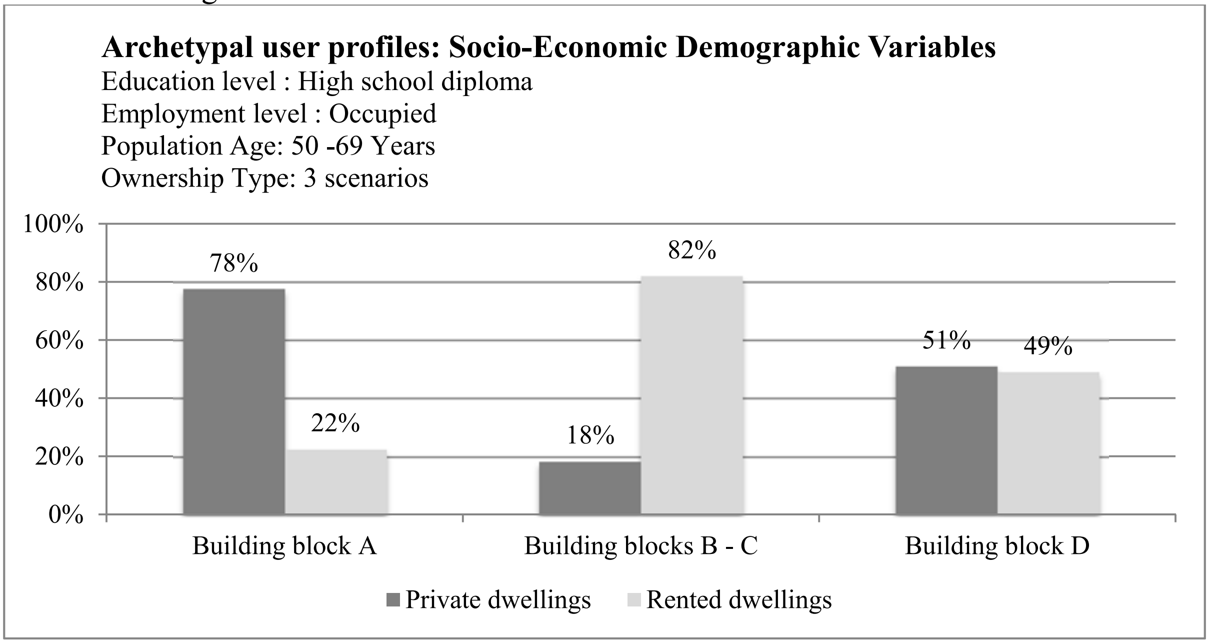

Figure 4. Socio-economic demographic variables characterizing the archetypal user profiles emerged among the 4 blocks of buildings.

Evaluation of the impact of the Socio-Economic Demographic Variables on the feasibility of retrofit measures at the urban scale

The goal of this session is to evaluate the renovation potential on the considered district. In a first step the global potential is evaluated (considering all the buildings to be refurbished), while in a second step the impact of cluster characteristics on the feasibility potential is quantified. As evaluated in the previous session, most the chosen socio-demographic variables (education level, employment level and population age) are homogeneously distributed within the district; moreover, their level do not impact negatively on the refurbishment potential since most of the population has a work occupancy, a medium education level and the age range is not to high to avoid the possibility to invest. The only variable that differs meaningfully from a census area to an other is the ownership type: in RBB-A only the 22% of the population lives in rented dwelling, in RBB-B and RBB-C most of the population (more than 80%) lives in rented dwelling while in RBB-D the distribution is balanced. This consideration has a weight in the feasibility of renovation works: the probability that population living in rented dwellings will invest in energy savings measures is very low. For that reason and considering that rental occupants are not all concentrated in the same buildings, in this preliminary approach it has been defined a feasibility index called "property factor (PF)" and dependent from users cluster's that differs from a building block to another:

- PF-A = 1; the property factor of RBB-A is equal to one, all the inhabitants will refurbish their dwellings;
- PF-BC = 0.12; the property factor of RBB-B and RBB-C is equal to 0.12 that means that inhabitants have a very low probability to refurbish their buildings (only 2 on a total of 17);
- PF-D= 0.5; the property factor of RBB-D is equal to 0.5 that means that 1 building on a total of 2 has a very high probability to be refurbished;

Table 4. Energy savings potential of the buildings blocks

ID	RBB	Consumption (kWh/m2/y)	Global Refurbishment (kWh/m2/y)
1	A	116.88	85.55
2	A	110.96	81.22
3	C	107.84	55.08
4	C	114.66	57.21
5	C	128.30	55.36
6	C	116.99	65.43
7	B	130.08	64.53
8	B	110.05	57.84
9	B	113.73	54.25
10	B	109.50	58.85
11	D	162.79	57.67
12	C	115.92	54.65
13	C	117.58	57.27
14	C	119.61	56.18
15	C	119.83	56.50
16	B	108.65	58.31
17	B	113.86	59.14
18	B	111.68	60.16
19	B	112.32	60.27
20	C	114.98	119.2
21	D	189.82	138.9

In Table 4 the global energy savings potential (considering all the buildings to be refurbished) has been evaluated. The considered interventions are the following: replacement of all windows for the lower classes, thermal insulation of the roof and the floor below the building, insulation of the walls. The energy savings resulting from renovation works have been quantified by considering the existing literature [7-9, 15].

Table 5. Impact of the cluster analysis on total energy savings potential

RB	**PF**	**Energy consumption (MWh/y)**			**Δconsumption (kWh/y)**		**Clusters' impact**
		Existing situation (E)	*Global retrofit (R)*	*Retrofit with clusters (RC)*	*(E-R)*	*(E-RC)*	
A	1	1858	1360	1360	498	498	0%
B and C	0.12	15,822	7959	14,753	7864	1069	86%
D	0.5	878	643	677	235	201	15%
Total		18,558	9962	16,790	8597	1768	79%

From Table 5 it is possible to observe that the cluster analysis impacts for a total of +79% on the energy savings potential deriving from the retrofit of the 21 district's buildings. Of course, as for buildings B and C, in the areas characterized by low feasibility index the cluster's analysis impact is very high. This result highlights the importance of including archetypal socio-economic users profiles in the estimation of the feasibility and penetration of energy policy and measures. In particular, if scaled at higher scale (f.i the urban scale) it can support decision making in policy formulation by catching spatial differences in social conditions of citizens; it can allow the promotion of tailored policies from zone to zone and the estimation of not only the potential of an intervention, but the real attended perception of the policy by investors.

DISCUSSION AND CONCLUSION

In this paper, a method to develop energy consumption strategies at urban level considering occupancy features is proposed and applied to a case study. Cluster analysis of socio-demographic variables for a neighborhood in Turin – Italy – highlighted three main users' typologies. In particular, education level (high school diploma), employment level (occupied) and population age (50-69 years) resulted to be homogenous. As a matter of fact, a report of the national Census given by [10] indicates the average population age in Italy is 43 years. Moreover, it confirmed that the progressive aging of Italian population is evident through the analysis of the comparison between the number of old people (65 years and older) and children under 6 years (for every child there are more than 3 elderly). Furthermore, ISTAT [10] counts more the 64% of resident people in North Italy having an employment. A greater variation emerged instead among house ownership conditions. Based on the resulted classification of Archetypal user profiles, three main scenarios of renovation potential were evaluated. From the results, it emerged the cluster analysis have an high impact on the energy saving potential, highlighting the importance of considering Archetypal user profiles in the estimation of penetration of refurbishment actions. Further, having a more heterogeneous dataset of a larger area data could demonstrate a higher deviation representing the variability on energy consumption due to the occupancy features.

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MODELING

LACK OF COMMON AGREEMENT ON VALIDITY AND EFFECTIVENESS OF OB MODELING AND SIMULATION APPROACHES

WHICH ARE THE STRENGTHS, SHORTCOMINGS AND NEEDS OF OB MODELING AND SIMULATION METHODOLOGIES?

PAPER 5 **S. D'Oca,** H.B. Gunay, S. Gilani, W.L. O'Brien, V. Fabi, S. Corgnati, A. Mahdavi
A review of the occupant modeling approaches in offices with illustrative examples
Submitted to JOURNAL OF BUILDING PERFORMANCE SIMULATION – June 2016

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A review of the occupant modeling approaches in offices with illustrative examples

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Manuscript Type:	Review Article
Keywords:	occupant behavior, modeling approaches, building energy simulation, literature review

Abstract

Characterizing the intrinsic randomness of occupants' behavior is a major step to quantifying uncertainty and improving the predictive accuracy of building simulation. However, over the last 30 years, adaptive energy-related behaviors in buildings – operating windows, blinds, and lights, and adjusting thermostats – have been modeled in building simulation tools using predefined rules and fixed schedules. Data-driven stochastic models are typically developed based on statistical analyses of the occupants' behavior and environmental conditions, and they predict occupants' interactions with various building components. The objective of this paper is to identify, illustrate, and discuss the strengths and weaknesses of the state-of-the-art modeling approaches of occupant behavior. To this end, we conducted a critical review of the existing occupant model forms from the literature. Illustrative examples of each model form were developed upon two data sets from an academic office building in Ottawa, Canada and a government building in Hartberg, Austria.

Keywords: occupant behavior, modeling approaches, building energy simulation, literature review

1. Introduction

Today's buildings consume more than one-third of the world's primary energy, with an expected growth by an average of 1.8 percent per year from 2010 to 2040 (IEA 2015). Energy is consumed in buildings for various purposes: space heating and cooling, water heating, ventilation, lighting, and appliances. This means that significant energy is used to maintain comfortable indoor environments for occupants.

Occupants are not passive agents of the buildings they occupy (Newsham et al. 1995). They change their indoor environment through their interactions with various building components such as opening/closing operable windows, closing window blinds, switching on electric lighting, and adjustment of thermostats (Nicol and Humphreys 2004; Borgeson and Brager 2008; Fabi et al. 2013). In tandem with these adaptive actions that *change the indoor climate*, occupants *adapt to their environment* by changing their clothing insulation (Newsham 1997; Nicol and Humphreys 2002; Morgan and de Dear 2003; Schiavon and Lee 2013), adjusting their position or orientation (Jakubiec and Reinhart 2012), and changing their activity level or drinking hot/cold beverages (Haldi and Robinson 2008). These behaviors were classified as adaptive behaviors (Gunay et al. 2013), as their primary intent is to restore comfort (thermal, visual, acoustic comfort or indoor air quality).

On the other hand, non-adaptive behaviors are actions mainly driven by contextual factors (non-physical factors affecting occupants' behaviors, habits, attitudes (Sadeghi et al. 2016)) rather than physical discomfort (O'Brien and Gunay 2014). In the reviewed literature, the plug-in appliance use, light switch off, and blinds opening behaviors were classified in this group (Gunay et al. 2013). For example, office occupants' computer (Menezes et al. 2014; Gunay et al.

2016) and light switch off (Pigg et al. 1996) behaviors at departure exhibit a close relationship with the duration of absence following the departure.

Similarly, occupants open their blinds to restore view and connection to outdoors (Inoue et al. 1988; Farley and Veitch 2001; Zhang and Barrett 2012; Lee et al. 2013) – after closing them to mitigate discomfort due to glare. As a result, it may take days or even weeks before occupants consider reopening their blinds (O'Brien et al. 2013).

Occupant behavior imposes significant uncertainty on a building's energy performance – having a factor of two or more (Norford et al. 1994; Haldi and Robinson 2011) – and the users' comfort, satisfaction, health, and productivity (Reinhart et al. 2006; Agha-Hossein et al. 2013). Therefore, without realistically representing occupants' interactions with the building control systems and components in building performance simulation (BPS), it is less likely that meaningful performance predictions and appropriate design or control decisions can be made.

An ever-increasing amount of data from building automation and control systems (BACS) and other indoor environmental data loggers represent an untapped opportunity to analyze occupants' presence and behavior patterns in commercial buildings.

Consequently, researchers – particularly within the International Energy Agency's Energy in Buildings and Communities Programme (IEA EBC) Annex 66 – have been entering the field of data-driven occupant modeling in buildings with the objective to more reliably represent occupants in building simulations.

In the past two decades, researchers have instilled the basics of modeling human presence and behavior (Haldi and Robinson 2011) – particularly in office buildings. However, the modeling methodologies remained fragmented amongst a large number of articles (Gunay et al. 2015; Gaetani et al. 2016).

The objective of this paper is to provide a critical review of the existing occupant modeling methodologies. We expect that this article will serve as a pedagogical resource in the training of new occupant behavior and presence modellers. To this end, a comprehensive survey of the state-of-the-art literature was conducted, and examples for each modeling approach were provided upon two data sets gathered from two office buildings in Ottawa, Canada and Hartberg, Austria.

Note that representing the randomness in occupants' presence and behavior patterns entails mimicking not only the day-to-day variations of a group of occupants' overall occupancy and behaviors but also the differences amongst these occupants (Haldi 2013; Mahdavi and Tahmasebi 2015). However, this paper focuses only on the methodologies to represent the former; the latter – studying the diversity amongst different occupants – is not within the scope of this article.

2. Case studies

Table 1 gives an overview of the characteristics of the data used in the illustrative examples, and Figure 1 illustrates the façade of the monitored offices in the two buildings located in Ottawa and Hartberg. The monitored offices were Northeast-facing in the Hartberg Building and West-facing in the Ottawa Building. The window-to-wall and window-to-floor ratios were 32% and 34% in the monitored offices in the Ottawa Building, and they were 24% and 18% in the Hartberg Building. Visible light transmission coefficientwas 70% in the Ottawa Building offices, whereas it was 75% in the Hartberg office building. The occupants of the Ottawa Building were full-time faculty members in a university, and they were full-time municipal employees in a government building in the Hartberg Building.

Table 1: Overview of the datasets employed in building the illustrative examples.

Figure 1: The buildings from which the datasets were collected (left image is Hartberg Building, and the right image is Ottawa Building).

3. Modeling adaptive behaviors

In the reviewed literature, four different adaptive behavior model forms were found: (1) schedules, (2) Bernoulli models, (3) discrete time Markov models, and (4) discrete event Markov models. The formalisms classify whether the models predict the occupants' adaptive actions or the state of the building components with which occupants interact. Hong et al. (2015) defined the first two model forms as implicit, and the last two as explicit. Implicit models predict the states of the building components with which occupants frequently interact, whereas the explicit models directly predict occupants' interactions with the construction components.

3.1. Building schedules

The traditional way of modeling adaptive behaviors is building schedules – e.g., presenting the ratio of the lights switched on or the mean blind occlusion rate averaged over a week or a month (Schweiker et al. 2012). Figure 1 presents the weekly lighting schedules for the two datasets. As illustrated in Figure 1, the approach provides information that is easy to interpret and does not require data from indoor environmental quality sensors. The underlying assumption of this method is steady-periodicity. In other words, the model form establishes that the time of the week or the month of the year alone is adequate to make predictions for adaptive occupant behavior. This assumption arises from the fact that indoor and outdoor environmental factors that influence adaptive behaviors tend to recur in daily or seasonal cycles. However, when a simulation expert or a building operator wants to determine the outcomes of a design or a control strategy, the indoor climatic conditions that affect the occupants' behavior will inevitably change. For example, changing the glazing material and geometry, shading material and controls, and lighting fixture and controls will change indoor environmental conditions, thereby playing a role over occupants' use of lighting. Because schedules do not incorporate indoor environmental proxies (e.g., workplane illuminance) to explain occupants' adaptive behaviors, these models may fail to mimic them under other building design and control scenarios (Hoes et al. 2009).

Figure 2: Lighting use schedule for weekdays in the two office buildings and the ASHRAE Standard 90.1 (ASHRAE 2013).

3.2. Bernoulli models

The second method used in the adaptive behavior modeling is the Bernoulli random processes (Haldi and Robinson 2008; Herkel et al. 2008). The Bernoulli behavior models predict the likelihood of finding a building component with which occupants frequently interact at a given state. Each scatter point in Figure 3 presents the ratio of the occupied duration when the lights were on to the occupied duration at varying solar irradiance levels. For example, the probability of finding the lights on when the incident solar irradiance on the façade is less than 50 $W.m^{-2}$ is 0.72 in the Ottawa building, while it is 0.74 when the horizontal solar irradiance is less than 50 $W.m^{-2}$ in the Hartberg building. This model form does not provide any information about the occupants' adaptive comfort (Gunay et al. 2015), despite being appropriate when the occupant models' purpose is to provide more realistic representation of a building's energy use. This is because occupants' adaptive actions are logical and predictable with discomfort proxies (e.g., workplane illuminance is a predictor for insufficient daylight levels). However the reversals of the adaptive action (blinds opening or light switch off) can happen long after the discomfort conditions disappear (Rubinstein et al. 1989; Foster and Oreszczyn 2001; Reinhart 2004; Sutter et al. 2006; Rijal et al. 2008). As a result, the environmental predictors often cannot explain a significant variation in the occupant controlled building components. For instance, as presented in Figure 3, even when the solar irradiance reaches to its upper limits, a considerable portion of the lights remained on in both buildings – meaning that users in these perimeter spaces do not actively adjust their blinds to exploit daylighting potential to replace electric lighting. In line with this, the blind occlusion rate exhibits no variation as a function of the incident solar irradiance on the façade of the Ottawa building – as shown in Figure 4. Although Bernoulli occupant models have been developed with both indoor and outdoor explanatory variables in the literature (Nicol and Humphreys 2004; Haldi and Robinson 2008), Gunay et al. (2016) discussed that they are more appropriate to be used with outdoor variables. This is because the adaptive behaviors trigger changes in the indoor environment, which contains both the explanatory and the response variables. For example, ratio of lights on when the workplane illuminance is less than 500 lux would be zero, if the electric lighting can provide 500 lux at the workplane when it is switched on. The advantages of developing models with outdoor variables instead of indoor variables are the reduction in the cost of sensors and data collection, and the reduced risk of gathering biased information due to the Hawthorne effect (Humphreys and Nicol 1998; Mahdavi 2011). The major weakness in using environmental conditions as the explanatory variables with the Bernoulli models is that they cannot be used in other buildings because they neglect the influence of the differences in buildings' geometry and material properties.

Figure 3: Bernoulli models predict the fraction of lights on as a function of the solar irradiance in the Ottawa and the Hartberg building. Solar irradiance values represent the incident irradiance on the façade in the Ottawa building and the horizontal irradiance in the Hartberg building.

Figure 4: A Bernoulli model predicts the blinds occlusion rate as a function of the solar irradiance in the Ottawa building.

3.3. Discrete time Markov models

The third method used in modeling adaptive behaviors is the discrete time Markov chains (Fritsch et al. 1990; Lindelöf and Morel 2006; Rijal et al. 2008; Haldi and Robinson 2009; Hong et al. 2016). The discrete time Markov models predict the likelihood of undertaking an adaptive behavior in the next timestep. They can be developed by both indoor and outdoor environmental variables because they are derived from the conditions just before occupants undertake the action. The Markov models treat adaptive actions and their reversals independently and have been suggested to predict behavior patterns more realistically. Note that realistic representation of the frequency and timing of adaptive actions can act as a proxy to occupants' comfort. From interaction with thermostats, researchers inferred thermal discomfort conditions, as well as visual discomfort conditions from overrides of lighting and blinds automation systems (Gunay et al. 2016). However, a common issue regarding the discrete time Markov models is their dependency on fixed timesteps (Gunay et al. 2014). They only provide the likelihood of an occupant action in the next timestep. The fixed timestep concept implies that the frequency of an occupant's instances of decision-making remains constant; it is logical that these cases increase in frequency during periods in which environmental conditions are rapidly changing (e.g., at arrival) (Gunay et al. 2014). Examples of the discrete time Markov models in the literature include Haldi and Robinson (2009)'s model for window opening/closing behaviors during intermediate occupancy; Haldi and Robinson (2010)'s model for blind closing/opening behaviors during intermediate occupancy; and Reinhart (2004)'s model for light switch on behavior during intermediate occupancy. Figure 5 presents two discrete-time Markov models predicting the likelihood of a light switch-on action in the next 15 min for the Ottawa building and the Hartberg building. The scatter points represent the ratio of occupied timesteps with a light switch-on action to the total number of occupied timesteps at a particular indoor illuminance level.

Figure 5: Discrete-time Markov models predicting the likelihood of a light switch-on action in the next 15 min as a function of the indoor illuminance. In the Ottawa building, the indoor illuminance measurements were taken on the ceiling and, they were taken at the workplane in the Hartberg building.

3.4. Discrete vent Markov models

Discrete event Markov models (fourth method) link an occupant action model to an external event (Reinhart 2004; Herkel et al. 2008; Rijal et al. 2008; Yun and Steemers 2008). For example, in Reinhart (2004)'s light switch model, simulated occupants are modelled to turn on their lights more likely at arrivals (event). In Rijal et al. (2008)'s window operation model, occupants were modelled to consider window opening and closing upon a change in the predicted mean vote (event) (ASHRAE 2004). In a similar fashion, Gunay et al. (2015) treated discrete events for the light switch-on behavior as a change larger than 100 lux in the workplane illuminance levels. When relevant events triggering the behavioral adaptation of the occupants can be identified, the models' predictive accuracy are shown to improve in contrast to discrete time Markov models (Gunay et al. 2015). However, the discrete event Markov modeling approach is challenged by the designation of an appropriate and significant event triggering the occupant's action, to replace the timestep concept. Another limitation of this method is that its predictive performance relies on the accuracy of the external events' predictions. For example, the predictive performance of the discrete event Markov light switch model for arrival is subject to our ability to detect the intermediate arrival and departure events accurately. Figure 6 presents two discrete-event Markov models predicting the likelihood of a light switch-on action at arrival (including the first and intermediate arrivals) for the Ottawa building and the Hartberg building. The scatter points represent the ratio of arrival timesteps with a light switch-on action to the total number of arrival timesteps at a particular indoor illuminance level.

Figure 6: Discrete event Markov model predicting the likelihood of a light switch-on action at arrival as a function of the indoor illuminance. In the Ottawa building, the indoor illuminance measurements were taken on the ceiling and, they were taken at the workplane in the Hartberg building.

3.5. Consideration on adaptive behavior regression models

The discrete likelihood's weights in adaptive behavior models (see Figure 3 to 6) are often fitted as regression models to represent the information of the model with a small number of parameter coefficients and to regularize them as continuous distributions.

In the reviewed literature on adaptive behavior modeling, two regression methods were found: (1) linear regression (e.g., linear or polynomial regression) (Warren and Parkins 1984; Inoue et al. 1988; Foster and Oreszczyn 2001; Inkarojrit and Paliaga 2004) and (2) generalized linear regression (e.g., logistic, probit regression) (Nicol 2001; Clarke et al. 2006; Rijal et al. 2007; Haldi and Robinson 2008; Inkarojrit 2008; Rijal et al. 2008; Haldi and Robinson 2009; Haldi and Robinson 2010; Haldi and Robinson 2011; Zhang and Barrett 2011; Zhang and Barrett 2012; Andersen et al. 2013; D'Oca et al. 2014).

The handicap of the linear regression is that it is not appropriate for probabilistic models where the response variables are bound between 0 and 1. Thus, the generalized linear regression has become the de-facto standard in adaptive behavior modeling (Haldi and Robinson 2011). It employs a non-linear link function (e.g., probit or logit) to map the explanatory variables (e.g., indoor temperature) onto bounded response variables (e.g., probability of observing a thermostat override). Employing the maximum likelihood method, one can develop the generalized linear models. Statistical packages for established programming environments provide built-in functions to develop generalized linear models (e.g., statsmodels in Python, glmfit or fitglm in

Matlab, glm in R-programming). Figure 7 presents a logistic regression fit for the discrete time Markov light switch-on model for the Ottawa building. The areas of the bubble plots in Figure 7 indicate the observed occupancy duration at each ceiling illuminance level. Note that the occupied durations are not homogeneously distributed at each illuminance level. Thus, an important consideration in building the generalized linear models is in binning the binomial observations (e.g., light switch on events). The model developers should ensure that the discrete likelihood of each bin is weighted proportional to the amount of the observations used in building it.

Figure 7: Probability of switching on the lights in the next 15 min (discrete time Markov) in the Ottawa Building. The univariate logistic regression model is in the following form: $p = 1/\left(1 + e^{-(a+bE_{lux})}\right)$.

The regression models can be univariate where the model is regressed with respect to a single predictor (e.g., predicting the blind closing action with the workplane illuminance) or multivariate where the model is regressed with respect to two or more predictors (e.g., predicting the blind closing action with the workplane illuminance and the indoor temperature). As stated in Haldi and Robinson (2011), increasing the number of predictors will provide diminishing improvements in the predictive accuracy. For the evaluation of the regression models, when the dataset is large enough to be partitioned into training and validation sets, the cross-validation method can be employed to ensure models' fitness (Haldi and Robinson 2009; Haldi and Robinson 2010). If a model does not over fit, the model developed by the training set would be in agreement with the model developed by the data retained for the validation. Alternatively, the relative model quality can be assessed by computing the Akaike or the Bayesian information criteria. For example, Figure 8 contrasts the quality of two univariate logistic regression models (discrete time and discrete event Markov models) for the same dataset from the Ottawa building. By looking at the Akaike information criterion values (smaller values are favorable), the discrete time model appears to be a relatively better model for the dataset. Another metric for the assessment of the regression models is R-squared. Note that for binomial data, ordinary R-squared should not be used. If needed, the modellers should use pseudo-R-squared values to assess the fitness of the model. The readers can refer to McCullagh and Nelder (1989) for further information on generalized linear model development, selection, and validation procedures.

Figure 8: Probability of switching on the lights in the next 15 min (discrete time Markov) and at arrival (discrete event Markov) in the Ottawa Building. The univariate logistic regression model is in the following form: $p = 1/\left(1 + e^{-(a+bE_{lux})}\right)$. *The properties of the regression parameters were annotated in the figure.*

4. Modeling non-adaptive behaviors

The non-adaptive behaviors such as plug-in appliance use, light switch off, and blind opening are driven primarily by contextual factors rather than physical discomfort. In the reviewed literature, three modeling methods have been identified for non-adaptive behavior modeling: (1) building schedules (e.g., Masoso and Grobler 2010; Menezes et al. 2012), (2) using the occupancy schedules (Mahdavi and Pröglhöf 2009), and (3) building survival models (Haldi 2010; Parys et al. 2011).

4.1. Building schedules

Similar to the adaptive behaviors, the traditional way of modeling non-adaptive occupant behaviors is building weekly schedules. For example, Figure 9.a presents the mean weekday plug-in appliance load intensity in the Ottawa building. This method may be appropriate for modeling the non-adaptive occupant behaviors if they are developed for different building archetypes – at a resolution higher than the current 16 reference commercial building models (Deru et al. 2011). Note that the Ottawa building had substantially different plug-in equipment schedules from the ASHRAE (2013) reference office building (see Figure 9.a). This difference can be explained by the fact that the schedules neglect the relationship between the behavior and the building occupancy.

4.2. Occupancy schedules

The low-occupancy Ottawa office building and the ASHRAE (2013) reference office building appeared to have similar plug-in appliance load intensities when they were normalized with the occupancy rate (see Figure 9.b). Using the occupancy schedules is the second model form found in the reviewed literature for the non-adaptive behavior modeling (Mahdavi and Pröglhöf 2009).

Figure 9: The average plug-in appliance load intensity on a weekday in the Ottawa building as (a) a schedule and (b) its relationship with the mean occupancy rate.

4.3. Survival models

The third method used in modeling non-adaptive behaviors is the survival models. The survival models found in the reviewed literature predict the lifetime of an occupant action or the state of a building component with which occupants interact (Haldi 2010; Parys et al. 2011). For example, the likelihood of a light switch off action at departure was modeled to increase as a function of the duration of absence following the departure (Boyce 1980; Pigg et al. 1996; Mahdavi and Pröglhöf 2009). In a similar fashion, the plug-in appliance load intensities during vacancy periods were modeled as a function of the duration of the vacancy period (Gunay et al. 2016). The survival models exploit the availability of matching occupancy data to elaborate the relationship between the non-adaptive behaviors and the occupancy/vacancy state, albeit with the added complexity to collect concurrent occupancy data. Figure 10 presents three survival models built upon the data gathered from the Ottawa building. The first one (Figure 10.a) presents the survival model for the time between consecutive blinds closing and opening actions. Results indicate that in 30% of the cases it takes more than a week to reopen the blinds once they are closed. This is in line with the literature suggesting that the users' blind opening behavior is quite infrequent (O'Brien et al. 2013). The second example (Figure 10.b) presents the ratio of departures with a manual light switch off action (when the lights were on) to the total number of departures as a function of the duration of absence. The results indicate that in almost 70% of the cases the users left their dimmable and motion detector automated idling artificial lighting (with a 30 min delay) during intermediate breaks. The third example (Figure 10.c) presents the plug-in appliance load intensities during vacancy periods as a function of the duration of the absence. The model was established upon the mean plug load values at varying durations of absence. The scatter points represent the mean plug load measured at different periods of occupancy/vacancy – in 12 h bins. Results indicate that the mean plug-in equipment load per occupant was about 8 $W.m^{-2}$ during occupancy, and it decreased to 3 $W.m^{-2}$ during absences longer than three days. This can be interpreted as occupants' tendency to turn off their plug-in equipment increases as a function of the duration of their absence. The model mimics this behavior through a regression model in which the mean plug load exponentially reduces as a function of the length of absence.

Figure 10: Different survival models built upon the data gathered from the Ottawa building: (a) time between consecutive blinds closing and opening actions, (2) likelihood of a light switch off at departure as a function of the duration of absence, and (3) plug-in appliance load intensity during vacancy as a function of the length of the absence period.

5. Modeling presence

Evidently, occupants' behaviors are conditional upon their presence. It is, therefore, essential to understanding and characterizing the randomness inherent in occupants' presence patterns to represent their behaviors realistically (Robinson et al. 2011). In modeling presence in buildings, three different methods have been typically adopted: (1) schedules (Chang and Hong 2013; Duarte et al. 2013), (2) discrete time Markov models (Parys et al. 2010; Wang et al. 2011; Andersen et al. 2014), and (3) survival models (Wang et al. 2005).

5.1. Occupancy schedules

The most common method is building weekly occupancy schedules – presenting the likelihood of presence as a function of the time of day and the day of the week (Gunay et al. 2015; Mahdavi and Tahmasebi 2016). Figure 11 presents the weekday occupancy schedule in the two office buildings and the ASHRAE Standard 90.1 (ASHRAE 2013). Results indicate that the occupancy in the Hartberg building peaks in the morning, whereas the occupancy in the Ottawa building peaks in the afternoon. The occupancy rates in the Ottawa building – an academic office building used by professors – was noticeably lower than the Hartberg building –a government building used by municipal employees. However, the occupancy rates in both buildings were substantially lower than those recommended by the ASHRAE Standard 90.1 (ASHRAE 2013). The advantage of this model form is that it is easy to interpret by building operators and controltechnicians.

Building specific occupancy schedules provide valuable insights that can help operators choose operating schedules. Simulation experts can incorporate them quickly in building models to represent occupancy. Recently, Mahdavi and Tahmasebi (2015) introduced a method to generate occupancy time-series data (i.e., sequential presence and absence information) from an occupancy schedule.

Figure 11: Occupancy schedule for weekdays in the two office buildings and the ASHRAE Standard 90.1 (ASHRAE 2013).

5.2. Discrete time Markov models

The second method used in occupancy modeling is the Markov chains (Page et al. 2008; Wang et al. 2011). The model predicts the likelihood of an arrival when occupants are absent, and it predicts the probability of a departure when occupants are present. For example, Figure 12 presents discrete time Markov models predicting the probability of observing a first arrival or a last departure in the next hour based on the two example datasets (Harberg and Ottawa buildings). The models were built by computing the ratio of the number of first arrivals (last departures) to the total number of unoccupied duration (occupied duration) at a certain hour of a weekday. Results indicate the occupants in the Hartberg building tend to arrive earlier and leave later than the occupants in the Ottawa building. The occupants' first arrival and last departure distributions exhibit a rather weak bimodality in the Ottawa building; meaning that occupants' first arrivals may take place in the afternoon, or their departures can occur in the morning. This type of behavior was not observed in the Hartberg building. The strength of this approach – unlike the traditional schedule-based models – lies in the fact that the likelihood of observing an arrival or a departure from the rest of the day can be estimated given current time and the current state of presence. This may help to make midday control decisions such as temperature setbacks when the likelihood of observing an arrival is slight for the rest of day (Gunay et al. 2015). The Markov occupancy models are also capable of creating realistic occupancy time-series which can be used in building performance simulation (BPS) models (Chang and Hong 2014). A weakness of the Markov occupancy models is that they treat arrival and departure events independently. In reality, occupants may depart early when they arrive early or they may depart late when they arrive late (Page 2007).

Figure 12: Discrete-time Markov models providing the likelihood of observing a first arrival or a last departure in the next hour on a weekday.

5.3. Survival models

Survival models (the third method) appear to be a promising alternative to tackle the limitation with Markov occupancy models as explained in Section 5.2 (Parys et al. 2011). Survival models can predict the duration of an intermediate vacancy period following a departure, or they can predict the length of an intermediate occupancy period upon an arrival (Wang et al. 2005).

Figure 13 presents survival models predicting the duration of an uninterrupted intermediate occupancy/vacancy period for the two example datasets (Hartberg and Ottawa building). Results indicate that more than 30% of the intermediate vacancy periods were longer than 1.5 h in the Hartberg building. This was about 2.5 h in the Ottawa building. Similarly, 30% of the uninterrupted intermediate occupancy periods were longer than 1 h in the Hartberg building. This was about 2 h in the Ottawa building. Therefore, the occupants in the Ottawa building tend to stay in their offices for longer periods without taking breaks. However, their intermediate breaks tend to persist longer than those in the Hartberg building.

Figure 13: Survival models predicting the duration of an intermediate vacancy or presence period.

6. Discussion

The modeling methods discussed in this paper have specific strengths and weaknesses. Nonetheless, depending on the nature of the use cases involved, they can be gainfully deployed in the BPS-based design process. Accordingly, Tables 2 to 4 provides a summary of the occupant modeling forms with regard to their use cases, as well as strengths, and weaknesses.

6.1. Use cases for occupant behavior modeling approaches

Some of the inappropriate use cases found in the literature – which are suggested to avoid in future research – can be listed as follows:

- *Schedules* and *Bernoulli models* for adaptive behaviors should not be used in comparing design alternatives that affect the distribution of the indoor physical stimuli of the behavior (Hoes et al. 2009). For example, changing the window-to-wall ratio will influence the users' lighting and blind use behaviors (Gilani et al. 2016). Similarly, simple variations in the interior shading systems (e.g., addition of lightshelves) can affect users' lighting use behavior significantly (Sanati and Utzinger 2013). However, the schedules and Bernoulli models (developed upon outdoor conditions) will not be able to mimic the changes in users' behaviors as they overlook the link between the indoor climate and the user behavior.
- *Bernoulli models* should not be developed with indoor environmental variables affected by the behavior – e.g., developing Bernoulli lighting use models with workplane illuminance data or developing Bernoulli window use models with indoor temperature data (Haldi and Robinson 2008; Gunay et al. 2015). For example, when the lights are switched on in a typical office environment, the workplane illuminance would not fall below 300-500 lux. As a result, the model predictions for the ratio of lights on become dependent on the lighting state. Note that this is not an issue for the Markov models as they use the conditions just before the adaptive actions take place.
- *Discrete-time Markov models* predict the likelihood of an occupant action in the next timestep (Haldi 2010). The modelers should report these timesteps, which must be implemented into the BSP correspondingly. *Discrete-event Markov models* predict the

likelihood of an occupant action at an event instance. Moreover, the modelers should define these event steps in which the occupant models will be invoked, and then stick to them in the energy simulation phase. Some of the early examples of occupant models found in the reviewed literature (e.g.,Hunt 1979) did not report when these models should be called during simulation (Gunay et al. 2016).

- *Survival models* should not be used for adaptive behavior modeling. For example, when Haldi and Robinson (2009) developed survival models to predict the duration windows remain open, they had to vary the shape of the survival model for different indoor and outdoor temperatures because the window closing behavior is influenced by the indoor and outdoor temperatures. Given that the indoor and outdoor temperatures can change substantially in time, the opening durations predicted by the survival model can become inappropriate before the predicted opening period elapses. Because the contextual factors mostly drive the non-adaptive behaviors instead of the indoor climate variables, the survival analysis is more appropriate in modeling non-adaptive behaviors.

6.2. Strengths and weaknesses of occupant behavior modeling approaches

Some of the strengths and weaknesses of occupant behavior modeling approaches emerged from the critical review of the literature – which are suggested to consider in future research – can be listed as follows:

- The main advantage of using *schedules* of occupant behavior is their ease of development, and application to a wide array of adaptive behaviors and building archetypes. The strength of average values model form is that only a single data type is necessary to build it and it is easy to interpret for building operators and simulators. For this reason, schedules have been extensively embedded in BEMs and introduced as recommended indices values for EU (UNI EN 15251) and US international specification for occupant comfort conditions and criteria (ASHRAE 90.1). Conventionally, building energy models represent occupants via standard design conditions – occupancy levels, ventilation rates, thermostat set points – illustrated by means of schedules and threshold values, without detailed consideration of occupancy or indoor and outdoor environmental parameters. One of the drawbacks of such standard schedules is their intrinsic weakness in sufficiently capturing diversity of building types, since different design alternatives are not studied, and individual behaviors, demonstrated varying up to a factor of 10 in even identical buildings (Dong et al. 2013), as well as actual system operation and control of IEQ level. In other words, the model form establishes that the time of week or the month of year alone is adequate to make predictions for the occupant behavior and presence. This assumption arises from the fact that occupancy and indoor and outdoor environmental factors that influence adaptive behaviors tend to recur in daily or seasonal cycles. However, when a building designer or operator wants to find out the outcomes of a design or a control strategy, the indoor climatic conditions that affect the occupants' behavior will inevitably change for different design alternatives. Because the average value models do not incorporate the indoor environmental proxies (e.g., work plane illuminance) to explain occupants' adaptive behaviors, these models will fail to mimic them under other building design and control scenarios. Moreover, the same occupant may respond differently, on different occasions, even in response to identical adaptive and non-adaptive stimuli; we may also encounter considerable differences in responses between individuals to identical stimuli (O'Brien and Gunay 2014, Fabi et al. 2012). This randomness can have significant implications for building energy demand, leading to inconsistencies between simulated and actual building energy performance (Turner and Frankel 2008).

- The *Bernoulli processes* provide some improvements in explaining correlations on the actual dynamic processes leading occupants to perform adaptive actions. As a correlated drawback, incorrect formulation of the correlation assumptions might lead to unanticipated fallacies in predicting behavioral adaptation. Moreover, this dependency from explanatory variables, make it unusable for even identical buildings. Another limitation derives from their nature to model behavior indirectly. Models are developed based on observations of a building component states (for example window states), but not the actual actions on it (window opening or closing). In other words, these models do not describe an actual probability of window opening or closing, but a probability for a window to be found open, provided relevant physical parameters. Furthermore, Bernoulli processes ignore the particular patterns caused by occupancy events, like arrivals or departures of occupants. Instead, such models describe direct correlation between control system state and occupant behavior via some sort of correlation model. However, since adaptive behaviors are implicitly modeled based on state of building components assumed as proxy for adaptive actions, there will be no need for human sensing, survey or feedback to build behavioral models. This leads to avoiding occupants reporting monitoring fatigue over time or sensor placing issues.
- *Discrete-time Markov Models* become popular among the research community because of the straightforwardness of pairing consecutive repetitive probabilities of explicit actions with some simulated changes in environmental conditions. This means Markov models fit simulation processes in BEMs in terms of discrete-time steps. Also, discretizing adaptive behavior in fixed time steps allows the possibility of coupling multiple behavioral models, solving different prediction probabilities in the same BEM. However, in reality, occupants' adaptive actions are events taking place at irregular time distance, which cannot be discretized over time. In such view, discrete-time Markov models fail to capture patterns of behavior, if some exists. As an example, occupants tend to close their blinds when it is bright; but they tend to forget them closed when the ambient conditions change and the risk of glare diminishes. Discrete-time Markov lighting and blinds use models are able to mimic this better than the Bernoulli lighting and blinds use model, because they predict the light switch or the blind closing/opening actions instead of the light state or the blind occlusion rate (Gunay et al, 2015). Discrete-time Markov models – unlike occupancy schedules – can represent the frequency and timing of the arrivals and departures. However, the major drawback of this model form is the arrival and departure events are independence from each

other. The other weakness of the discrete-time Markov models that utilize the environmental conditions as proxies is that they cannot be transferred to other buildings.

- *Discrete-event Markov Models* link the calling points of an occupant action model to an external event. This modelling approach can address some of the limitations of the aforementioned methodologies. It overcomes barriers of using fixed average values (schedules), implicit modeling adaptive action based on variables influencing state of building components (Bernoulli models), and discretizing adaptive behaviors in prescribed time steps — inherent in discrete-time Markov models. It is, however, challenged by finding an appropriate event definition to replace the time step concept. Another limitation of this approach is that its predictive performance relies on the accuracy of the external events' predictions, and stochasticity in the modeling results may not be easy to interpret.
- *In survival models*, the ratio of the "state" or the "state-transition" of an occupant behavior is modeled based on the variation of some identified stimuli. This makes the modeling approach suitable for transferability to other building models and archetypes. The limitation of this model form is that its predictive performance relies on the accuracy of the occupancy model to describe the zone level occupancy patterns. In contrast to deterministic schedules, the advantage of the survival model form is that it can be compatible with buildings with different occupancy patterns than it is derived from. While discrete-time Markov occupancy models may fail to capture potential dependencies between arrival and departure times – because they treat these two variables independently – survival model form can tackle the limitations, by linking the timing of the arrival and departure events with each other. Survival models can infer the relationship between the arrival and departure events by predicting the length of the occupancy/vacancy periods. However, because they are continuous time random processes, the rounding errors can be significant when used with large timesteps in BPS.

Table 2: Use cases, strengths, and weaknesses of formalisms for adaptive behavior modeling (operable window use, window blind closing, light switch on, thermostat use, and clothing adjustment).

Table 3: Use cases, strengths, and weaknesses of formalisms for non-adaptive behavior modeling (plug-in appliance use, light switch off, and window blind opening).

Table 4: Use cases, strengths, and weaknesses of formalisms for presence modeling.

6.3. Unresolved modeling issues and future requirements.

The first main question when looking for a model of occupant behavior is the model choice. Actually, the selection of a behavioral model depends mainly on a data set and the quality of the data themselves. Starting from a monitoring campaign of both indoor and outdoor environmental conditions, a crucial point is defining the best model able to describe correctly the relationship between occupants and the monitored variables. In this, models should strive to achieve a compromise between complexity and usability. A sufficient set of estimated model parameter coefficients or explanatory variables that genuinely influence observed actions must be isolated, to infer a model formulation, which adequately describes these relationships.

A following point regards the way to consider adaptive action themselves performed by users. The most common approach to thinking of them is to define separately the prediction of actions and the assessment of comfort. One suggestion is to take account of comfort and actions just as a single concept and to assess the impact of measures on comfort using adaptive increments. This incremental concept could allow then to express the impact of physical environmental variables, for example air temperature or CO_2 concentration, changed according to the occupants' adaptive actions. These adaptive increments then could match with physical environmental factors, psychological (or physiological) factors and the possibility to act on the environment. Some adaptive actions do not have a binary nature like the opening and closing of windows, switching on and off fans or consumption or not of drinks, but can rather be integrated incrementally or on a continuous basis. This is the case – just to mention – of clothing level or the use of blinds. Occupants have been found to not change blind positions or change their clothing insulation frequently (Robinson and Haldi 2011). Because some behaviors are so rarely executed, and because it becomes very expensive (and time consuming) to gather an adequate dataset, this raises the question whether or not having a dynamic adaptive behavioral model is necessary.

The accuracy and appropriateness of occupant models are dependent on the quality of the data used to develop them. The challenge in gathering occupant behavior/presence data from buildings in use extends beyond selecting the suitable sensors as indicators of the behavior to placing them considering the contextual factors. For example, workplane illuminance measurements, despite being common in occupant comfort and behavior research, can become susceptible to user actions such as placing an object that covers the sensor. There is a need for guidelines to collect in-situ data to be used in occupant modeling. The guidelines should entail a standard method to report contextual factors as well as recommendations for sensor types and placement.

The reference commercial building archetypes commonly used in North America (Deru et al. 2011) and in Europe (Schimschar et al. 2011, Mata et al. 2013) should be refined with the insights acquired in studying occupant behavior and presence. For example, as shown in this study, the occupancy patterns in an academic office building can be vastly different from an office building used by public employees – while the data from both buildings are greatly distinct from the current modeling practice (ASHRAE 2013).

7. Conclusions

In this paper, a critical review of the occupant modeling methodologies from the literature was conducted. The occupant models were categorized into three groups: (1) adaptive behavior models, (2) non-adaptive behavior models, and (3) occupancy models. The adaptive behaviors are occupant actions undertaken primarily to restore occupant comfort – e.g., light switch-on, blinds closing, thermostat use, window use, and clothing adjustments. The non-adaptive behaviors are actions mainly driven by contextual factors rather than physical discomfort – e.g., plug-in appliance use, light switch off, and blind opening. The occupancy models predict occupants' presence, arrival/departure patterns, and the duration of vacancy/occupancy periods.

In the reviewed literature, the adaptive behavior models were developed as weekly schedules, Bernoulli models, and discrete time and discrete event Markov models. The Bernoulli models predict the ratio of active adaptive states as a function of the explanatory variables (e.g., ratio of lights switched on at a certain outdoor illuminance level). The Markov models predict the likelihood of an adaptive action as a function of the explanatory variables (e.g., probability of a light switch-on in the next timestep for the discrete time Markov models or in the next event step such as at next arrival for the discrete event Markov models). The non-adaptive behavior models were developed as weekly schedules, survival models, or by using the occupancy schedules from a similar building. The survival models for non-adaptive behaviors predict the lifetime of an occupant action or the state of a building component with which occupants interact (e.g., lifetime of a blind position before it is changed). The occupancy models were developed as weekly schedules, discrete-time Markov models predicting the timing and frequency of the arrivals/departures, and survival models predicting the duration of an uninterrupted occupancy/vacancy period.

Illustrative examples were developed upon two independent datasets from an academic office building in Ottawa, Canada and from a government building in Hartberg, Austria. Based on the literature and the analyses of these datasets, the strengths, weaknesses, and use cases of each model form were discussed.

The critical analysis of existing models, the test of some illustrative example and a discussion of empirical and simulation outcomes of research lead to the conclusion that discrete-event Markov models could address a number of weaknesses observed by other modeling approaches.

However, the truthfulness and suitability of model selection is function of the specific use cases for occupant behavior modeling approaches. Some of the inappropriate use cases found in the literature have been highlighted and listed, in a way to drive modelers away from fallacies and misusages in future research. Moreover, the absence of comprehensive datasets with indoor and outdoor environmental indicators from different building archetypes remains a fundamental limitation in occupant modeling methodology choices.

Authors stress the need for an occupant modeling data repository where researchers can exchange open source and candid information resources. However, data privacy and disclosure remains a challenging matter in studying human subjects.

The principal obstacle to the wider use of occupant behavior models remains the lack of quality-validated models to support the choice of the appropriate probability distribution for the random variables of the models. Nevertheless, only few models have been ever gone through a real validation process (Schweiker et al. 2012, Andersen et al. 2016).

In these perspectives, future work recommendations are developed. Further steps of research will embrace the application of a standardized ontology and data formatting for systematically including a large number of model forms – including but not limited to the ones discussed in this paper – to be shared with the research community as a whole (Hong et al. 2015).

New modelling methods (e.g., ANNs, fuzzy logic, etc.), and their inherent modeling characteristics need to be further investigated. Also, new ways to incorporate softer attributes (i.e., contextual factors, social norms, personal norms, etc.) as a predictor variable of adaptive behavior need to be tested. It is currently undefined how to apply stochastic models of occupant behavior in open-plan spaces, where multiple occupants having variable schedules and behaviors must be characterized. How to represent the social and contextual interferences of group behavior with respect to energy use in buildings is an unexplored field.

In this context, a multidisciplinary research approach to energy-related occupant behavior is foreseen as a way to explore practices and solutions that could overcome limitation and shortcomings in the state-of-the arte research field.

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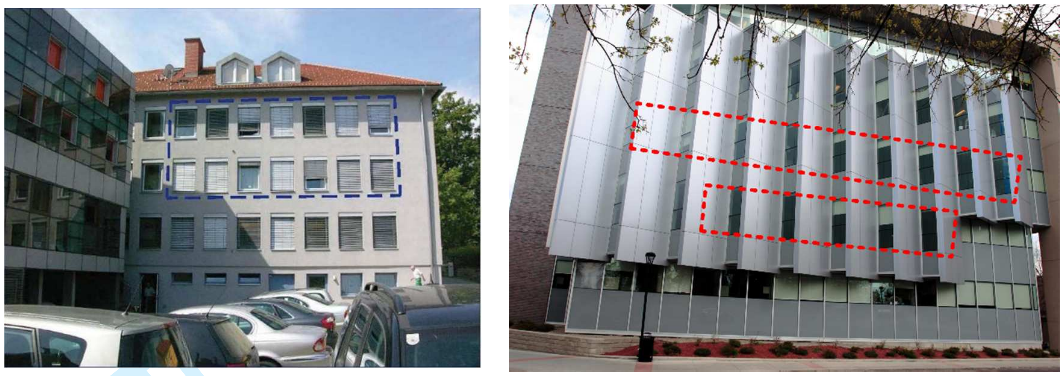

Figure 1: The buildings from which the datasets were collected (left image is Hartberg Building, and the right image is Ottawa Building).

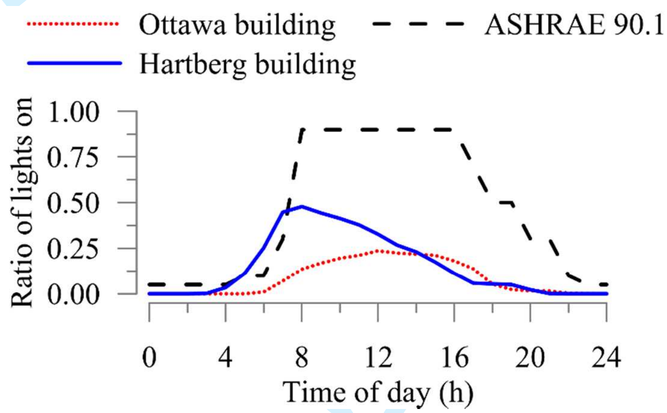

Figure 2: Lighting use schedule for weekdays in the two office buildings and the ASHRAE Standard 90.1 (ASHRAE 2013).

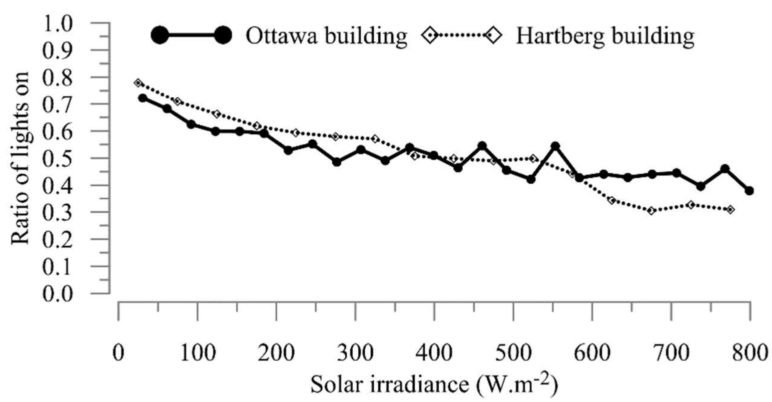

Figure 3: Bernoulli models predict the fraction of lights on as a function of the solar irradiance in the Ottawa and the Hartberg building. Solar irradiance values represent the incident irradiance on the façade in the Ottawa building and the horizontal irradiance in the Hartberg building.

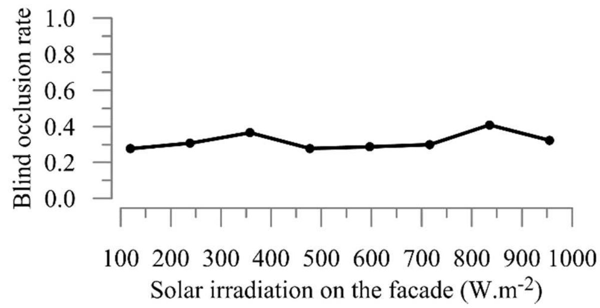

Figure 4: A Bernoulli model predicts the blinds occlusion rate as a function of the solar irradiance in the Ottawa building.

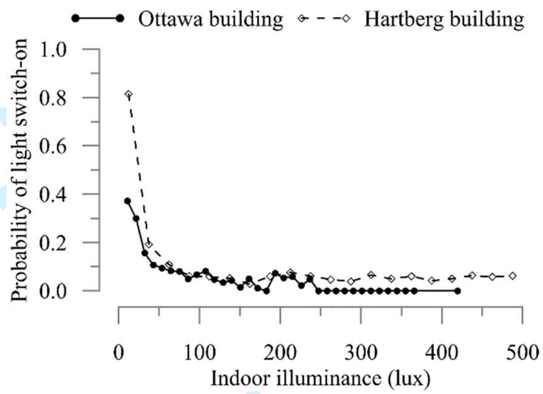

Figure 5: Discrete-time Markov models predicting the likelihood of a light switch-on action in the next 15 min as a function of the indoor illuminance. In the Ottawa building, the indoor illuminance measurements were taken on the ceiling and, they were taken at the workplane in the Hartberg building.

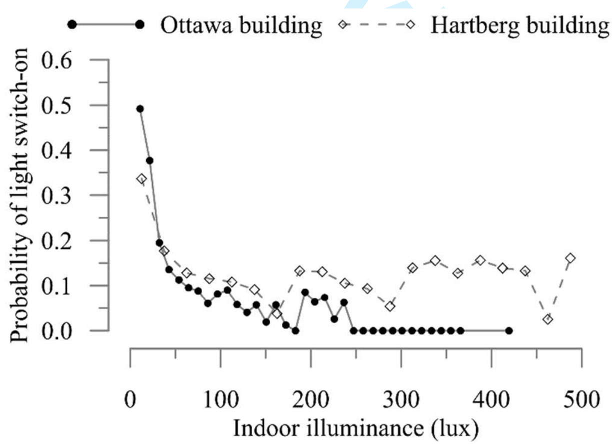

Figure 6: Discrete event Markov model predicting the likelihood of a light switch-on action at arrival as a function of the indoor illuminance. In the Ottawa building, the indoor illuminance measurements were taken on the ceiling and, they were taken at the workplane in the Hartberg building.

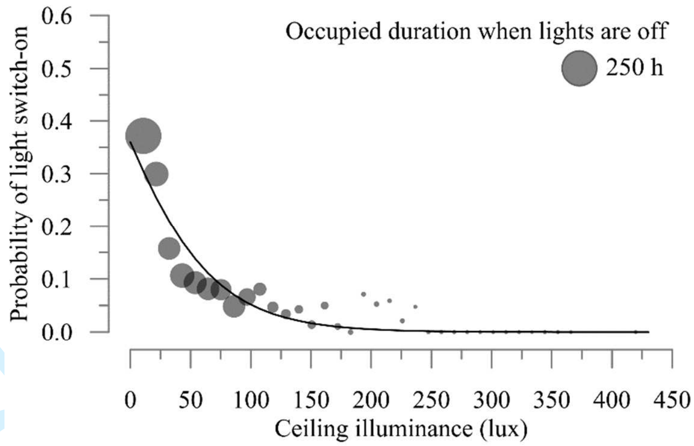

Figure 7: Probability of switching on the lights in the next 15 min (discrete time Markov) in the Ottawa Building. The univariate logistic regression model is in the following form: $p = 1/\left(1 + e^{-(a+bE_{lux})}\right)$.

Discrete-time logistic fit properties

	Coefficients	Standard Error	p-value		
				AIC	216
a	-0.573	0.063	0.000	**Null deviance**	731
b	-0.023	0.001	0.000	**Residual deviance**	123

Discrete-event logistic fit properties

	Coefficients	Standard Error	p-value		
				AIC	242
a	-0.171	0.067	0.011	**Null deviance**	824
b	-0.026	0.001	0.000	**Residual deviance**	150

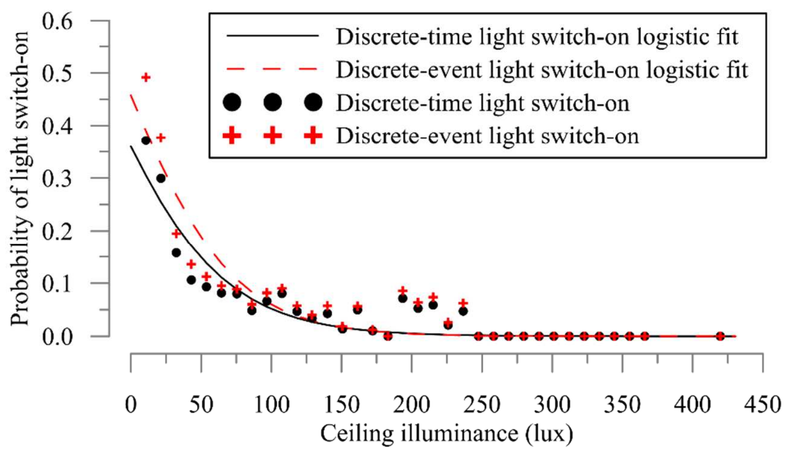

Figure 8: Probability of switching on the lights in the next 15 min (discrete time Markov) and at arrival (discrete event Markov) in the Ottawa Building. The univariate logistic regression model is in the following form: $p = 1/\left(1 + e^{-(a+bE_{lux})}\right)$*. The properties of the regression parameters were annotated in the figure.*

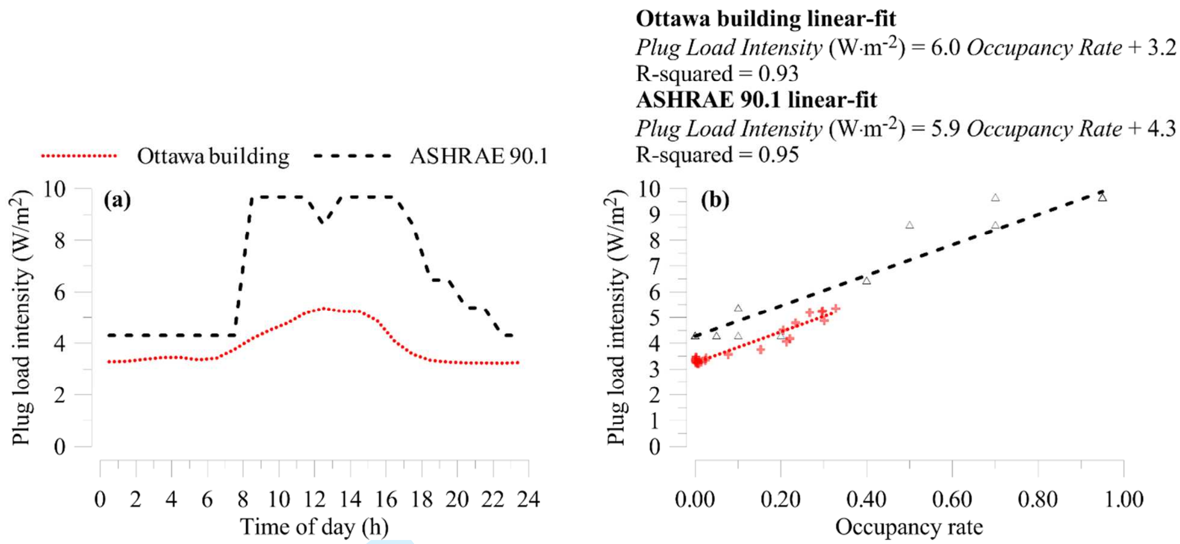

Figure 9: The average plug-in appliance load intensity on a weekday in the Ottawa building as (a) a schedule and (b) its relationship with the mean occupancy rate.

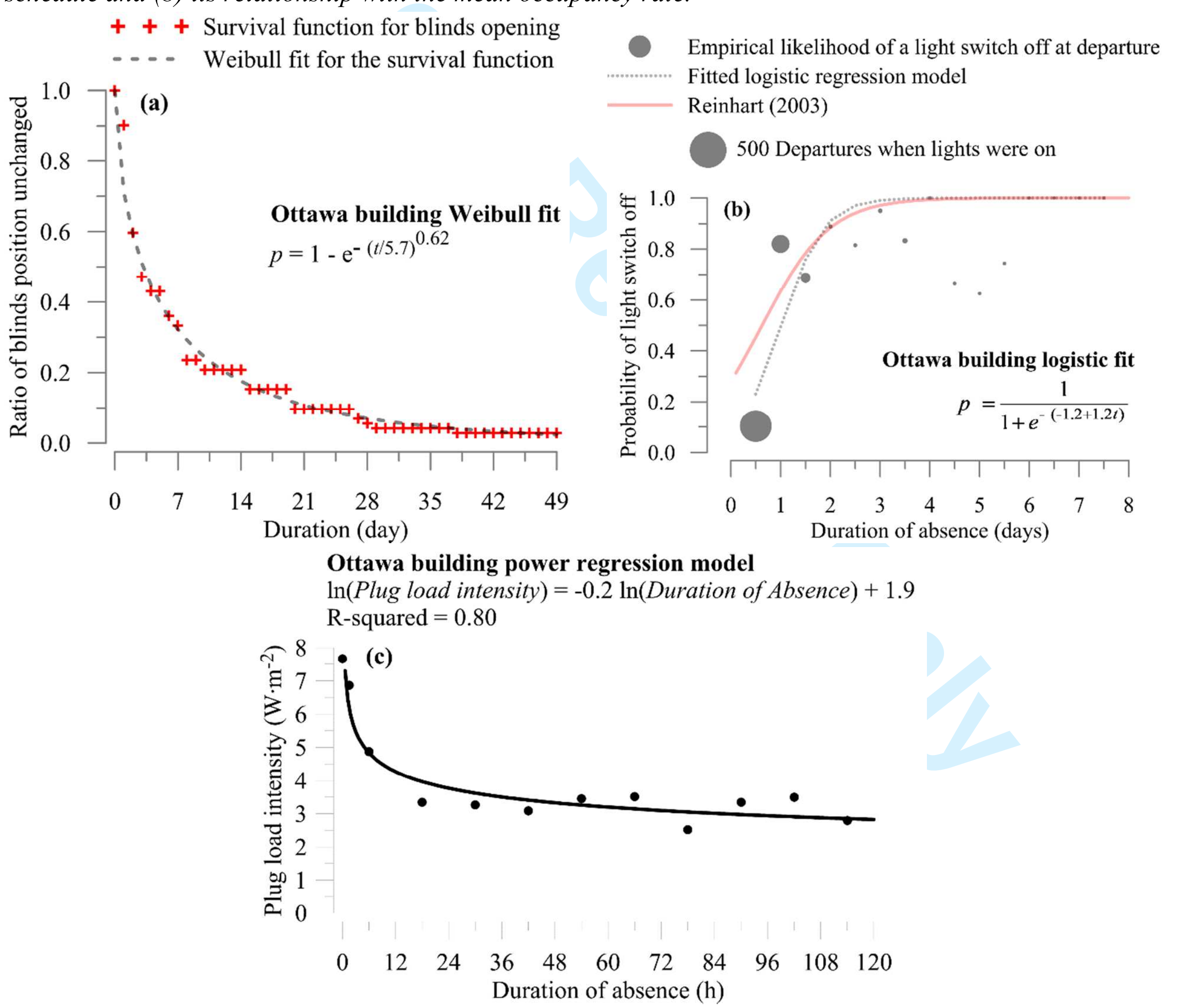

Figure 10: Different survival models built upon the data gathered from the Ottawa building: (a) time between consecutive blinds closing and opening actions, (2) likelihood of a light switch off at departure as a function of the duration of absence, and (3) plug-in appliance load intensity during vacancy as a function of the length of the absence period.

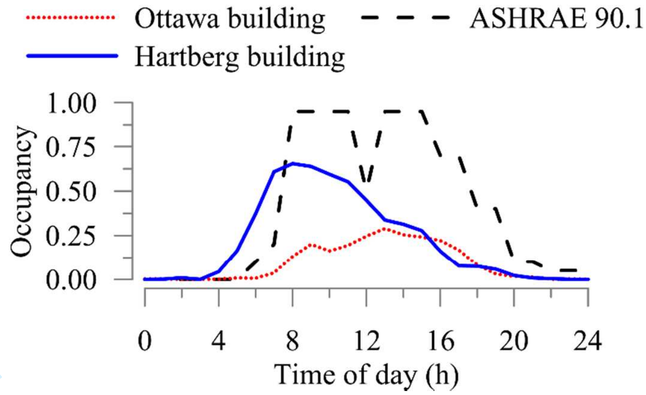

Figure 11: Occupancy schedule for weekdays in the two office buildings and the ASHRAE Standard 90.1 (ASHRAE 2013).

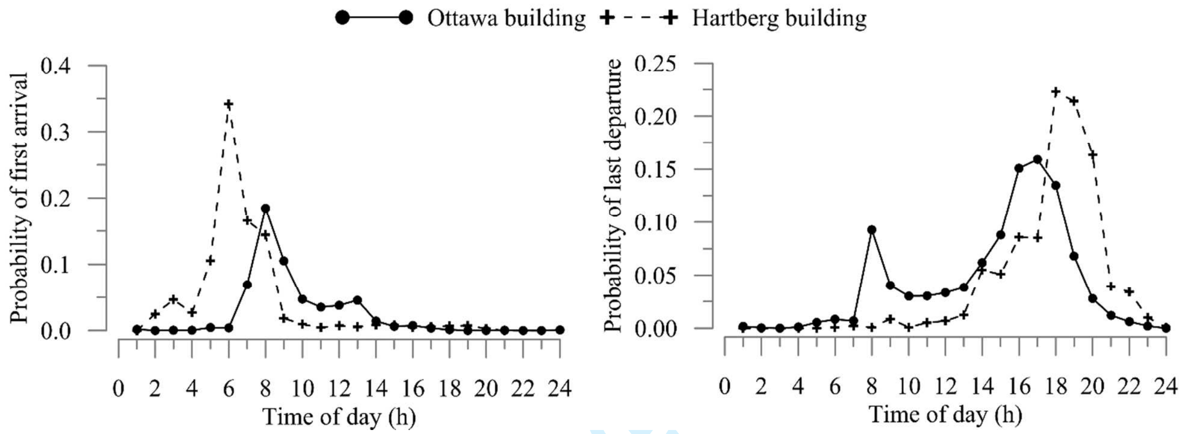

Figure 12: Discrete-time Markov models providing the likelihood of observing a first arrival or a last departure in the next hour on a weekday.

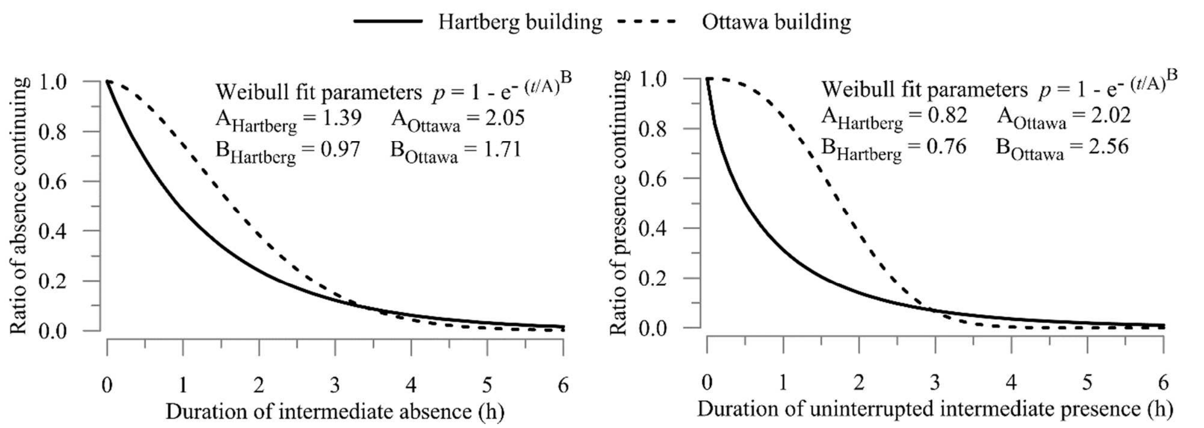

Figure 13: Survival models predicting the duration of an intermediate vacancy or presence period.

Table 1: Overview of the datasets employed in building the illustrative examples.

Data type	Hartberg Building, Austria	Ottawa Building, Canada
Lighting state Occupancy	4 shared and 2 private offices Nov 2005 – Aug 2006	10 private offices Jan 2012 – Apr 2016
Blinds state	–	10 private offices Feb 2014 – Nov 2016 Sampling in 30 min intervals
Plug loads	–	10 private offices Nov 2014 – Mar 2016 Sampling in 60 min intervals
Indoor illuminance	Workplane illuminance sensors 4 shared and 2 private offices Nov 2005 – Aug 2006 Sampling in 5 min intervals	Ceiling illuminance sensors 10 private offices Mar 2015 – Apr 2016 Sampling in 15 min intervals
Solar irradiance	Global horizontal radiation Nov 2005 – Aug 2006 Sampling in 5 min intervals	Incident solar irradiance on the facade Oct 2013 – Mar 2016 Sampling in 15 min intervals

Table 2: Use cases, strengths, and weaknesses of formalisms for adaptive behavior modeling (operable window use, window blind closing, light switch on, thermostat use, and clothing adjustment).

Schedules (Figure 2)	**Use cases:** They can be used for a similar building archetype, and if different design alternatives are not studied.	**Strengths:** • Easy to develop, interpret, and use in BPS. • Indoor or outdoor climate data are not required. **Weaknesses:** • Lack of transferability • Limitations of the use cases lead to widespread misuse • Provides no insight about the user's adaptive comfort
Bernoulli models (Figures 3 and 4)	**Use cases:** Same as the schedules.	**Strengths:** • No indoor climate data are required. • Provides some improvements in explaining the adaptive behaviors at different climatic conditions. **Weaknesses:** • Same as the schedule-based models. • They require concurrent occupancy and outdoor climate data.
Discrete time Markov (Figure 5)	**Use cases:** They can be used in other buildings, if the contextual factors are similar.	**Strengths:** • Transferability to other building types. • Ability to mimic the adaptive behaviors. **Weaknesses:** • Stochasticity in the modeling results may not be easy to interpret. • Concurrent indoor and/or outdoor climate data and occupancy data required. • Dependence on fixed and prescribed timesteps.
Discrete event Markov (Figure 6)	**Use cases:** Same as the discrete time Markov models.	**Strengths:** • Same as the discrete time Markov models with the exception that they can tackle the timestep dependency issues **Weaknesses:** • Same as the discrete time Markov models except that they also need to predict the events triggering the simulation step accurately.

Table 3: Use cases, strengths, and weaknesses of formalisms for non-adaptive behavior modeling (plug-in appliance use, light switch off, and window blind opening).

Schedules (Figure 9.a)	**Use cases:** They can be used for a similar building occupancy characteristics and if different design alternatives are not studied.	**Strengths:** • Easy to develop, interpret, and use in BPS. **Weaknesses:** • Neglect the connection between occupancy state and behavior. • Limitations of the use cases lead to widespread misuse.
Using the occupancy schedules (Figure 9.b)	**Use cases:** Can be used if an occupancy schedule is available from a building with similar occupancy characteristics.	**Strengths:** • Acknowledges the relationship between occupancy and behavior. **Weaknesses:** • Neglects the variations in the behavior patterns at different vacancy periods.
Survival models (Figure 10)	**Use cases:** They can be used in other buildings, if the contextual factors are similar.	**Strengths:** • Elaborates the relationship between the vacancy state and behavior patterns. • Transferability to other building types. **Weaknesses:** • Requires concurrent occupancy data records to develop.

Table 4: Use cases, strengths, and weaknesses of formalisms for presence modeling.

Schedules (Figure 11)	**Use cases:** They can be employed if they were designed for similar building occupancy characteristics.	**Strengths:** • Easy to develop, interpret, and use in BPS. **Weaknesses:** • Zone level arrival/departure patterns cannot be represented realistically. • Limitations of the use cases lead to widespread misuse.
Discrete-time Markov (Figure 12)	**Use cases:** They can be used in other buildings if the contextual factors are similar.	**Strengths:** • They can generate realistic zone arrival/departure patterns. **Weaknesses:** • They treat arrival and departure events as independent from each other.
Survival models (Figure 13)	**Use cases:** They can be used in other buildings if the contextual factors are similar.	**Strengths:** • Elaborate the relationship between the arrival/departure events by predicting the length of the occupancy/vacancy periods. **Weaknesses:** • Because they are continuous time random processes, the rounding errors can be significant when used with large timesteps in BPS.

MODELING

LACK OF COMMON AGREEMENT ON VALIDITY AND EFFECTIVENESS OF OB MODELING AND SIMULATION APPROACHES

WHICH ARE THE STRENGTHS, SHORTCOMINGS AND NEEDS OF OB MODELING AND SIMULATION METHODOLOGIES?

PAPER 5 **S. D'Oca,** H.B. Gunay, S. Gilani, W.L. O'Brien, V. Fabi, S. Corgnati, A. Mahdavi
A review of the occupant modeling approaches in offices with illustrative examples
Submitted to JOURNAL OF BUILDING PERFORMANCE SIMULATION – June 2016

PAPER 6 T. Hong, **S. D'Oca**, W.J.N. Turner, S.C. Taylor-Lange.
An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs Framework.
BUILDING AND ENVIRONMENT – 2015

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An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework

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ABSTRACT

Reducing energy consumption in the buildings sector requires significant changes, but technology alone may fail to guarantee efficient energy performance. Human behavior plays a pivotal role in building design, operation, management and retrofit, and is a crucial positive factor for improving the indoor environment, while reducing energy use at low cost. Over the past 40 years, a substantial body of literature has explored the impacts of human behavior on building technologies and operation. Often, need-action-event cognitive theoretical frameworks were used to represent human-machine interactions. In Part I of this paper, a review of more than 130 published behavioral studies and frameworks was conducted. A large variety of data-driven behavioral models have been developed based on field monitoring of the human-building-system interaction. Studies have emerged scattered geographically around the world that lack in standardization and consistency, thus leading to difficulties when comparing one with another. To address this problem, an ontology to represent energy-related occupant behavior in buildings is presented. Accordingly, the technical DNAs framework is developed based on four key components: i) the *Drivers* of behavior, ii) the *Needs* of the occupants, iii) the *Actions* carried out by the occupants, and iv) the building *systems* acted upon by the occupants. This DNAs framework is envisioned to support the international research community to standardize a systematic representation of energy-related occupant behavior in buildings. Part II of this paper further develops the DNAs framework as an XML (eXtensible Markup Language) schema, obXML, for exchange of occupant information modeling and integration with building simulation tools.

1. Introduction

To secure sustainable energy development in the buildings sector, occupant behavior needs to be directed towards a more efficient use of energy. Due to the stochastic nature of occupant behavior, the mutual influences between humans, buildings, and the environment cannot be described in a simplistic way. Rather, it requires appropriate methodologies and techniques to be able to describe and reproduce the intricate network responsible for real energy performance during the wholebuilding life cycle (design, operation and maintenance, retrofit). In 2013, the buildings sector was responsible for 41% of the total energy consumption in Europe [1] (27% for residential buildings and 14% for commercial buildings) and in the United States [2] (22% for residential buildings and 19% for commercial buildings). In 2010, China's buildings sector surpassed the United States as the largest consumer of energy in the world, with carbon dioxide emissions following an increasing trend [2]. The energy crisis, diminishing natural resources and global warming are driving developed countries to conserve energy in the buildings sector. Organizations are making strong efforts to accelerate the uptake of energy-efficiency technologies and practices in buildings, by setting aggressive goals at different governmental levels. However, technology alone does not guarantee low energy use in buildings. Achieving energy conservation is a dual challenge: partly technical and partly human. As stated by Turner and Frankel [3], "*as technical performance standards ratchet tighter, behavioral factors gain relative importance*". Consequently, so-called energy-

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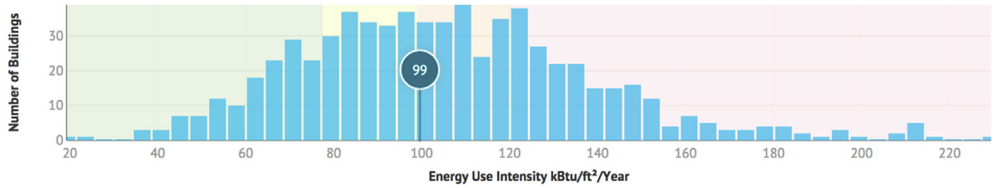

Fig. 1. Distribution of delivered energy intensities for commercial buildings in Baltimore, USA [4].

efficient green buildings exhibit large fluctuations in energy consumption due to how occupants interact with building systems. Fig. 1 shows the distribution of delivered energy use intensities (EUIs) for U.S. commercial buildings (Baltimore, MD) occupied by financial institutions. Even omitting the extreme cases, the EUIs can vary by up to a factor of five, from around 40 to 200 kBtu/ft^2/year [4].

With reference to residential buildings, Andersen et al. [5] analyzed the energy consumption of a block of 35 apartments located near Copenhagen, Denmark. The apartments had almost identical characteristics in terms of orientation, building systems and building envelope composition. Results showed that differences in household behavior might lead to differences in energy consumption by a factor of three, again omitting the extreme cases (Fig. 2). Similarly, a study conducted on measured residential summer air-conditioning electricity consumption in China [6] showed that EUIs varied dramatically, up to a factor of 10, across apartments of similar sizes within a single building (Fig. 3).

Energy efficiency in buildings is not just about new technologies, it's about optimal decisions and an overall improvement in *human* behavior. This paper refers alternately to "human" behavior with respect to the more general concept of the stochastic nature of a human being, and to "occupant" behavior when specifically indicating actions undertaken by building users. *Occupant* behavioral changes in the use of energy and water will help ensure a sustainable future for the buildings sector. This study focuses on *energy-related building occupant behavior*, taking into account actions and activities people perform in buildings to provide themselves with good indoor environmental quality (IEQ) (thermal comfort, visual comfort, acoustic comfort, indoor air quality, etc.). To define what is meant by *energy-related occupant behavior*, the International Energy Agency (IEA) Energy in Buildings and Communities Programme (EBC) Annex 53, "Total Energy Use in Buildings: Analysis and Evaluation Methods" [7], dedicated a section to occupant behavior modeling [8]. The term 'behavior' refers to "*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*". Annex 53 introduced quantitative descriptions of occupant behavior in the field of building energy performance, and reviewed probabilistic models for predicting occupant behavior in residential and office buildings. Hundreds of ongoing studies among the international scientific community focus on understanding how energy-related behaviors impact building energy performance. New methodologies (modeling approaches) and techniques (monitoring hardware and software platforms) for analyzing real building total energy use and for investigating the factors which influence occupant behavior in buildings, have emerge. In all of these studies, macroeconomic, cultural and climatic factors accounted for some of the locational variation, but not the variation across users. Different researchers and groups have developed models intended to predict the energy impact of building occupants. Studies scattered across the world (Europe, North America, Japan, and China), used different methodologies, and introduced different variables, instances, metrics, climates and contextual and cultural differences. Moreover, no standardized way of reporting or comparing results from different studies has emerged. This lack of structure in the field means that behavior models are difficult to compare and can be difficult to incorporate into building simulation tools. Currently, building simulation tools are used to predict the energy use of buildings during the design phase. It is this predicted energy use to which the real, operating energy use of the building is compared. While the building physics models and algorithms used by the simulation tools are now fairly mature, there is a distinct shortcoming in quantifying the energy use attributable to the building occupants.

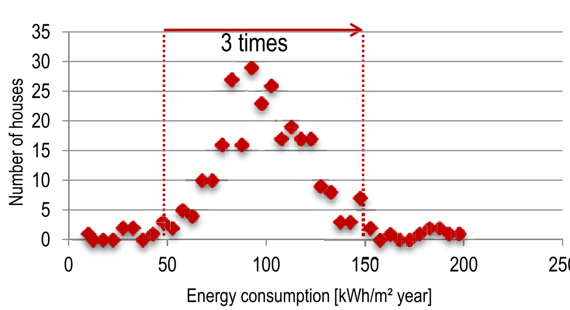

Fig. 2. Energy consumption of 35 apartments of the same block of building in Copenhagen, EU [5].

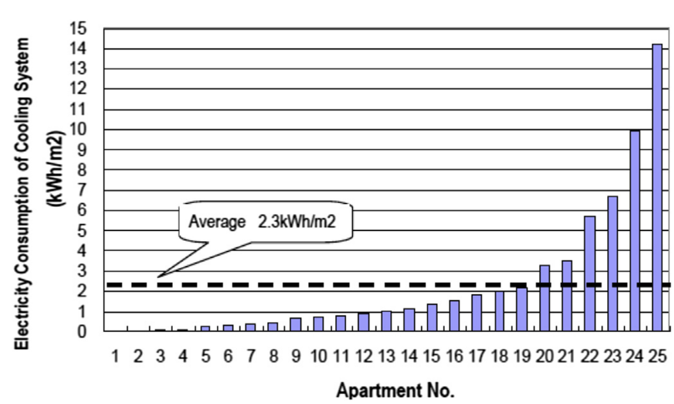

Fig. 3. Residential building summer air-conditioning electricity consumption, Beijing, China [6].

The analysis methods, developed models and results of Annex 53 were taken as the starting point for the newly dedicated IEA EBC Annex 66, "Definition and Simulation of Occupant Behavior in Buildings" [9]. Through Annex 66, a survey was circulated to experts in the field on the use of occupant behavior models in simulation tools. The results indicated that among researchers, energy modelers and software developers, no common consensus has been reached on the standardization of modeling approaches, simulation tool usability and documentation or interoperability issues. Significantly, none of the surveyed experts appeared satisfied by the quality of existing models of energy-related behavior in buildings.

To address these issues, a DNAs 'Drivers - Needs - Actions - Systems' framework providing an ontology to standardize the representation of energy-related occupant behavior in buildings, is described in this study. The study is composed of two parts (Part I and Part II).

In Part I of this paper, Section 1 introduces the issues related to *energy-related occupant behavior* in buildings and highlights the needs for the proposed ontology. Section 2 contextualizes the DNAs framework. Section 3 provides a review of more than 130 published investigation studies on the monitoring, modeling and simulation of energy-related behavior in buildings to support the structure of the DNAs framework. Finally in Section 4, the technical details of the DNAs framework are illustrated, based on four key components: i) the *drivers* of behavior, ii) the *needs* of the occupants, iii) the *actions* carried out by the occupants, and iv) the building *systems* acted upon by the occupants. Part II of this paper describes the DNAs ontology in the form of an XML (eXtensible Markup Language) schema known as obXML (occupant behavior XML), and discusses its potential applications.

2. Review of human behavioral frameworks

Theorized in the literature over the last 40 years are several frameworks describing human behavior using a need-action-event cognitive process. Table 1 lists nine cognitive-behavioral frameworks that consider users as reactive agents instead of passive receptors within a contextual environment. These models try to capture the stochastic nature of the human cognition process by describing the connection between the *human* 'inside world' inputs (drivers and needs) and the *environmental* 'outside world' outputs (actions and events). The nine cognitive-behavioral frameworks are described as follows:

- Perceptual Control Theory (PCT) is one of the earliest theories of human cognitive behavior conceptualized by Powers [10]. PCT is based on the principle that "*behavior is the control of perception*". The 'controlling' behavior fits in between the reaction to external events and circumstances such as stimuli, reinforcements (*drivers*), and the generation of *actions* by cognitive plans or *needs*.
- Human Operator Simulator (HOS) was proposed by Wherry [11] to describe human behavior as interactions among agents. The agents represented different user types in a specific environment, able to perform different tasks and activities for which no executive or pre-defined schedules or controls existed.
- Cognitive Complex Theory (CCT) was proposed by Card et al. [12] as a framework of the human cognition based on the concept of Goal – Operator – Method – Selection (GOMS) topology. Accordingly, users attain their goals through rational actions. Given the structure of the task, the inputs coming from the contextual environment are systematically organized based on users' experiences, abilities and available devices and hence selected to perform actions.
- The Executive Process Interactive Control (EPIC) framework was proposed by Kieras and Meyer [13] and was suited for modeling human multi-task performances, especially in the field of human-computer interactions.
- The State, Operator and Result (SOAR) framework was proposed by Lehman et al. [14]. Human behavior was modeled as movement throughout the space environment, in a specific time and as a function of the goal which motivated the driver to solve a task.
- The Adaptive Control of Thought (ACT) framework was proposed by Anderson and Liebere [15]. ACT is a cognition framework that can be used to implement predictive models of human behavior. Specifically, ACT focused on how humans organize their knowledge in order to behave intelligently.
- The Cognition as a Network of Tasks (COGNET) framework was proposed by Zachary et al. [16] as a theoretical framework of tools and techniques for building real-time models of human interactions within multi-tasking environments. In the COGNET framework, the 'outside world' (visual, acoustical and thermal environments) is conceptualized as human sensations and perceptions. The model developed a human-working memory which translated these 'inside world' inputs into cognitions (drivers, needs, etc …) leading humans into physical actions.
- The Architecture for Procedure Execution (APEX) framework was postulated by Freed [17] to simulate the human performance in complex, dynamic environments. APEX is a model used to predict human actions based on limited information resources, also taking into account human error causing system performance to deviate under certain circumstances.
- More recently, the Business Redesign Agent-Based Holistic Modelling System (BRAHMS) was proposed and tested by Sierhuis et al. [18] as a multi-agent modeling environment for simulating work practices in working spaces, such as users' interaction, activities, use of tools as well as presence and movement over time.

Table 1
Theoretical framework of human behavior.

Acronym	Name	Author	Date
PCT	Perceptual Control Theory	Powers [11]	1953
HOS	Human Operator Simulator	Wherry [12]	1976
CCT	Cognitive Complex Theory	Card et al. [13]	1983
EPIC	Executive Process Interactive Control	Kieras and Meyer [14]	1995
SOAR	State, Operator and Result	Lehman et al. [15]	1996
ACT	Adaptive Control of Thought	Anderson and Liebere	1998
COGNET	Cognition as a Network of Task	Zachary et al. [17]	1998
APEX	Architecture for Procedure Execution	Freed [18]	1998
BRAHMS	Business Redesign Agent-Based Holistic Modelling System	Sierhuis et al. [19]	2007

Most of the models capture the stochastic and reactive nature of human behavior in a complex environment, simulating users as agents acting in a specific space as a function of time. However, none of the models focuse on *energy-related behavior* in the *building indoor environment*, framing the cognitive processes of the 'inside world' that lead building occupants to perform *actions* in the 'outside world', such as interacting with control *systems* in the building spaces, when *driven* by *needs* from the 'inside world'.

3. Review of occupant behavior investigation methodologies

Over the last few decades, a number of studies have focused on overcoming the ‘credibility gap’ [19] - the loss of credibility when designed building energy performance and actual building energy consumption differ substantially due to variations in operation. Researchers have devised various approaches to assess the impact of occupant behavior on building energy performance. A stochastic approach to modeling occupant behavior has recently gained popularity, in contrast to the static description of occupant behavior based on assumptions made using fixed profiles. This new approach accounts for the fact that occupants do not always make logical choices and act stochastically rather than deterministically [20]. The human-building interaction has been typically studied according to a three-step methodology: monitor, model, and simulate, with the eventual outcome including validation (Fig. 4).

Existing monitoring studies of drivers, needs, actions and systems, behavioral models, and simulation studies, have captured the principal aspects of energy-related human behavior within a building (see Appendices for details). Monitoring studies which assessed the correlations between building components and control system states, have mostly focused on windows, shades and blinds, lighting systems, thermostat set points, space occupancy, and electrical equipment. From the correlations identified in this review, the DNAs behavioral ontology was developed and refined.

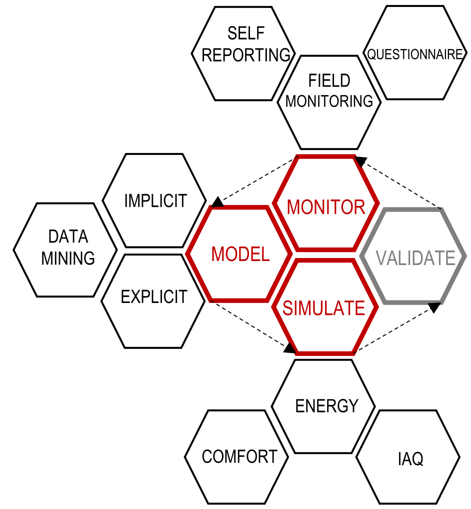

Fig. 4. Graphical representation of the methodological approach on occupant behavior modeling.

3.1. Monitoring studies

Researchers have monitored building systems (i.e. natural ventilation, heating, shading or lighting systems) in order to identify the correlation between observed system states (i.e. window open/closed), indoor and outdoor conditions/variables (i.e. indoor and outdoor air temperature, relative humidity), subjective occupant behaviors and energy performance. Two main methodological approaches, one more objective (field monitoring) and one more subjective (self-reporting and questionnaires) are used widely by the scientific community to gain a better understanding of energy-related occupant behavior in buildings (see Appendix A for details) [21–90].

3.1.1. Field monitoring

In almost all of the published experimental studies, observations of occupant behavior are coupled with ‘primary indicators’ such as indoor and outdoor environmental conditions. This includes data from a large array of field sensors (thermometers, anemometers, globe thermostats, CO_2 sensors, lux meters, photometers, etc.) as well as from weather stations (outdoor temperature and relative humidity, wind speed, rainfall, solar radiation and solar hours, etc.). Data collection techniques often include direct monitoring of the building control systems, using magnetic switches for windows [22–26], electromechanical sensors for shading systems, blinds and electric lighting [27–32], recording TRV (thermostatic radiator valve) switches [26,33–35], AC thermostat set points [36,37], presence detectors such as motion sensors [38–40], intelligent control of building systems and real-time building visualization [41], security systems [42], PIR (passive infrared) sensors [43], ultrasonic detectors for light switching [44], and smart/wireless electric outlet meters [45–52]. Occupant behavior can also be indirectly monitored by sensing ‘secondary’ environmental variables, parameters or actions and then performing extrapolation information. Relevant secondary indicators include the CO_2 concentration level [26,53,54], other tracer gas techniques [55–58], or metering the building energy flows (thermal, hydronic, power, etc.) [59]. Surrogate information on energy related behaviors can be deduced by using already available data such as occupancy derived from light switch sensors [41,58–60], computer switches [61,62], IT (information technology) infrastructure [63] and from equipment load profiles [64]. Other widespread techniques to monitor control system state or occupancy movement and presence include imaging analysis such as time-lapse photography taken from the exterior building façade [23,28,29,32,65–73] as well as camera-based [74,75] and internal personal visual survey, such as personal building walkthroughs [28,31,41,73,76].

3.1.2. Questionnaires and self-reporting

Another data collection approach is to ask occupants to provide information through self-reporting [26] or by using different interview techniques such as questionnaires [23,24,29–31,37,50,52,55,65,73,77–87], web-based questionnaires [88], computer-assisted telephone interviews [33,89] or mail surveys [90]. Questionnaire surveys are often used to identify the most important factors affecting occupant interactions with building control systems including: window opening behavior [23,24,26,55,73,76–78,88], the use of heating [26,33,83,85,89] and cooling [37,84,87], solar shading and blinds [20,26,29,65], electrical lighting [26,31,81] and equipment [52,86]. The surveys are typically carried out by sending out invitations to a consistent amount of building occupants which are representative of the building population. Subjects are asked about preferences in control system settings and repetitive actions. Often self-reporting techniques are used to record the human-building interaction when direct monitoring is not allowed. Data on occupant behaviors and preferences are typically coupled with information on dwelling characteristics, meteorological and census data (when available).

3.2. Modeling studies

Based on monitoring and questionnaire data, researchers have investigated which predictor variables drive occupant decisions to interact with building systems. Behavioral models are then developed to predict the probability of an occupant interacting with a building system. Implicit models are used to understand the driving forces behind the behavior itself or to predict the state of a building system or the occurrence of an occupant's action, based on the predictor variable(s). Explicit models are used to provide a personalized description (or future prediction) of the state of a building system or the actions of an agent (i.e. the occupant in a building), based on the monitored real behavior (movement and control action) of the agent itself (See Appendix B) [37,39,90–131]. In both cases, statistical and data-mining methods are used to obtain information on repetitive patterns of occupant behaviors and human-building interactions, and to provide insights into user profiles related to occupant behavior [42,128–133].

3.2.1. Implicit models

Implicit models of energy-related human behavior include linear regression models [36,37,55,76,91], logistic regression models with a single variable [22,23,25,29,37,47,48,68,73,92–100] or multiple variables [27,35,36,53,68,92,101–109]. Other types of statistical models have been used to simulate the stochastic nature of human interaction in buildings, such as simple probability equations [42,71,72,110–112], sub-hourly occupancy-based control models (SHOCC) [113] and Bayesian estimations [114].

3.2.2. Explicit models

Explicit models of human behavior are commonly based on occupancy presence and movement data and are used to predict the probability distribution of an event (e.g. occupant being present in a space) or behavior (e.g. occupant moving within a space) to occur. Such action- and agent-based models are centered on the use of random numbers to generate stochastic variables. Typical Monte Carlo methods are Markov Chain models [32,37,49,50,73,90,115–118], as well as discrete [21,80] and semi-hidden [38,39,119,120] Markov Chain models. State transition analysis is also used to develop real-time agent- and action-based models [121–127].

3.2.3. Data mining to support modeling studies

In the past 10 years several systematic data-mining methodologies (Cluster Analysis, Association Rules Mining, Decision Trees, and Rule Induction) [42,128–133] have been tested to identify and improve occupant behavior modeling in buildings.

Due to the stochastic nature of human behavior evolving randomly with time, in many applications it is difficult to extrapolate useful building occupant information from monitored buildings by means of statistical analysis. Due to data scattering at this level, statistical analysis techniques may fail to obtain reliable mathematical models by over fitting or under fitting the data. Instead, patterns of data discovered through data mining techniques may highlight commonsense knowledge, applicable to fit both direct and indirect models. In this context, data mining techniques have been shown to automatically extrapolate valid, novel, potentially useful and understandable building occupant patterns from big data streams [131,147]. Data mining techniques are not intended to substitute or contrast the direct stochastic models or indirect agent-based models already developed for the integration of occupant behaviors into building energy simulations. More likely, data mining techniques aim to overcome the shortcomings of more traditional techniques, specifically when dealing with big data streams, by providing reliable models of energy-related behavior with fast legibility and high replication potential.

Table 2
Typical building components and characteristics included in published simulation models of occupant behavior.

Building type (office, residential)
Spaces layout, geometry, location
Building envelope thermo-physical characteristics
Façade orientation and height
Window geometry and height
Type of window device (manual/motorized/automated)
Type of dwelling (detached house, house, flat)
Type of office (open space, cubicle, private vs. shared office)
Type of ventilation system (natural, mechanical, mixed-mode, night ventilation)
Type of HVAC/AC system
Type of lighting control (manual/automatic)
Type of shade device (manual/motorized/automated)
Internal loads, occupancy schedules
Type of indoor temperature control

3.3. Simulations

Mathematical models of human behavior translated into computer simulation draw the connection between the theoretical world and the observed world. Researchers have incorporated behavioral models into building energy simulation tools with the aim of predicting and leveraging the impacts of occupant behavior on 1) building energy performance, 2) comfort levels and 3) indoor air quality (IAQ). The most widespread building simulation tools include EnergyPlus [134], IDA Ice [135], ESP-r [136], TRNSYS [137], DeST [138], and DOE-2 [139]. In some cases, ad-hoc software tools, simulation engines, interfaces or wizards have been used to simulate specific aspects of human behavior (i.e. DAYSIM [140] and Light-switch Wizard in Visual Studio [141]). Simulation engines allow researchers to assess the implications of different stochastic occupant behaviors within the context of building components and characteristics (Table 2) as well as geographical contextual factors.

Different models suitable for exploring the diversity of occupant behavior over several timescales using computer simulation are proposed in the literature (for which excellent comprehensive reviews are provided by the Annex 53 Final Report [7] and Gunay et al. [20]). For each of the principal building-system interactions under investigation, Table 3 illustrates the most common metrics and simulation outputs, according to published simulation studies.

4. The DNAs occupant behavior framework

An initial concept of the DNAs framework was proposed by Turner & Hong [142], as a brief introduction to the DNAs 'Drivers – Needs – Actions – Systems' ontology developed in this study (Fig. 5). The impact of the behavior of the occupant (or groups of occupants) on building energy use, can be described using four main components, namely *drivers, needs, actions* and *systems*. The four components inhabit the 'outside world' (i.e. the building environment) and the 'inside word' (i.e. the cognitive processes of the human being). ***Drivers*** represent the environmental factors from the outside world that stimulate occupants in their inside world to fulfill a physical, physiological or psychological need. ***Needs*** represent the physical and non-physical requirements of the occupant's inside world that must be met in order to ensure the satisfaction of the occupant with their environment. ***Actions*** are the interactions with systems or activities that an occupant can conduct to achieve environmental comfort. Actions connect occupants' inside-world needs with the environmental outside word.

Table 3
Typical metrics and simulation outputs included in published simulation models of occupant behavior.

Techniques	Windows	Shade/blinds	Lighting system	Thermostat	Space occupancy	Plug loads
Metrics	air change rate (n/h) ventilation losses (kwh/m2), thermal comfort, indoor air quality	mean shade occlusion (MSO) shade movement rate (SMR) visual/thermal comfort, glare discomfort index	daylight illuminance level (lux) light switch frequency, visual comfort	primary energy consumption for space heating (kwh/m^2) internal gains thermal comfort	occupancy rates, nominal occupancy profiles, vacancy activity, transition probability, presence/absence probability and distribution, frequent pattern detection	occupancy patterns, operational schedules

Systems refer to the equipment or mechanisms within the building outside world with which an occupant may interact to restore or maintain environmental comfort.

As an example of the DNAs concept, consider the following simple scenario: An occupant is working inside a naturally-ventilated office with operable windows during the summer. The indoor room temperature increases throughout the morning until the occupant becomes thermally uncomfortable. The occupant then opens the window to allow cooler outside air into the building. As a result the room temperature decreases and the occupant becomes satisfied with the indoor thermal environment. In the above example the *driver* is the indoor air temperature. The *need* is the requirement for thermal comfort of the occupant. The *action* is the opening of the window by the occupant. The *system* is the window. The nature of each component of the DNAs ontology will be discussed in Sections 4.1–4.4.

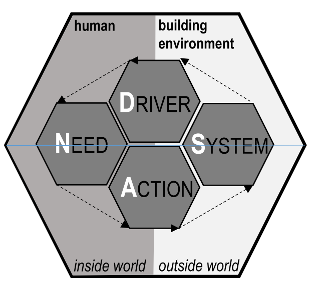

Fig. 5. Four key components of the human-building environment interaction framework.

4.1. Drivers

Drivers represent the stimulating factors that provoke energy-related occupant behavior. A driver prompts a building occupant to perform either an action or in-action with a building system, impacting the energy use of a building (Fig. 6). The drivers can include environmental factors, such as indoor air temperature and solar radiation, as well as non-physical factors such the time of day or the season. Within the topology of drivers, five main categories were identified, (i) building, (ii) occupant, (iii) environment, (iv) system and (v) time.

(i) *Building* – The building category encompasses the physical properties of the building itself that can act as drivers [143].

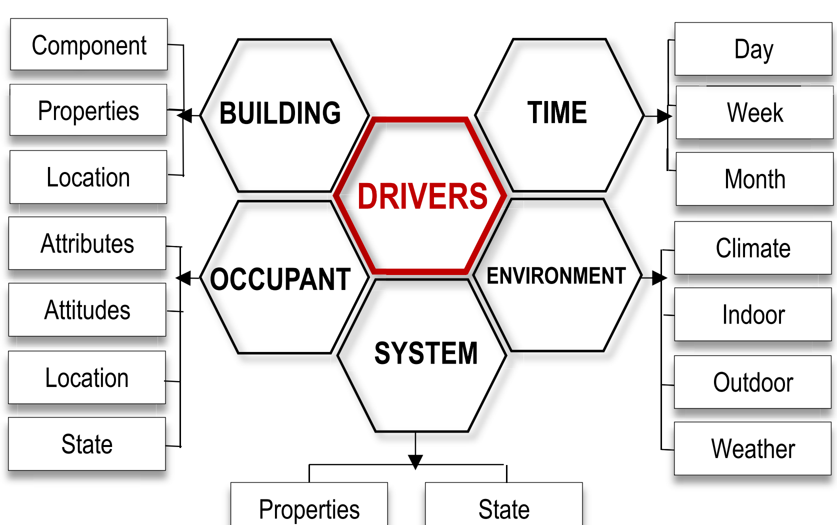

Fig. 6. Drivers behind energy-related occupant behavior.

This includes the building's orientation (façade exposure to solar radiation), construction material, floor layout etc. The location of the building in relation to other buildings, busy roads, fields can also affect the behavior of the occupants [16].

(ii) *Occupant* – The attributes of an occupant relate to the occupant's age and gender [144], as well as physical mobility [145] etc. which can dictate how an occupant behaves and their response to environmental drivers and hence, how they interact with building systems. Specifically, the 'energy attitude' of the occupant is important [146–149]. The DNAs framework provides a platform to allow a range of occupant energy attitudes from 'energy frugal' to 'energy profligate' via 'energy indifferent'. The energy attitude of the occupant will govern how the occupant interacts with energy-related building systems. The location of the occupant determines their exposure to environmental drivers. The state of the occupant describes their metabolic rate and whether they are arriving at a space, remaining in a space, or departing from a space. The metabolic rate is a widely-accepted input for thermal comfort models [150,151] and has a profound impact on occupant behavior. Window opening, blind use and lighting use have been found to be more frequent when occupants first arrive or leave, compared with when they remain in a space [9,26,36,101–105,113,131,147].

(iii) *Environment* – Environmental factors such as climate, weather and indoor and outdoor conditions (e.g. air temperature, humidity, solar radiation, IAQ) are all fundamental drivers behind the response of occupants to their environment [152]. In the field of behavior modeling there lacks agreement as to which environmental drivers are optimal when modeling certain actions. In the example given in Section 4, the driver behind the window-opening action was given as the indoor air temperature. However, it has been argued that the indoor air temperature is actually driven by the outdoor air temperature, and so the outdoor air temperature is the real driver behind the window-opening action. To address this conflict researchers introduced the concept of direct and indirect drivers. The direct drivers immediately impinge on the comfort of the occupant, whereas the indirect drivers impinge upon the direct drivers. In the example of window opening, the direct driver would be the indoor air temperature and the indirect driver would be the outdoor air temperature.

(iv) *System* – Studies have shown that the existing state of a building system acts as a statistically significant predictor of the probability of an occupant interacting with the system. An example of this effect would be the state of a window. For example, studies have shown that once a window has been opened or closed by an occupant in the morning, the window is more likely to remain in that state, independent of other driving forces [22,27,131].

(v) *Time* – The time of day and the day of the week are fundamental to the presence and location of occupants in a building. Some personal habits are time-driven, for example opening windows when first arriving at work or closing windows before leaving the office, or turning on lights when first arriving and turning off lights before leaving. The day of the week is important because it impacts occupancy presence in office buildings or equipment usage in homes during working and non-working days. The change in season (month of the year) also affects the interactions between occupants and building systems, resulting in different conditions inside a building [24,144].

4.2. Needs

Needs represent the requirements of the occupant that must be met in order to ensure satisfaction with their surrounding environment (Fig. 7). As stated by Milliken [153]: "*there are certain physical needs that people must meet in order to survive. There are others that make people more comfortable. In the specific ways they strive to meet these needs, people are different*". An occupant will have certain criteria or expectations of their environment which

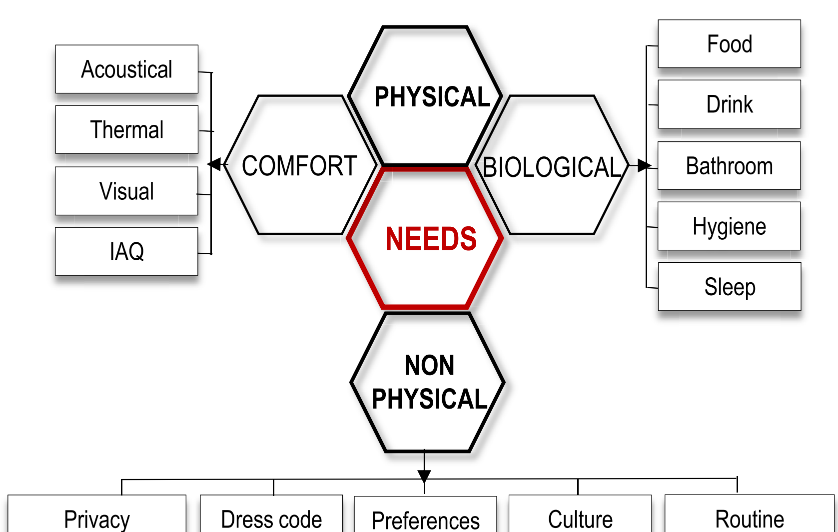

Fig. 7. Needs of building occupants that may result in an action that changes the building energy use.

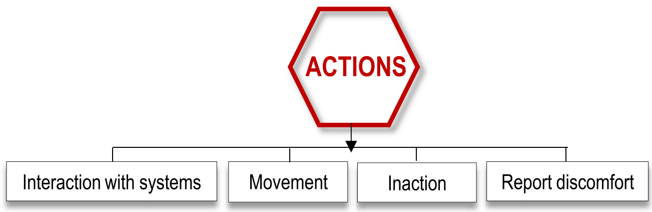

Fig. 8. Actions undertaken by building occupants when their needs are not met.

relates to their overall comfort. When this criteria is met, the occupant can be described as comfortable. If the criteria is not met, the occupant can be described as uncomfortable. When the state of physical discomfort exceeds the tolerance of the user, it causes a psychological response which prompts the user to perform actions to adjust their environment (e.g. opening a window) or adjust themselves to the environment (e.g. adjusting clothing level). However, comfort levels are individual and may vary largely from user to user. Moreover, they are not triggered at regular thresholds, but depend upon environmental and contextual factors which fluctuate over time. Therefore, the occupant behavior for satisfying comfort needs must be taken into account. Needs can be physical or non-physical. The two categories have been chosen for the DNAs framework so that all needs could be encompassed and easily classified, while still leaving flexibility in scope.

Physical needs include: (i) thermal comfort or satisfaction with the thermal environment, which is a combination of indoor air temperature and humidity, surrounding surface temperatures, indoor air velocity, activity level, incident radiation and clothing level of the occupant [88,107,150,151]; (ii) visual comfort such as not being subjected to glare, excessive contrast or unacceptable levels of brightness; (iii) acoustic comfort, with the level of background noise within an acceptable range; (iv) indoor environmental health, meaning good IAQ or humidity. Non-physical needs include factors such as the need for privacy or the need to maintain outside views. Both of these contribute to the overall satisfaction of the occupant, but can also impact building energy performance by influencing the manner in which an occupant may interact with building systems.

4.3. Actions

Actions are interactions with systems or activities that an occupant can conduct in order to satisfy their needs. The violation of one or more of an occupant's needs leads to discomfort. Therefore, this uncomfortable state for the occupant will provoke an action (Fig. 8). The action may be an interaction with a system in which the occupant conjectures that their action will restore comfort. An example of an action would be to adjust the level of clothing, open a window, or turn down the thermostat temperature etc. Actions can also include other measures such as reporting discomfort to a building manager, moving to a different location, or leaving the building entirely.

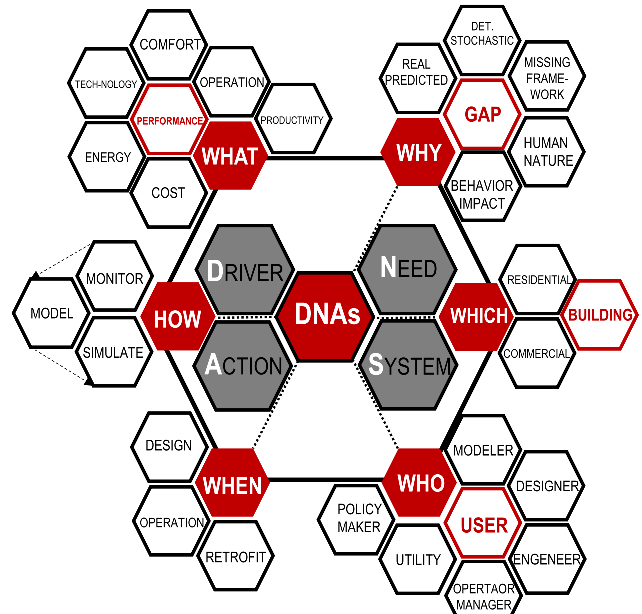

Fig. 10. A graphical representation of the DNAs framework applications.

There is also the possibility for inaction, when the occupant decides to do nothing but to suffer the discomfort. This could be caused by the occupant deeming the effort required to mediate the discomfort too high, or the occupant is without access to suitable systems. Energy attitudes and social pressure may also cause inaction, whereby an occupant modifies their willingness to perform a discomfort-alleviating action due to the presence of other occupants who would be affected by the action.

4.4. Systems

Systems are the equipment, mechanisms or measures with which an occupant may interact to restore comfort, or satisfaction with their environment. The resulting interaction my impact the energy performance of the building (Fig. 9).

For a system to affect the occupant-related energy performance of a building, it needs to be acted upon or controlled by an occupant. Common systems that are subject to occupant control and actions include windows, window blinds/shades, lights,

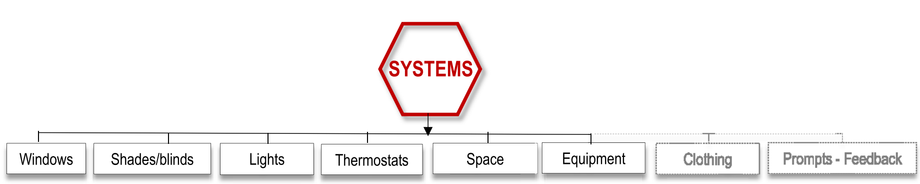

Fig. 9. Building systems with which an occupant may interact causing a change in building energy use.

thermostats, space occupancy, and electrical equipment. The control method of the systems becomes important when considering the energy performance of the building. Manual systems, such as non-programmable thermostats (or programmable thermostats which simply have not been programmed) and operable windows, can be directly controlled by occupants. Automated systems, such as programmable thermostats and automatic blind systems, can be acted upon by occupants using an override function. The clothing worn by an occupant, or the interactions which prompt feedback energy from visualization systems, can also be considered a system in the framework.

5. Discussion

This section discusses the possible applications of the described ontology developed to standardize the representation of energy-related occupant behavior in the buildings sector, at the international level (Fig. 10).

5.1. What types of behavior are accounted for in the DNAs framework?

Interactions between occupants and building systems can have a dramatic impact on global building performance in terms of comfort (thermal, visual, acoustical, IAQ), energy loads (heating, cooling, ventilation, lighting, plug-loads, electricity peak loads), technology efficiency, operational costs and occupant productivity. In the DNAs framework, energy-related behavior refers both to individuals and groups of occupants and their interactions with building energy services systems, appliances and facilities to control the indoor environment (such as windows, blinds and shades, heating and cooling thermostats, lighting and electric appliances). The movement and presence of occupants in indoor spaces is also included in the framework.

5.2. Why a framework to standardize the representation of energy-related behavior in buildings?

While building performance drivers such as climate, building envelope, and building equipment are well recognized and studied, the representation of energy-related occupant behavior is often oversimplified partly due to the stochastic nature of human behavior. The goal of the DNAs framework is to provide an ontology of energy-related occupant behavior in buildings to solve discrepancy issues mostly rooted in: (a) oversimplifying or ignoring human behavior in the building design and operation process, (b) a broken interface between human behavior and building system controls and, (c) lack of reliable technology and system controls performance. The effectiveness of the DNAs framework will be measured by its capability to bridge some of the 'credibility gaps' [10] between:

- predicted vs. real energy consumption in buildings
- modeled vs. actual occupant behavior in buildings
- deterministic vs. stochastic nature of human behavior in energy modeling
- perceived vs. realistic performance of technologies
- assumed vs monitored occupant behavior impact on building performance.

5.3. Which building types can be addressed when adopting the proposed ontology?

Occupant behavior has been shown to have a profound impact on the energy performance of both residential and commercial buildings, even within a narrowly-defined cohort of similar building types of a particular age, size, and principal use. The DNAs framework will provide researchers, designers, energy modelers, building operators, managers and policy makers with an ontology to standardize the representation of energy-related occupant behavior in buildings and quantify its impact. Specifically, the impact on building operation scenarios, technology and system performance, as well as design and retrofit strategies. The conceived structure of the framework is generic enough to allow the description of solutions for different climate zones and geographical locations.

5.4. Who can use the DNAs framework, for what purposes and to what extent?

The DNAs framework will be used to address issues held by building energy modelers, building designers, building engineers, building operators and managers, building utilities, and policy makers. Building energy modelers can use the framework to simulate occupant behavior in buildings consistently. Simulation results can be shared with other modelers in a structured and consistent way. In the long term, the DNAs framework will allow occupant behavior modeling to become a standard component in building information modeling (BIM). Building designers will be able to use the DNAs framework for stochastic spatial mapping of occupants. Typical occupational working profiles developed using the DNAs framework will support strategic choices made during the early design and retrofit stages of buildings. Building engineers will receive strategic knowledge on the performance of their technology, equipment or systems, by simulating the impact of the energy-related behavior reviewed in the DNAs framework as part of overall building energy performance. Building operators and managers will profit from the knowledge collected using the DNAs framework, which will provide actionable information that allows optimal tuning of space heating/cooling set points, comfort levels, and operational schedules of HVAC and lighting systems. Building utilities will receive strategic support from the application of the DNAs framework when adjusting their priorities to user-oriented energy-efficiency requirements and behavioral programs, and also modifying their technology and equipment production. Policy makers will apply the DNAs framework to guide behavioral program design, implementation and evaluation. Also, the DNAs framework can be envisioned as the fundamental setting-body structure of a new generation of ISO (International Organization for Standardization) standards to represent and describe energy-related occupant behavior in the buildings sector at the international level.

5.5. When can the DNAs framework be used?

The DNAs framework can benefit building energy performance during the whole building life cycle, including the design, operation, management and retrofit phases. During the design phase, the DNAs framework allows for more accurate prediction of actual building energy use. Occupant behavior models utilizing the DNAs framework and implemented in energy modeling programs, such as EnergyPlus, will support decision making in the early design stage. During operation and maintenance the predictive models and algorithms of occupant behavior covered by the DNAs framework will advise users through smart human-machine integrated communication (i.e. embedded in personal mobile devices and control technologies), as well as allow for building energy flows, control systems, appliance usage, and comfort level mapping. During a building retrofit, the DNAs framework could aid in the evaluation and impact assessment of different building technology solutions influenced by occupant behavior.

5.6. How can energy-related behavior be represented using the DNAs framework?

The different applications of the described ontology aim to overcome some unbridged gaps in methods, models, and simulation tools, to represent the impact of energy-related occupant behavior on whole-building energy performance. Monitoring methods, modeling methods and simulation engines are three specific areas which will be highly influenced by the adoption of the DNAs framework. Currently, no common agreement exists among the scientific community on which data to collect, which parameters to monitor and with which sensor and accuracy, which length time step, and what duration of monitoring period. The monitoring methods of different types of behaviors and actions can be guided by the DNAs framework, eliminating ambiguity. Moreover, the DNAs framework addresses current challenges with modeling methods. The research community is in strong need of enhanced behavioral models to meet experts' requirements. Firstly, qualitative behavioral actions are not adequately supported by a common language when translated into quantitative models and simulations. Starting from the monitoring phase, gathering data over a significant time range, covering diverse building types, organizational culture, populations and geographical areas would assure statistical relevance to the model development. Nonetheless, this is rarely achieved, due to lack of resources, tools and time. The DNAs framework provides a cohesive ontology that can advance modeling methods specific to energy-related occupant behavior in buildings. Lastly, there is no common consensus as to the most effective tool to use to develop reliable behavioral simulations. Several independent codes have been written and implemented into existing simulation tools. Nonetheless, the applicability and interoperability of these models are still affected by local disparities, coding languages and design issues. Different technical advances in the implementation of behavioral models have been realized in different simulation environments. However, very often such advanced controls come without appropriate graphical user interfaces, making them difficult and time-consuming to learn. The proposed DNAs framework is intended to be integrated into current building energy modeling programs like EnergyPlus and other domains (ESP-r, TRNSYS, IDA ICE, DeST, DOE-2, etc.) or Functional Mock-up Interfaces (FMI) to support both model exchange and co-simulation of dynamic models using a combination of xml-files and compiled codes, within the structure of the XML Schema.

6. Conclusion

The DNAs framework described in this study presents an ontology providing a common technical language for the building simulation community to observe, model, and simulate energy-related occupant behavior in buildings. The proposed framework captures the vast majority of occupant behavior which directly or indirectly impacts building energy use. The ontology comprises of four main components: the *drivers* behind the occupant behavior that influence the energy performance of buildings; the *needs* of the occupants which must be met in order for the occupants to be comfortable and satisfied with their environment; the *actions* which occupants can take in order to satisfy their needs; and the building *systems* with which occupants can interact to perform the actions which affect building energy performance. Describing, predicting or influencing energy-related occupant behavior are challenging tasks, due to the stochastic nature of humans. Currently, the field of building occupant behavior modeling suffers from a lack of standardization in methods, models and simulations. To this extent, the DNAs framework presented in this paper, facilitates the quantification of the impact of occupant behavior on building energy efficiency. The aim is to provide more robust descriptions of the motivations driving occupants to interact with the building envelope and building systems, in order to bring about desired comfort conditions. The DNAs framework is envisioned as a common information-exchange language supporting stakeholders (architects, engineers, operators, owners, occupants) and policy makers, toward the standardization of the representation of energy-related occupant behavior. The final aim of the framework is to allow the incorporation of more accurate behavioral models into building simulation tools to provide comparable metrics and results on: 1) the behavioral factors that impact building energy performance, 2) the potential energy savings from improved occupant behavior in buildings, and 3) the design of robust building operation scenarios, technologies, systems and retrofit strategies. Applications of the DNAs framework include building energy modeling and simulation, building design, energy benchmarking and performance rating, development of codes and standards, and policy decisions. In the long term, the DNAs framework can evolve into occupant information modeling (OIM), as a new and critical addition to building information modeling (BIM). An XML schema called obXML will further implement this framework to promote comparison and validation of occupant behavior models, while also facilitating their integration with building simulation tools. The deployment of the DNAs framework and the obXML schema into current modeling practices must then face some of the intrinsic constraints of human behavior simulation in buildings, such as the level of modeling detail for individual and group behavior, the interaction between external and internal drivers and action scenarios, as well as the implication of multiple behaviors and choices in buildings [20,22], just to mention some.

More detailed analysis of the constraints on the application of the DNAs framework and insights into the obXML schema are provided in Part II of this paper.

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Appendix A

Techniques		Windows	Shade/Blinds	Lighting system	Thermostat set points	Space occupancy	Equipment
Objective field monitoring	Sensoring the control system directly	Magnetic switches [2–25,105,131]	Electromechanical sensors [29,30,93]	Electromechanical sensors [31,117,120]	TRV/cooler temperature set point [33–36,118]	Presence detectors [39,42,43,94–98,109, 112,115,121,123,133, 146,147]	Smart plugs, electrical current measurement, wireless electric outlet meters [45–52]
	Sensoring the control system indirectly	CO_2 concentration levelVaisala GMW22 sensor [26], WMA-3 monitor [53]. Tracer gas techniques [55–58]		Electrical recording of the illuminance level luxometer [60], photometer [32].	Gas energy use heated floor area [61], heat flux meters, air and water flow meters, power meters [42].	CO_2 concentration [54], light switch sensors [59], computer switch [62,63], computer IP address [64], sensor network [149]	
	Sensoring physical and non-physical variables	Indoor and outdoor parameters [21,25,26, 28,53,55,99,100,105–107]	Indoor and outdoor parameters [30,32, 65–67,72,73,78,93, 101,110]	Indoor and outdoor parameters [41,101, 104,108,110,111,113, 114,140]	Indoor and outdoor parameters [35,83–87, 102,148]	Indoor and outdoor parameters [39]	
	Photographic analysis	Time lapse photography of the exterior of the building façade [23,28,73,93].	Time lapse photography of the exterior of the building façade [29,32, 65–70].	Time lapse photography of the interior of the building façade [71,72].		Camera-based methods [74,75]	
	Internal visual survey (personal observation and record)	Building walkthroughs [76]	Building walkthroughs [93]	Building walkthroughs [31]			
Subjective field monitoring	Self reporting	Questionnaires [24,26]			Questionnaires [102,148]		
	Interview techniques	Questionnaires [23,55,73, 77,78,80,88] Mail survey [99]Web based survey [88,107]	Questionnaires [29,30,50,65,73,78]	Questionnaires [31, 81]	Questionnaires [82–85,89]		Questionnaires [52,86,87]

Appendix B

Techniques	Windows	Shade/Blinds	Lighting system	Thermostat set points	Space occupancy	Equipment
Implicit models Stochastic models	Single variable linear [76] and logistic regression [23,73] Multi variable logistic regression [5,36,53,100,103,105–107,115]	Lightswitch algorithm [41,101,113,140] Single variable logistic regression [22,28,29] Multivariate logistic regression [93,95,108,109]	Lightswitch algorithm [41,101, 104, 110, 113,140] Linear regression analysis [91] Probability equation [49, 71, 72, 111] SHOCC Sub Hourly Occupancy based control model [48] Bayesian estimations [114]	Statical analysis [33,35,148] Linear regression analysis [37] Multivariate Logistic Regression [36,102,103]	Statistical analysis [40,59,112,146] Logistic regression models [94–98] SHOCC Sub Hourly Occupancy based control model [116]	Logistic regression models [46–48, 52]
Explicit models Monte Carlo Simulation	Discrete Marcov Chain [21,25,50,80,100,119]	Markov Chain [22,32,50]	Markov Chain [115,117]	Markov Chain [37,50,79]	Semi Markov model [120] Hidden Markov model [39] Agent based model [121–127]	Markov chain, semi-Markov process [49–51]
Data mining	Cluster Analysis, Association Rules Mining [131]				Cluster analysis, association rules [128–131] Hierarchical models [132] Decision trees [133]	Cluster Analysis, Association Rules Mining [128–130,132]

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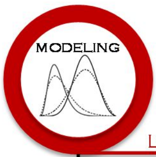

LACK OF COMMON AGREEMENT ON VALIDITY AND EFFECTIVENESS OF OB MODELING AND SIMULATION APPROACHES

WHICH ARE THE STRENGTHS, SHORTCOMINGS AND NEEDS OF OB MODELING AND SIMULATION METHODOLOGIES?

PAPER 5 **S. D'Oca,** H.B. Gunay, S. Gilani, W.L. O'Brien, V. Fabi, S. Corgnati, A. Mahdavi
A review of the occupant modeling approaches in offices with illustrative examples
Submitted to JOURNAL OF BUILDING PERFORMANCE SIMULATION – June 2016

PAPER 6 T. Hong, **S. D'Oca**, W.J.N. Turner, S.C. Taylor-Lange.
An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs Framework.
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An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema

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ABSTRACT

Energy-related occupant behavior in buildings is difficult to define and quantify, yet critical to our understanding of total building energy consumption. Part I of this two-part paper introduced the DNAS (Drivers, Needs, Actions and Systems) framework, to standardize the description of energy-related occupant behavior in buildings. Part II of this paper implements the DNAS framework into an XML (eXtensible Markup Language) schema, titled 'occupant behavior XML' (obXML). The obXML schema is used for the practical implementation of the DNAS framework into building simulation tools. The topology of the DNAS framework implemented in the obXML schema has a main root element *OccupantBehavior*, linking three main elements representing *Buildings*, *Occupants* and *Behaviors*. Using the schema structure, the actions of turning on an air conditioner and closing blinds provide two examples of how the schema standardizes these actions using XML. The obXML schema has inherent flexibility to represent numerous, diverse and complex types of occupant behaviors in buildings, and it can also be expanded to encompass new types of behaviors. The implementation of the DNAS framework into the obXML schema will facilitate the development of occupant information modeling (OIM) by providing interoperability between occupant behavior models and building energy modeling programs.

1. Introduction

Based on a comprehensive review of 130 published academic papers, Part I of this paper introduced the DNAS (Drivers, Needs, Actions, Systems) framework intended to formalize the modeling of energy-related occupant behavior (OB) in buildings [1]. The DNAS framework was developed to help fully understand and capture the principal aspects of energy-related human interactions within buildings [2]. In this context, studies conducted by the US Environmental Protection Agency [3] and the European Commission [4], highlighted that Americans and Europeans spend on average 85%–90% of their time in indoor environments. However, building occupants are not passive receptors to their indoor environment. Instead, occupants interact with building systems to bring about desired thermal, visual, and acoustic comfort and good indoor air quality (IAQ). These interactions are typically grounded in the Humphreys' principle of adaptation, which states: "if a change occurs such as to provide discomfort, people react in ways which tend to restore their comfort" [5]. As stated by Parson [6], occupants acclimatize to their environment through three main adaptive responses: physiological, psychological and behavioral. A physiological response is any type of unconscious reaction which allows the human body to adapt thermally to the indoor environment. In a cold environment the human body reacts by vasoconstriction to reduce blood flow to the skin, limiting heat dissipation. Shivering is an involuntary bodily reaction that forces the muscles to increase their heat production by a factor of 10. In a warm environment, the human body reacts by vasodilation to increase blood flow to the skin and increase heat dissipation. A psychological response is any type of individual reaction to the indoor environment due to discomfort, strain, pressure, motivation or adaptation to the environment. This reaction may vary based upon the habits and

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expectations of the individual. A psychological response involves the cognitive and cultural variables of each individual with respect to their perception of the indoor environment. A psychological response may evoke many different behaviors in response to possible sources of stress causing discomfort. A behavioral response is any type of action performed to maintain or restore a state of comfort when the indoor environmental conditions cause discomfort. In everyday practice, and often without fully considering the consequences, occupants interact with the building systems in their homes and workplaces in order to achieve desired environmental conditions. In this context, this paper focuses on behavioral comfort-driven responses of occupants within the built environment.

Energy-related OB in buildings includes actions such as turning on/off local HVAC (Heating, Ventilation, and Air-Conditioning) equipment, opening and closing windows for thermal comfort and ventilation, turning on/off or dimming lights, using shades and blinds to prevent glare or excessive solar heat gains, adjusting thermostat settings, using fans, moving to warmer/cooler spaces, etc. Historically, the human-building interaction has been modeled based on limited evidence from field studies. Existing models typically include assumptions on OB in buildings based on generic input data. Commonly, OB models used in building simulation are formed under the assumption that occupants behave in a set way according to standard deterministic design conditions such as occupancy levels, ventilation rates, thermostat set points and other threshold values. The inclusion of the adaptive comfort model [7] into European (EN 15251 [8]) and U.S. standards (ASHRAE 55 [9]) has promoted interest in: (1) the prediction of OB actions performed by individuals to restore their personal comfort, and (2) the quantification of the energy impact of OB to understand the factors driving the difference between predicted and actual building energy use. Of particular importance are the actions of turning on/off HVAC equipment, adjusting thermostats, lights, windows and blinds, and moving into/out of spaces. Over the past 30 years, building-occupant interaction models have been developed to describe human behavior in a need-action-event cognitive process and have been the focus of investigation for a substantial body of scientific research [7,10]. Recent efforts have been made within the framework of the International Energy Agency (IEA) Energy in Buildings and Communities Programme (EBC) Annex 53 to categorize the most relevant types of energy-related OB for residential buildings [10]. A dedicated section of Annex 53 focuses on OB modeling, exploring existing theories on OB and behavioral models, and providing a comprehensive literature review of the influencing parameters (referred to as 'driving forces') for the various types of energy-related OB.

The most significant conclusion drawn from the literature review in Part I of this paper was the lack of a standardized method or technical structure for describing energy-related OB in buildings and for reporting modeling results. Authors using different variables, instances, and metrics introduce climatic, contextual and cultural differences in their results. For example, Mahdavi and Proglhof [11] and Karjalainen [12] suggested the important factors that affect occupants' behavior in manual shade operation were indoor temperature, transmitted solar radiation, and window luminance. Independent of Karjalainen [12], Mahdavi and Proglhof [11] found workplane illuminance and the geometry of the transmitted solar radiation were also important factors. In agreement with Mahdavi and Proglhof [11], Nicol and Humphreys [13] found workplane illuminance and the geometry of transmitted solar radiation were important drivers, but neglected to consider indoor temperature, transmitted solar radiation, and window luminance. Similarly, Turner and Hong [14] showed that different authors listed indoor air temperature [15] or outdoor air temperature [16] to be the primary driver for window-opening actions. From these examples, the selection of different drivers for similar occupant behavior models makes it difficult to compare the models and incorporate them into building energy modeling (BEM) programs. In order to bridge this classification gap, an ontology was developed to describe the main behavioral adaptation mechanisms. This ontology was used to formulate the DNAS framework described in Part I and provides the foundation for the obXML schema presented here in Part II. The obXML schema allows relationships to be formed/defined between different drivers and the eventual action, in a standardized way. obXML is designed to provide enough flexibility for both existing and future occupant behavior, building energy and system models to be captured in a consistent way. The obXML schema follows extensible design criteria to provide a wide range of stakeholders (researchers, designers, energy modelers, building engineers etc.) with a new tool to standardize the representation of energy-related occupant behavior in buildings, and quantify the impact on building operations, technology and system performance, as well as design and retrofit strategies.

1.1. XML — eXtensible Markup Language

A number of data formats were considered for the implementation of the DNAS framework in a schema. The two main viable candidates that emerged were JSON (JavaScript Object Notation) and XML (eXtensible Markup Language). JSON documents are widely used for targeting web browser display applications using Java and JavaScript code. An XML document is a machine- and human-readable document used to provide a convenient and simple way of storing and transferring data between applications and software tools. An XML schema provides a platform to facilitate and standardize the sharing, storage and management of data, especially when data is collected from heterogeneous sources. A schema describes the data content, format and structure of an XML document. For example, the Green Building XML schema (or gbXML) [17], was developed to facilitate the transfer of building information stored in CAD building information models, enabling integrated interoperability between building design models and a wide variety of engineering analysis tools and models. The ifcXML schema, developed by buildingSMART [18], is derived from the Industry Foundation Classes (IFC) EXPRESS model. ifcXML is a neutral, open, and object-based data format intended to facilitate interoperability in the architecture, engineering and construction industries. IFC is also commonly used in a collaborative format within Building Information Modeling (BIM) based projects, and its model specification is described by the International Standard ISO 16739:2013 [19].

Researchers in fields external to building engineering have also adopted XML standards. For example, Babaie and Babaei [20] focused on modeling geological objects and earthquakes using logical models of seismology and plate tectonics. Zheng et al. [21] developed an XML schema that focused on large-scale proteomics studies in the field of functional genomics. Yan et al. [22] used a framework based on XML for standardizing and optimizing marine metadata. For each of the above studies the overall objective was to use XML to provide a standardized language that would reduce data redundancy, increase efficiency and simplify data management.

1.2. Occupant behavior modeling

The XML language was chosen because of its ability to provide an automated mechanism which can capture the data syntax and structure needed to represent the DNAS framework in the form of an interoperable language for energy-related OB in buildings. Part II of this paper focuses on the creation of an XML schema, called obXML, used to describe the data content and structure of the DNAS ontology while providing a standardized representation of energy-related OB in buildings. The obXML schema is intended to be integrated into current building energy modeling (BEM) programs or Functional Mock-up Units (FMUs), to support both model exchange and co-simulation of OB models.

Currently, a realistic description of occupants' adaptive responses is a significant factor hindering accurate simulation predictions of real building energy consumption. When used in whole-building energy simulation obXML will help to eliminate model and data ambiguity and narrow the gap between the simulated and actual energy consumption of buildings. The implementation of the obXML schema into an FMU (which enable co-simulation environments) via a Functional Mockup Interface (FMI) [23] such as Modelica [24], will allow simultaneous simulations with current BEM programs to be performed. FMI is a tool-independent interface standard intended to support both model exchange and co-simulation of two or more dynamic models. FMI uses a combination of XML files, C-header files, and C-code in source or binary form [25]. A simulation model or program which implements the FMI standard is called an FMU. An FMU comes along with a small set of easy-to-use C-functions (FMIfunctions) whose input and return arguments are defined by the FMI standard. The co-simulation of energy-related OB through more dedicated simulation engines will help to identify design shortcomings and improve building performance predictions during both the building design and operation phases.

The integration of human behavior simulation with BIM is one way to bridge the gap between predicted and actual building energy consumption [26]. However, there has been little effort exerted to establish such integration. BIM is defined by the United States National BIM Standard as “a digital representation of physical and functional characteristics of a facility” [27]. BIM, an intelligent model-based process, provides interoperability and information exchange during the whole-building life cycle. BIM involves the generation and management of digital representations of the physical characteristics of buildings as well as the technical and functional properties of building envelopes, systems, controls and technologies. Building data are drawn into transferable formats which allow and support information exchange and networking among different stakeholders who plan, design, construct, operate and maintain buildings. With constant access to building data streams, BIM could provide a core for building OB models, supporting a new generation of Occupant Information Modeling (OIM) that will enable the simulation of tailored scenarios of occupant operation and management for specific building cases.

In the long term, the obXML schema is aimed to facilitate the development of OIM, a future key component of BIM. In this regard, an online repository has been created at the web address behavior.lbl.gov where the obXML schema may be downloaded for practical use. The intention of this publication is not to present a manual of the schema but rather introduce version 1.0 of the obXML schema to the scientific community and justify its creation based on technical merit. The development of the obXML schema will be an ongoing process with future versions to be made freely and publically available.

2. Implementing the DNAS framework into a schema

2.1. Categorizing occupant behaviors using the DNAS framework

Findings from the literature review in Part I of this paper [1] were used to develop the obXML schema using XMLSpy [28]. The topology of the schema follows the DNAS framework, with each adaptation mechanism described using the four key components: drivers, needs, actions and systems. *Drivers* represent the environmental factors that stimulate occupants to fulfill a physical, physiological or psychological need. *Needs* represent the physical and non-physical requirements of the occupant that must be met in order to ensure satisfaction with their environment. *Actions* are the interactions with systems or activities that occupants can perform to achieve environmental comfort. *Systems* refer to the equipment or mechanisms within the building with which occupants may interact to restore or maintain environmental comfort. Table 1 shows six examples of energy-related occupant behavior from the literature, and how the behaviors are described within the context of the DNAS ontology.

2.2. Implementing the DNAS framework into the obXML schema

The topology of the DNAS framework was implemented in the obXML schema based on a main root element *OccupantBehavior* branching into five sub-elements *Behaviors*, *Buildings, Occupants*, *Seasons*, and *TimeofDay* (Fig. 1). The *OccupantBehavior* root element has an ID and version attribute, indicating a unique ID and version. The sub-elements from the main element provide a choice for specific building, occupant, behavior, season and time of day inputs, with seasonal and time of day information being optional.

The *Buildings* element (Fig. 2) pertains specifically to the inputs related to occupant behaviors in the building. It has a unique ID attribute, and required *Type* and *Spaces* children elements. The *Type* element contains 39 enumeration building types, consistent with those commonly used in BIM schemas (such as gbXML). The *Building* element has optional children elements of *Address* and *Description* to be input as a string. The *Spaces* element allows for an infinite number of building spaces to be defined. Each *Space* element includes a unique attribute ID, and the required child elements of *Type* (MeetingRoom, Corridor, Outdoor, Office, ResidentialOwn, ResidentialRent, OfficeShared, OfficePrivate, Other) and *GroupPriority* (Majority). In addition, description, maximum or minimum number of occupants within the space and meeting information are optional inputs. If the space is communal, the *Meeting* element contains child elements describing the *Duration*, *StartTime*, *EndTime*, and the *Probability* of the meeting occurring. The *Building* parent element hosts the *Systems* child element, describing the physical equipment or components with which an occupant may interact. The child elements of the *Systems* element include the *Window*, *Shade*, *Light*, *Thermostat*, *Equipment*, and *HVAC* control, each with a unique ID attribute, an optional *Description* element, and an enumeration selection for the *Type* of control: window – operable or fixed; shade – operable or fixed; light – on/off, dimmable, two step, three step; thermostat – adjustable, none, fixed; HVAC system – central, zonal controllable, zonal fixed.

The *Occupants* root element (Fig. 3) describes the occupants within the building. Each parent *Occupant* element has a unique attribute ID and optional child elements of *Name*, *Age*, *Gender*, *Lifestyle*, *Jobtype*. A behavior ID referencing the *Behaviors* root element tags an occupant to a specific behavioral action.

The topology of the schema for the *Behaviors* root element branches into *Drivers*, *Needs*, *Actions* and *Systems* child elements, following the DNAS framework (Fig. 4).

The *Drivers* element has six child elements, namely (1) *Time*, (2) *Environment*, (3) *EventType*, (4) *Habit*, (5) *Spatial* and (6) *OtherConstraint* (Fig. 5). The *Time* child element includes the *Time of Day* (morning, noon, evening etc …), *Day of Week Type* (Monday, Tuesday, Wednesday etc …), and *Season Type* (spring, summer, fall etc …). The *Environment* child element *Parameter* includes the four sub-elements *Name*, *Description*, *Type*, *Unit* and an attribute ID. The *Type* element includes 30 different enumerations within the

Table 1
Six examples of energy-related occupant behavior from the literature, and how the behaviors are described within the context of the DNAS ontology.

Behavior	Drivers	Needs	Actions	System	Reference
Window opening	IAQ	IAQ comfort	Open window	Window	[29–32]
Shade control	Work-plane illuminance	Visual comfort	Operate blinds	Blinds	[33–36]
Lighting control	Work-plane illuminance	Visual comfort	Turn on lights	Lights	[37,38]
Thermostat control	Indoor temperature	Thermal comfort	Adjust setpoint	HVAC	[39]
Electric equipment usage	Organizational policy	Culture to save energy	Turn off computer	Plug loads (computer)	[40–43]
Space occupancy	Daily routine	Food	Break for lunch	Building space	[44]

general categories of temperature, IAQ, daylight factor, illuminance, glare, relative humidity, solar irradiance, raining and noise. These enumerations are separated according to indoor or outdoor applications. Each *Type* has a unique attribute ID and associated unit. The *EventType* child element details the circumstances that may be driving occupant actions such as waking up, sleeping, leaving for work or returning from lunch. The *Habits* child element lists personal enumeration traits such as smoking. The *Spatial* child element has the sub-child element *SpaceType* (residential, office; owned, rented) and a space reference ID referencing the *Space* child element defined under the parent *Building* element. Lastly, *OtherConstraints* includes the option of signifying that there are no occupants in the room.

The *Needs* are categorized into *Physical* and *Non-physical* child elements (Fig. 6). The *Physical* needs are comprised of the 4 child elements *Thermal*, *Acoustic*, *Visual* and *IAQ*. Each child element in the *Physical* category references a unique *ParameterRange* signifying an acceptable input comfort range with a unique ID, and

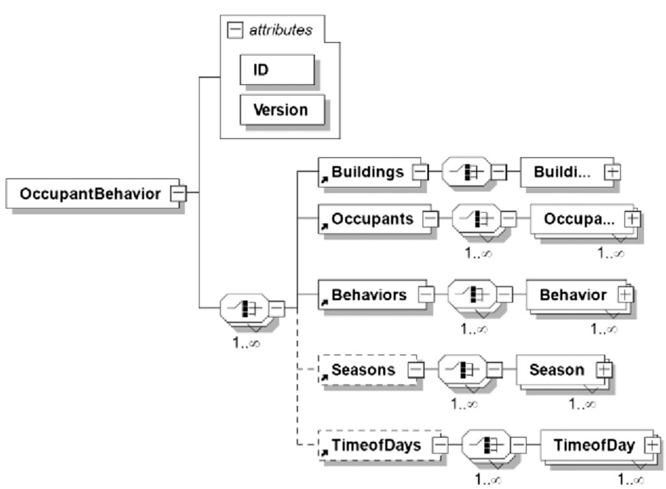

Fig. 1. The main root element **OccupantBehavior** from the xsd file with ID and version attribute and showing buildings, occupants, behaviors, seasons and time of day elements.

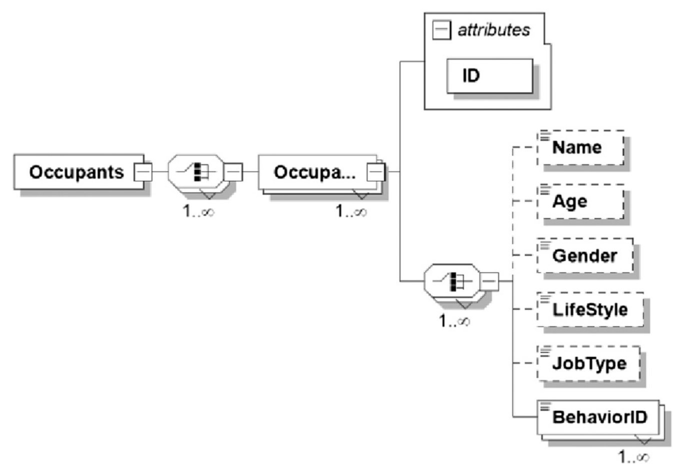

Fig. 3. The tree diagram from the xsd file identifying the input characteristics of the **Occupants**.

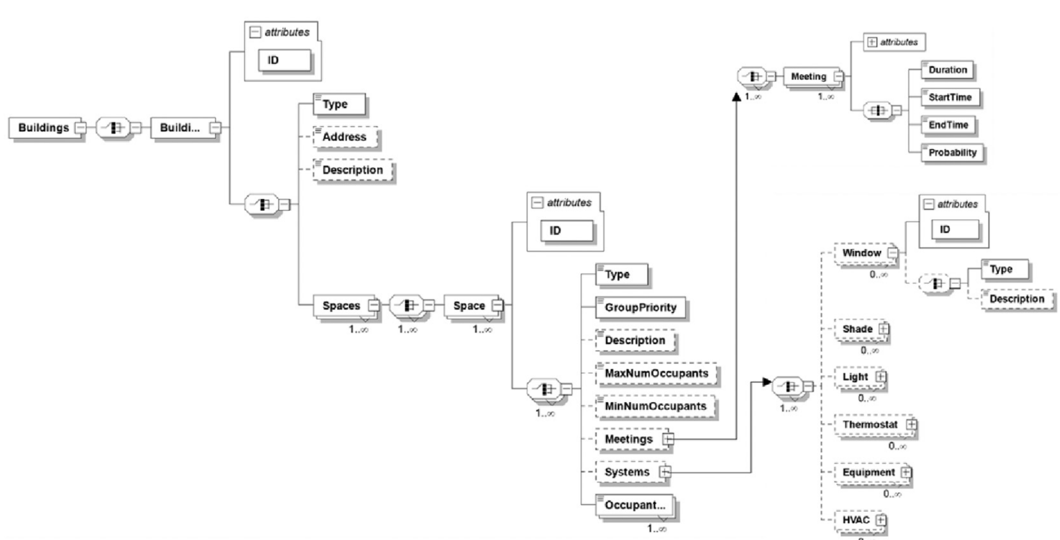

Fig. 2. The tree diagram from the xsd file showing the general characteristics of the **Buildings** element, with children Spaces branching into Meetings and Systems.

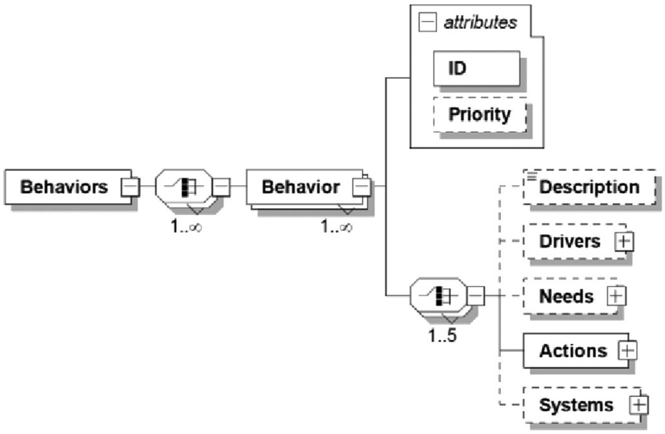

Fig. 4. The topology of the **Behaviors** element taken from the xsd file showing the general characteristics of how the behavior element branches into drivers, needs, actions and systems child elements.

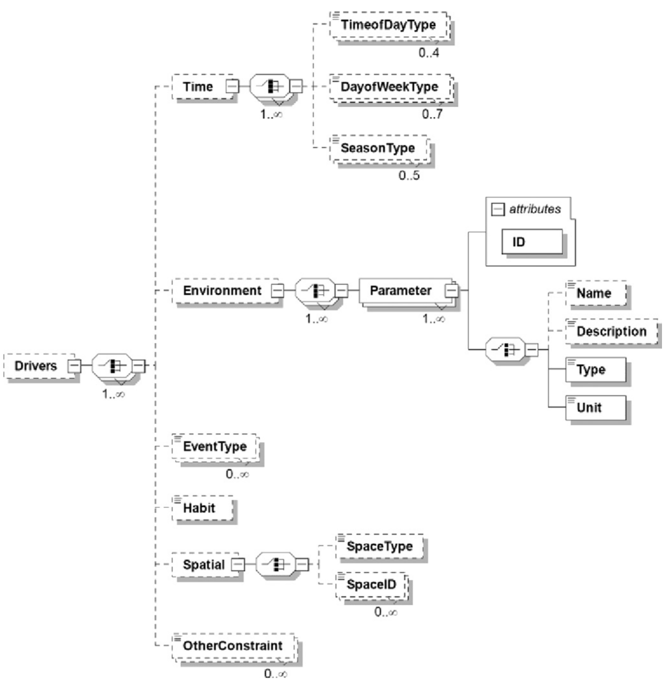

Fig. 5. The topology of the **Drivers** element taken from the xsd file showing the primary parameters of Time, Environment, EventType, Habit, Spatial and OtherConstraint.

minimum and maximum attributes. The *Thermal* child element allows for 4 different comfort element options following the ISO adaptive comfort standard [45], the ASHRAE adaptive comfort standard and comfort envelope [9], or a user-defined comfort envelope. The *Non-physical* element is less quantitative, consisting of descriptive enumerations such as privacy, view, preference, safety and other.

The *Actions* element has the 4 child elements of *Interaction*, *Inaction*, *Report*, and *Movement*. Child elements of *Interaction* include different mathematical methods (i.e. constant value, linear 1D, 2D, 3D, quadratic 1D, logit1D, 2D, 3D and Weibull 1D) to model the probability of actions occurring. The independent variables in the mathematical expressions reference the child element *Parameters* defined by *Drivers*. The equation coefficients are decimal inputs. Fig. 7 displays the topology of the *Actions* element taken from the xsd file showing the child elements which capture the mathematical format (parameters, coefficients) used to capture the probability of occupant actions in the obXML schema.

This method of providing a standard equation to characterize an occupant's action allows for a less deterministic representation of behavior, potentially leading to more insight into the impact of occupant behavior on building energy consumption [46]. Moreover, there are alternative ways to effectively implement actions using obXML. For example, Li and Lam [47] proposed an exchange language formulated in the XML format to facilitate the integration of functions and algorithms with existing tools. CapeML (Computer Aided Process Engineering Markup Language) [48] is an XML-based intermediate format for describing process engineering models. MathML (Mathematical Markup Language) [49] is an application of XML used for describing mathematical formulas and their integration into other documents. OSiL (Optimization Services Instance Language) [50] is a general schema used for multistage stochastic programs. OSiL forms part of a larger XML-based schema that is designed to allow the expression of a wide variety of different linear and nonlinear stochastic equations, random variables and Markov Chains. For obXML version 1.0, our approach of using a data structure was deemed simple and effective.

The *Inaction* child element represents the decision of an occupant to not act and remain uncomfortable within a space. The *Report* child element indicates that an occupant seeks assistance or files a complaint about their personal discomfort, but does not take direct action to satisfy their needs. The *MarkovChainModel* [51] or *OtherModel* children elements are derived from the *Movement* parent element and require the specification of occupancy in spaces or details about events occurring within the space.

The *Systems* element contains the details of building equipment or components that an occupant may interact with to satisfy their needs. The 6 child elements under the *Systems* parent element include *Windows*, *Shades*, *Lights*, *Thermostats*, *Equipment* (electrical appliances, office equipment), and *HVAC* (Fig. 8). Each has a control *Type* that describes the type of allowable actions e.g. a window is operable or fixed; a light can be switched on/off, dimmable, two steps, or three steps; a shade is adjustable or fixed; a thermostat is adjustable or fixed; HVAC is controllable, zonal controllable or zonal fixed. The unique attribute ID refers to the child element of the detailed system (window) defined by the *Building* parent element.

Lastly, the *Seasons* and *Time of Day* elements are optional providing the user the ability to input additional information about seasonal specifics (start month, end month, start day, end day) and details about the time of day (start hour, start minute, end hour, end minute) Fig. 9.

3. Examples using the obXML

In this section, the implementation of a Weibull distribution and logistic regression equation are implemented into the obXML schema as examples. Specifically, two models representing (1) the probability of turning on the air conditioner (AC) when feeling hot and (2) the closing of the blinds [52,53] are presented. Other human-building interactions (e.g. thermostat, equipment, lights interactions, or occupant movement) can be implemented using a similar methodology.

3.1. Turn on the air conditioner

To highlight the versatility of the obXML schema an example is presented representing the hypothetical probability of an occupant turning on the air conditioner when feeling hot. For this a Weibull distribution was used to describe the probability of turning on AC as a function of the indoor air temperature (Eq. (1)):

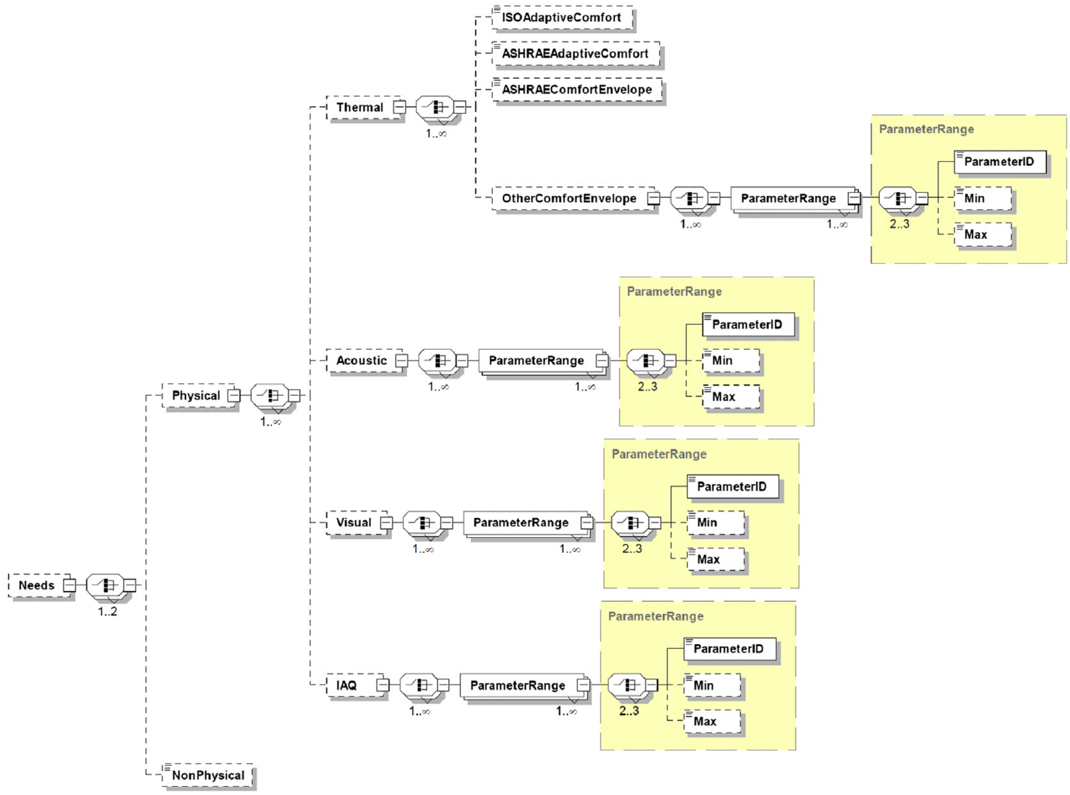

Fig. 6. The topology of the **Needs** taken from the xsd file showing the primary physical and nonphysical elements.

$$p = 1 - e^{\left\{\left[\left[\frac{U-X}{L}\right]\right]^k\right\}\Delta t} \quad (1)$$

where: p is the probability of turning on the AC; L represents the difference between the maximum and minimum comfort range (26 °C–31 °C); U is the threshold minimum temperature (26 °C); k is a constant representing the slope of the probability curve (taken as 8); Δt is the time interval (taken as 10 min), X represents the indoor air temperature. Using this information, the obXML schema can be used to represent the scenario and generate an XML file which will be read in the future by a functional mockup interface for co-simulation with a building energy simulation software. Fig. 10 shows a code snippet showing the main root *Behavior*, with *Drivers*, *Needs*, *Actions* and *Systems* of an occupant turning on the AC.

To describe the actions of turning on the AC (*Drivers* → *Time*), the time of day is evening, the day of the week is the weekday, the season type is all seasons. Under *Drivers* → *Environment* → *Parameter*, the primary parameter is the indoor air dry-bulb temperature. The *Needs* necessitating the AC-turn-on action were derived from the physical needs of thermal comfort (*Needs* → *Physical* → *Thermal*). Under *Actions*, a one-dimensional Weibull equation is used with an ‘s’ shaped curve probability function. The coefficients are determined to be (U, L, k) of 26, 5, 8, respectively. The *System* is the HVAC system that has zone on/off function. For this scenario, the schema provides a standardized way to describe the probability of the occupant action of turning on the AC.

3.2. Closing the blinds

Another example of occupant behavior action is presented by using a field study of venetian blind usage in air-conditioned office buildings. Between September 2004 and February 2005, Inkarojrit [52,53] monitored the Tang medical center and an administrative building at the Lawrence Berkeley National Laboratory, located in Berkeley, California. The field study was supported by a survey of building occupants within the Tang Building. Inkarojrit [52,53] provides 13 different models to calculate the probability of the window blind being completely closed. The 13 models use different combinations of inputs and coefficients, with the most accurate model described as follows (Eq. (2)):

$$\log\left(\frac{p}{1-p}\right) = \alpha + b_{win}\cdot L_{win} + b_{mxwin}\cdot L_{mxwin} + b_{vert}\cdot r_{vert} + b_{sen}\cdot L_{sen} \quad (2)$$

where: p is the probability of closing the window blinds; L_{win} is the average luminance of the window or source luminance (cd/m^2); L_{mxwin} is the maximum luminance of the window (cd/m^2); r_{vert} is the vertical solar radiation (W/m^2); L_{sen} is the occupants' self-reported ‘sensitivity to brightness’ (least sensitive 1 and most sensitive 7); a and b are coefficients. Fig. 11 shows a code snippet of only the *Behaviors* primary branch, representing blind-closing behavior, showing the *Drivers*, *Needs*, *Actions* and *Systems*.

To describe blind-closing actions in the obXML schema under *Drivers* → *Time*, the season is winter representing the September 2004 and February 2005 testing period. The independent variables (L_{win}, L_{mxwin}, r_{vert}, L_{sen}) (Eq (2)) would be represented under *Drivers* → *Environment* → *Parameter*. The four drivers are luminance from the window, maximum luminance from the window, vertical solar radiation, and occupant sensitivity to brightness. For the *Drivers* → *Spatial* category, the private office best represents the cubical nature of the Tang Buildings [53]. The *Needs* necessitating the blind-closing action were derived from two possible

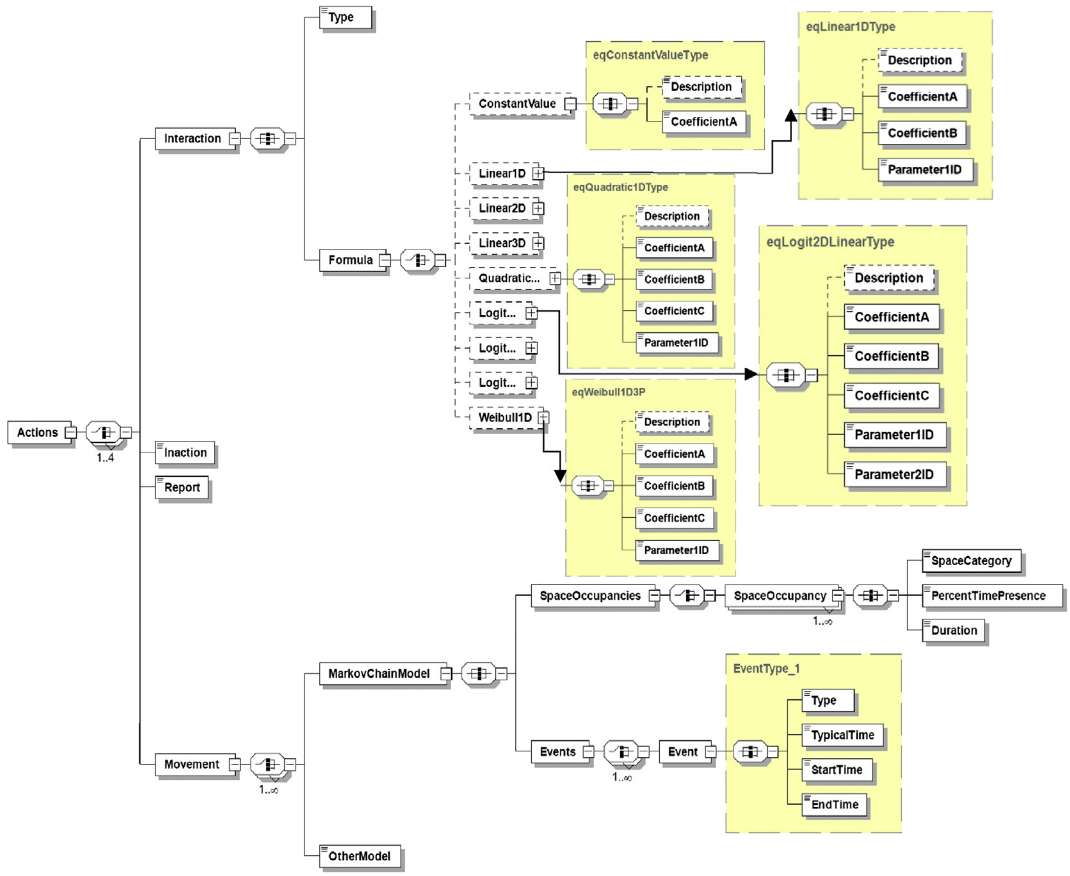

Fig. 7. The topology of **Actions** taken from the xsd file showing the primary parameters of Interaction, Inaction, Report and Movement (each equation type displays similar constituents including an optional description, reference parameter(s) and coefficients depending upon the structure of the equation).

motivators: (1) the vertical solar radiation at the window for the regulation of thermal comfort (*Needs* → *Physical* → *Thermal*) and, (2) the window or background luminance level, indicating an adjustment needed to obtain visual comfort (*Needs* → *Physical* → *Visual*). Under *Actions*, a 4D logit equation would be used referencing the *Drivers* input parameters. Using the most accurate model, the coefficients (α, b_{win}, b_{mxwin}, b_{vert}, b_{sen}) were −14.66, −5.82, 6.20, 3.29, 1.22, respectively [53]. The *System* is the blinds which are operable. It was observed that using the aforementioned drivers with this model allowed a prediction accuracy of 84–89% of the observed window blind control behavior [52].

4. Discussion

It has been well established that interactions between occupants and building systems can significantly increase or decrease the total building energy use. With a disproportionate amount of attention directed towards system or technological efficiency, the low priority placed on energy-related OB research has resulted in large discrepancies in building design optimization, energy diagnosis, performance evaluation, and building energy simulations. Current simulation-based evaluations of building energy performance oversimplify assumptions on occupant behavior creating inconsistencies between simulated and actual building energy performance. The main aim of the obXML schema is to facilitate the development of new methodologies to enable robust and standardized occupant behavior descriptions which can better capture real-life complexity and uncertainty during simulation. The schema structure has been conceived to maximize its flexibility and its potential application for occupant behavior modeling standardization. In a sense, the actual drivers, needs, actions and systems that are included in the schema are placeholders used to establish a common language and platform to homogenize the representation of energy-related OB in buildings for the international research community. The obXML schema allows the creation of obXML instance files which contain a representation of occupant behaviors in buildings following the DNAS framework ontology. The obXML schema facilitates the development of a quantitative description of human interactions with building systems. For actual implementation and practical use an online repository has been created at behavior.lbl.gov where the obXML schema may be downloaded.

One challenge with the development of the schema is establishing the order of events, considering multiple occupants and multiple actions. To account for this, each behavior within a group of behaviors is defined by a unique ID and priority indicator. An example of a situation with multiple actions is as follows: The indoor temperature is too warm (*Driver*) so the occupant wants to obtain thermal comfort (*Needs*). The occupant has the option to perform multiple *Actions*, such as open the window, close the blinds or turn on the HVAC system. The question becomes which action is performed first and how is this sequence of events captured by obXML? In the current version of the schema (version 1.0) a priority ranking may be applied manually to each behavior. For example, if the outdoor temperature is greater than the indoor temperature, and the time of day is night (no outdoor illuminance), then turning on the AC may be the best action considering the circumstance, with a priority ranking.

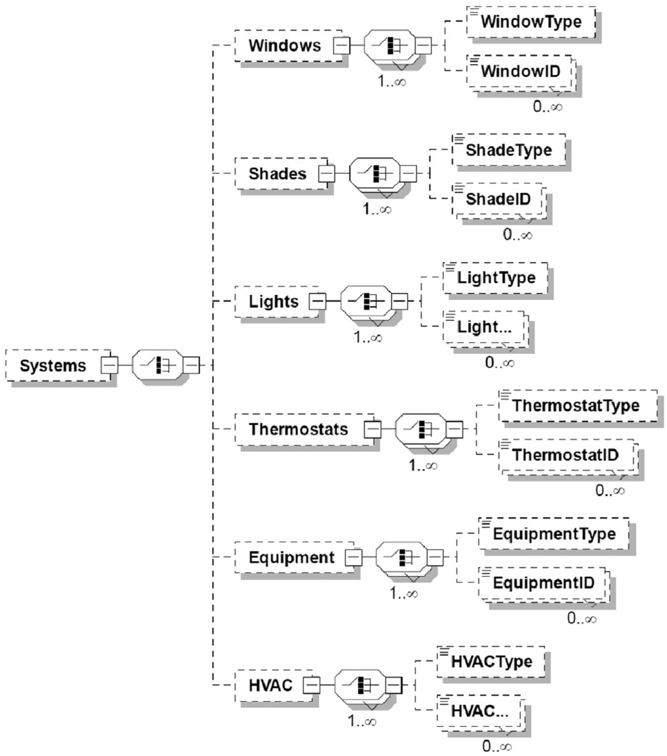

Fig. 8. The topology of the **Systems** in the building which are operable by occupants, including Windows, Shades, Lights, Thermostats, Equipment and HVAC.

In future obXML versions it is envisioned to have an automated priority ranking system linked to specific *Drivers* (e.g. time of day, outdoor temperature, outdoor wind speed) (Fig. 12). Future work will address the algorithms needed for this priority ranking system with improvements to include constraints associated with (1) group versus individual behavior, (2) the occurrence of simultaneous multiple-actions, (3) the sequence of occupant actions and, (4) better accountability for culturally-motivated actions. Addressing these issues will occur in conjunction with the development of an obFMU (occupant behavior Functional Mockup Unit) which can utilize the xml file generated by the schema. More broadly, capturing these diverse aspects of behavior in simulation and co-simulation with other BEM programs (e.g. DeST, ESP-r) requires an alliance in the time-step duration and sequencing of steps.

Under current practices, the obXML schema is being used to describe occupant behavior models as part of a software module being developed in Subtask D of the IEA EBC Annex 66 [54]. The behavior software module can be used in three different ways: (1) to pre-calculate schedules or settings which are used as inputs for occupancy or actions without feedback; (2) to direct code integration via function calls to dynamic link libraries (DLLs); and (3) to facilitate co-simulation with current BEM programs via FMIs. The advantages of this approach against the direct implementation or coupling of advanced OB models in/with building simulation programs are that it (1) utilizes the capabilities of domain-specific simulation and provides the flexibility to be integrated with an array of building modeling programs, extending beyond EnergyPlus, (2) allows users the option to select preferred simulation programs and directly enhances the occupant modeling component of the select simulation program and, (3) enables standardize representation of occupant behavior models for flexibility, future expansion and interoperability. Theses aspects support the overall objective to gain a better understanding and quantification of the impact occupant behavior has on total building energy consumption.

5. Conclusions

The DNAS framework (e.g. drivers, needs, actions and systems) described in Part I [1] was implemented into the form of an XML

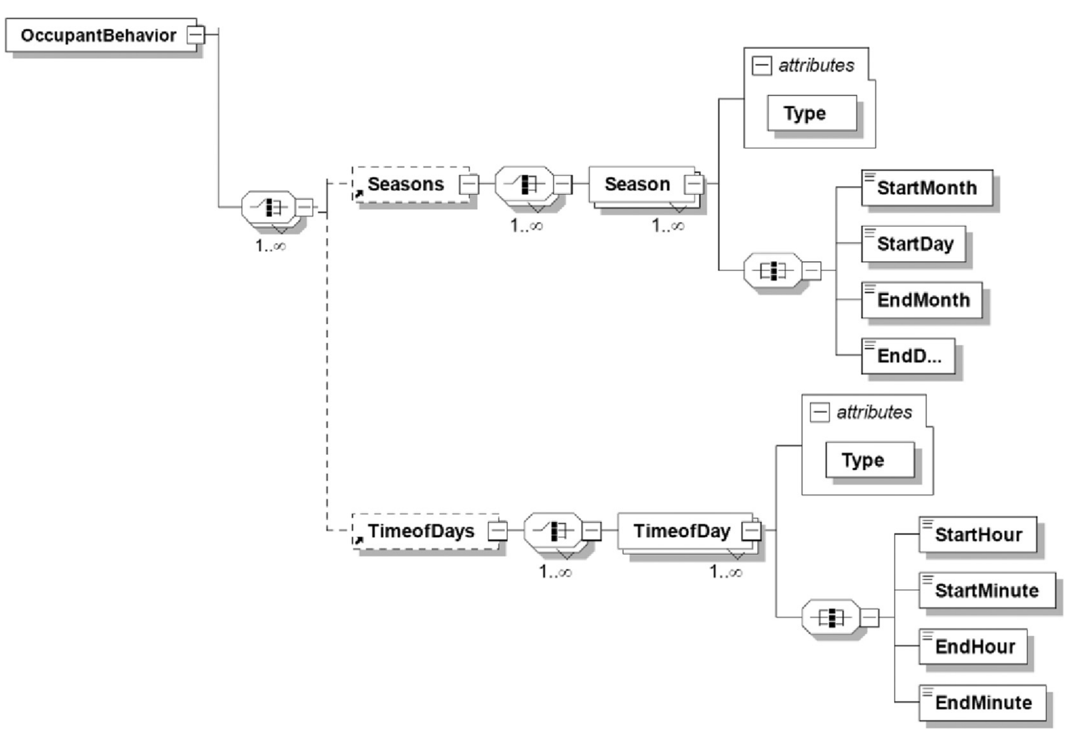

Fig. 9. The topology of the **Seasons** and **TimeofDays** optional main elements specifying details about the season and time.

```
<Behavior ID="B_AC2">
    <Description>Hot AC On</Description>
    <Drivers>
        <Time>
            <TimeofDay>Evening</TimeofDay>
            <DayofWeek>Weekday</DayofWeek>
            <SeasonType>All</SeasonType>
        </Time>
        <Environment>
            <Parameter ID="P11">
                <Name>Room dry-bulb air temperature</Name>
                <Type>RoomAirTemperature</Type>
                <Unit>C</Unit>
            </Parameter>
        </Environment>
    </Drivers>
        <Needs>
            <Physical>
                <Thermal>
                <OtherComfortEnvelope>
                <ParameterRange>
                    <ParameterID>P11</ParameterID>
                    <Min>26</Min>
                    <Max>31</Max>
                </ParameterRange>
                </OtherComfortEnvelope>
                </Thermal>
            </Physical>
        </Needs>
        <Actions>
            <Interaction>
            <Type>TurnOn</Type>
                <Formula>
                <Weibull1D>
                <Description>S Shaped Curve Probability Function</Description>
                <CoefficientA>26</CoefficientA>
                <CoefficientB>8</CoefficientB>
                <CoefficientC>5</CoefficientC>
                <Parameter1ID>P11</Parameter1ID>
                </Weibull1D>
                </Formula>
            </Interaction>
        </Actions>
        <Systems>
            <HVAC>
            <HVACType>ZoneOnOff</HVACType>
            </HVAC>
        </Systems>
</Behavior>
```

Fig. 10. Representation of the turning on the AC generated using the obXML schema.

schema called obXML. The notable contributions of the development of the obXML version 1.0 include the following:

1. The obXML schema provides a standardized structure to describe occupant behavior which can be used by researchers and industry stakeholders to standardize the language of occupant behavior studies.
2. The obXML schema provides a platform to describe occupant behavior in buildings and assess the impact of occupant behavior on building energy modeling in more detail than present methods allow.
3. The design of the obXML schema allows for flexibility and extensibility with easy adaptability, so that it can be modified to include additional elements or attributes if so desired.
4. The obXML schema is intended to be integrated into current BEM programs or Functional Mock-up Units to support both model exchange and co-simulation of dynamic models.

Further development and improvements to the obXML schema are foreseen and will be released in future versions. Similar to gbXML, the obXML schema can evolve as the core of Occupant Information Modeling (OIM), to provide a clear and robust representation of building occupants and their interactions with building systems. A new generation of virtual building models and building simulation frameworks need to be enriched with additional data models able to express the dynamic behavior of a building due to the energy-related behavior of the occupants. The development of the obXML schema is one step in this direction.

```
<Behavior ID="OB2">
    <Drivers>
        <Time>
            <Season ID="B">
                <Type>Winter</Type>
                <StartMonth>9</StartMonth>
                <EndMonth>2</EndMonth>
            </Season>
        </Time>
        <Environment>
            <Parameter Type="WindowLuminance" Unit="cd/m2" ID="C">
            <Parameter Type="MaxLuminance" Unit="cd/m2" ID="D">
            <Parameter Type="SolarRadiation" Unit="W/m2" ID="E">
            <Parameter Type="BrightnessIndex" Unit=" numerical" ID="F">
        </Environment>
        <Spatial>
            <SpaceType>OfficePrivate</SpaceType>
        </Spatial>
    </Drivers>
    <Needs>
        <Physical>
            <Thermal>
                <OtherComfortEnvelope>
                    <ParameterLimit ParameterIDREF="E" min="5.13" max="355"/>
                </OtherComfortEnvelope>
            </Thermal>
            <Visual>
                <ParameterLimit ParameterIDREF="C" min="478" max="5754"/>
                <ParameterLimit ParameterIDREF="D" min="2454" max="33884"/>
                <ParameterLimit ParameterIDREF="F" min="1" max="7"/>
            </Visual>
        </Physical>
    </Needs>
    <Actions>
        <Interaction Type="BlindsClosed">
            <Description>action of closing the blinds</Description>
            <Formula>
                <Logit4D ID="H">
                    <Description>4D logit equation</Description>
                    <CoefficientA>-14.66</CoefficientA>
                    <CoefficientB>-5.82</CoefficientB>
                    <CoefficientC>6.20</CoefficientC>
                    <CoefficientD>3.29</CoefficientD>
                    <CoefficientE>1.22</CoefficientE>
                    <Parameter1IDREF>C</Parameter1IDREF>
                    <Parameter2IDREF>D</Parameter2IDREF>
                    <Parameter3IDREF>E</Parameter3IDREF>
                    <Parameter4IDREF>F</Parameter4IDREF>
                </Logit4D>
            </Formula>
        </Interaction>
    </Actions>
    <Systems>
        <Shades>
            <ShadeType>Operable</ShadeType>
        </Shades>
    </Systems>
</Behavior>
```

Fig. 11. Representation of the blinds closing behavior using the obXML schema.

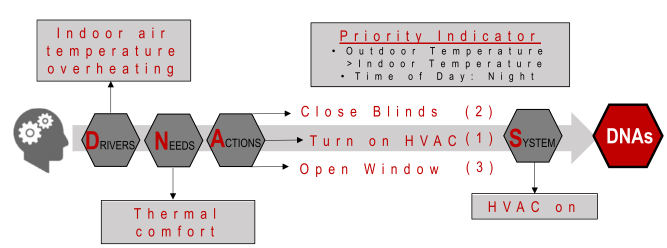

Fig. 12. Representation of applying priority indicators for an example of possible multiple actions.

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Gap between predicted and actual building energy consumption

Is there sufficient benefit in quantifying OB in building energy simulations?

PAPER 8 — **S. D'Oca,** S.P. Corgnati, V. Fabi, R.K. Andersen.
Effect of thermostat and window opening occupant behavior models on energy use in homes
BUILDING SIMULATION – 2014

PAPER 9 — **S. D'Oca,** S.P. Corgnati.
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Effect of thermostat and window opening occupant behavior models on energy use in homes

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Research Article

Architecture and Human Behavior

Abstract

Existing dynamic energy simulation tools exceed the static dimension of the simplified methods through a better and more accurate prediction of energy use; however, their ability to predict real energy consumption is undermined by a weak representation of human interactions with the control of the indoor environment. The traditional approach to building dynamic simulation considers energy consumption as fully deterministic, taking into account standardized input parameters and using fixed and unrealistic schedules (lighting level, occupancy, ventilation rate, thermostat set-point). In contrast, in everyday practice occupants interact with the building plant system and building envelope in order to achieve desired indoor environmental conditions. In this study, occupant behavior in residential building was modelled accordingly to a probabilistic approach. A new methodology was developed to combine probabilistic user profiles for both window opening and thermostat set-point adjustments into one building energy model implemented in the dynamic simulation tool IDA Ice. The aim of the study was to compare mean values of the probabilistic distribution of the obtained results with a singular heating energy consumption value obtained by means of standard deterministic simulations. Major findings of this research demonstrated the weakness of standardized occupant behavior profile in energy simulation tools and the strengths of energy models based on measurements in fields and probabilistic modelling providing scenarios of occupant behavior in buildings.

Keywords

occupant behavior,
residential buildings,
building energy modelling,
window opening,
thermostat set-point

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1 Introduction

Being able to assess the energy consumption to a certain level of accuracy is a key factor in the aim of sustainability and efficiency in buildings.

Moreover, reducing the energy use for space heating is a challenging task not only related to the technical performance of a building, but also strongly related to occupant behavior. In fact, de Dear and Brager (2001) and Baker and Standeven (1996) claim that occupants adaptive behavior has potential to reduce heating and cooling energy consumption by allowing greater variations in indoor thermal conditions when personal environmental control is made available. However, such reductions require that the occupants are allowed to affect building performance, by manipulating control devices such as windows, radiator valves, shades and devices to bring about desired indoor environment conditions.

Apart from simplification and numerical assumption of actual energy simulation tools, this active participation of users to building performance has been suggested (Andersen et al. 2007; Fabi et al. 2013) as being one of the paramount aspects affecting the discrepancy between simulated and measured energy uses in buildings.

Several investigations (Marchio and Rabl 1991; Andersen 2012; Emery and Kippenhan 2006) show significant uncertainties in the estimation of energy consumption in dwellings, highlighting a gap between calculated and actual energy consumption that may exceed 300% in extreme cases. Occupants having the possibility to control their living or working indoor environment have been found to be generally more satisfied than users exposed to environments of which

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they have no control (Leaman and Bordass 1998; Paciuk 1989; Toftum et al. 2009). Giving occupants the possibility to interact with the building control system results in a better perceived indoor environmental quality and higher occupant's satisfaction. But occupant behavior could vary enormously between individuals and groups, resulting in large variations in building energy consumption. Due to natural uncertainties in human behavior, developing a single deterministic description of occupant behavior is neither possible nor accurate; instead, probabilistic modelling is required (Nicol 2001). In the last decade a broad use of probabilistic approach in modelling human adaptive behavior is emerging in the field of building energy efficiency, ventilation and thermal comfort in indoor environments.

Different actions have been modelled for different cases such as window opening, thermostat adjustments, blind and lighting use (Nicol 2001; Clevenger and Haymaker 2006; Bourgeois 2005; Rijal et al. 2007; Borgeson and Brager 2008; Page et al. 2008; Andersen et al. 2007; Hoes et al. 2011; Wei et al. 2010; Haldi 2013; Korjenic and Bednar 2011; Wang et al. 2011; Fabi et al. 2013; Schweiker et al. 2011). In this paper, we propose a new methodology to quantity both the effect of thermostat and window opening occupant behavior on energy use in homes. To do this, we applied a probabilistic methodology in modelling occupant behavior in building energy models.

2 Method

The presented research was an extension of a previous probabilistic modelling approach (Andersen et al. 2011; Fabi et al. 2012a, b) taking into account separately windows control and heating set-point adjustments in residential buildings. A new methodology was developed to combine these two probabilistic inputs into a single building energy model by using the dynamic simulation software IDA Ice.

2.1 Probabilistic modelling approach

The probabilistic modelling approach we used can be simplified in five main steps (Fig. 1):

1. Collecting real data from field measurements (environmental and behavioral).
2. Data analysis and definition of the most influencing parameters (inference of behavior models from data) on occupant energy related behavior in residential buildings.
3. Implementation of probabilistic models of occupant behavior as inputs in the dynamic energy simulation program.
4. Run of a set (10) of simulations.
5. Consideration of a probabilistic distribution of the outputs.

2.1.1 Data collection and analysis

A field monitoring campaign of indoor and outdoor climate conditions and occupants control actions was performed in fifteen naturally ventilated dwellings located 10 to 25 km from Copenhagen in the period from January to August 2008 (Andersen et al. 2011). Ten minutes step indoor condition data were recorded both in living room and bedroom in each dwelling regarding indoor temperature [℃], indoor relative humidity [%], CO_2 concentration [ppm] and luminance [lx]. Outdoor condition data were gathered

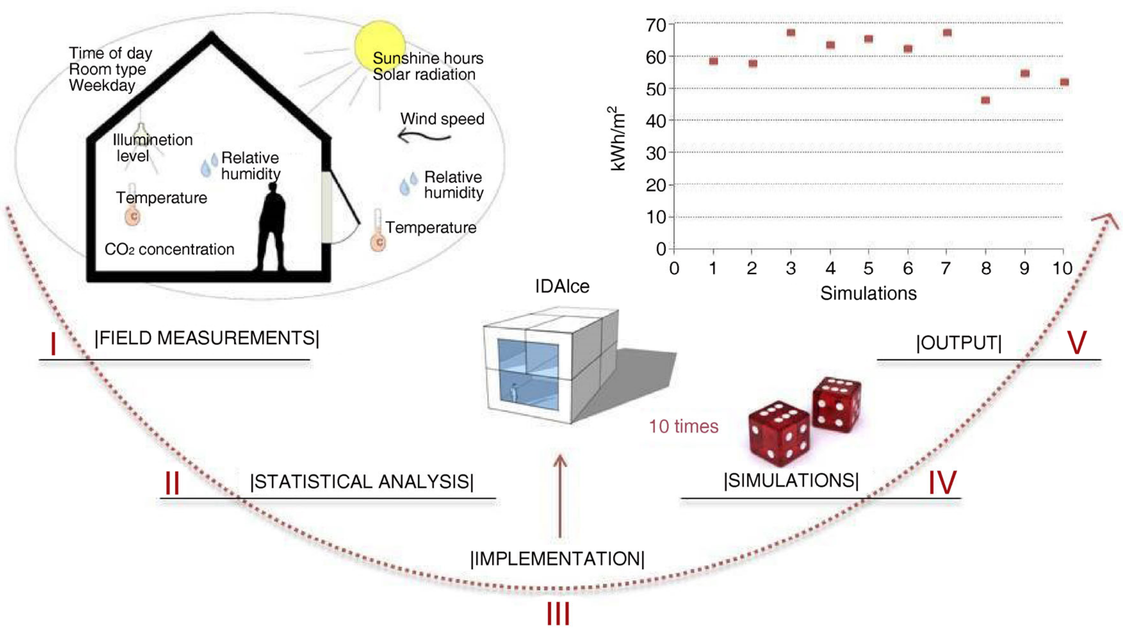

Fig. 1 Approach to the statistical modeling of occupant behavior

from the closest weather station regarding outdoor temperature [℃], outdoor relative humidity [%], global solar radiation [W/m^2], wind speed [m/s] and number of solar hours per day. Moreover, interactions of occupant with regard to window position [open/close] and heating set-point on thermostatic radiator valves [℃] were recorded. Window sensors were installed on windows that inhabitants declared to use more often when ventilating the dwellings. Large variety between individual behaviors was recorded and the dwellings were eventually grouped after the number of interactions with window and thermostat occurred during the monitoring period. As shown in Table 1, the total number of window openings varies from dwelling number 1 (334) to number 12, in which window has been opened only one time during the whole period of monitoring survey. Similar patterns occurred for thermostat adjustment monitoring. As a result, three users' type representing Active, Medium and Passive users were settled and the probability of opening window and adjusting the thermostat was inferred for three different statistical models.

2.1.2 Statistical analysis

Data collected during measurements were statistically treated by means of the statistical software R in order to determine which variables had an influence on opening and closing a window or turning up or down the thermostat in a previous correlated study (Andersen et al. 2013). A multiple logistic regression formula was used to infer the probability of opening windows and adjusting the thermostat for each of the Active, Medium and Passive user type.

Table 1 Windows opening frequency for monitored dwellings, considering bedroom and living room variation

Dwelling number	Total number of window openings	Number of window openings in bedroom	Number of window openings in living room
1	**334**	202	132
3	82	63	19
4	235	109	126
5	73	55	18
6	337	137	200
7	718	559	159
8	258	131	127
9	25	7	18
10	65	61	4
11	82	80	2
12	**1**	1	0
13	341	263	78
14	241	82	159
15	166	55	111
16	153	93	60

2.1.3 Implementation

To replicate probabilistic control actions of window opening and thermostat set-point, two logistic regression formulas were implemented in the dynamic building simulation software IDA Ice. These formulas describe a relationship between the change in window or thermostat state and a set of independent predictors used when the outcome is binary, that is when there are only two possible accounts (0 or 1) in the case:

- open/not open windows – turn up/not turn up thermostats;
- close/not close windows – turn down/not turn down thermostats.

The outcomes of the models were probabilities of an action occurring (windows open/close heating set-point increase/decrease) within the next 10 minutes (since the independent variables were measured in 10-minute intervals). To determine the state of the windows and heating set-point, the probabilities were compared to a random number that was generated with 10-minute intervals. An action occurred in the simulation if the calculated probability was higher than the random number. The window would stay open or the thermostat would stay turned up until the probability of closing the window or turning down the thermostat was higher than the matching random number.

Window sensor recorded a binary state of window being open or closed, no information about window tilting angle was available. For this reason, the opening signal in the simulation model was multiplied with a fixed degree of opening of 20%.

2.1.4 Simulations

The logistic regression formulas were implemented in IDA Ice for both system controls by using a two-room model consisting of living room and bedroom, for which a suitable room is provided by the European Standard 15265:2005 "*Thermal performance of buildings—Calculation of energy use for space heating and cooling—General criteria and validation procedures*". Thermo physical properties of the transparent and opaque components are summarized in Tables 2 and 3.

Table 2 Thermo physical properties of the transparent components

Type of component	Double pane 4.12.4 glass
Size and orientation of component	2 windows (1.2 m × 1.2 m), west
U_w value	2.9 W/(m^2·K)
Solar transmittance	$T = 0.7$
Solar heat gain coefficient	$g = 0.76$

Table 3 Thermo physical properties of the opaque components

	Material	Thermal conductivity (W/(m·K))	Density (kg/m^3)	Specific heat (J/(kg·K))	*U*-value (W/(m^2·K))	Thickness (cm)
External wall	Internal plastering	70	1.400	85	49	365
	Masonry	79	1.600	85		
	Insulation layer	4	30	85		
	Outer layer	99	1.800	85		
Internal wall	Gypsum plaster	21	900	85	36	125
	Mineral wool	4	30	85		
	Gypsum plaster	21	900	85		
Floor covering	Acoustic board	6	400	84	241	40
	Mineral wool	4	50	85		
	Concrete	210	2.400	85		
	Mineral wool	4	50	85		
	Concrete	140	2.000	85		
	Floor covering	23	1.500	15		
Roof	Rain protection	23	1.500	13	438	284
	Insulation layer	0.04	50	0.85		
	Concrete	2.10	2400	0.85		
External floor	Concrete	2.10	2400	0.85	76	284
	Mineral wool	0.04	50	0.85		
	Concrete	140	2.000	85		
	Plastic floor covering	23	1.500	15		

Both bedroom and living room were naturally ventilated and heated by waterborne radiator from September to June, working with a dead band of 2℃ and a maximum power of 2500 W placed under the windows in the two rooms. 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. Both living room and bedroom had only one wall facing the exterior environment in the west orientation, only one operable window and external shading (Fig. 2).

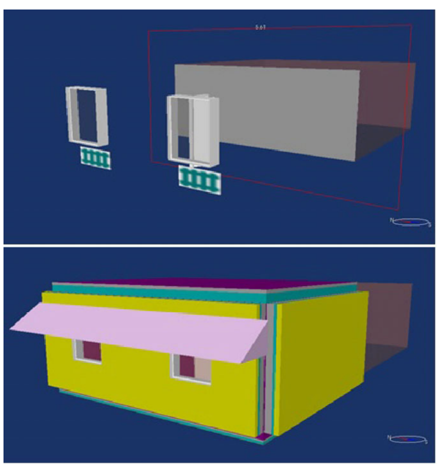

Fig. 2 Visualization of the two-room model in IDA Ice

As internal source, a house living schedule for weekday from Monday to Friday has been fixed. In both bedroom and living room one person was considered present from 17:00 to 8:00 and half occupation has been taken into account from 15:00 to 17:00 at an activity level of 70 W/m^2 and a metabolic activity of 1.2 met. The lighting schedule followed 100% the presence of people. Moreover, lights in the room with an emitted heat per unit equal to 50 W automatically switched on if the minimum work plane illuminance was lower than 100 lx; on the contrary, light switched off automatically at an illuminance level of 500 lx.

The electrical equipment consumed 50 W from 18:00 to 22:00 from Monday to Friday, and from 15:00 to 22:00 on weekends. In the standard schedule, windows opened if the indoor temperature exceeded a certain value (25℃±2℃) and the outdoor temperature was lower than the indoor temperature. Windows opened with a fixed degree of opening corresponding to a tilting angle of 20% of the total opening. Moreover, windows would stay close whenever the room is unoccupied.

2.1.5 Outputs

Each model was run 10 times. Since window openings and heating set-points were modelled stochastically, the 10 simulations did not have identical results. The mean value of a probabilistic distribution of results (fluctuation of 10 simulations) instead of single deterministic value was considered as more representative of actual energy consumption. In the simulation phase, for every model we simulated a set of 10, 20 and 30 runs, in order to highlight the oscillation among results distribution. No evident benefits emerged in running each model more than 10 times since (a) small variation (from 10% to 12%) among results distribution was found between the sets of 10, 20 or 30 runs and (b) one IDA Ice yearly simulation implementing probabilistic inputs for window and thermostat operation lasted up to 2 hours.

2.2 Methodology

The presented study developed a new methodology to combine probabilistic window openings and thermostat set-point schedules in building energy models. The methodology of the research is synthesized in Fig. 3 and explained hereafter.

In order to highlight the magnitude of occupant behavior leverage on energy consumption, simulations were performed for three different climate locations: Mediterranean (Athens), Continental (Frankfurt) and Nordic (Stockholm) climate. Additionally, with the aim to investigate the influence of thermal comfort and air quality perception on occupant behavior, simulations were performed for the three comfort category conditions (Categories I, II, III) as defined in Standard EN 15251:2006 (Table 4), both for heating set-point acceptability (21°, 20°, 18°) and for ventilation rate values (0.49 L/(s·m^2), 0.42 L/(s·m^2), 0.35 L/(s·m^2)).

Table 4 Standard EN 15251:2006. Recommended internal temperature ranges in residential buildings

Type of building/space	Category	Operative temperature for heating (winter season) ~1 clo (℃)	Air change rate (L/(s·m^2))
Residential building: living spaces (bedrooms, drawing room, kitchen, etc.)	I	21–25	0.49
	II	20–25	0.42
	III	18–25	0.35

Firstly, we treated dwelling energy performance as normally performed in the design stage of energy consumption simulation. Secondly, a model considering probabilistic of the interaction between users and window opening and closing was built, with heating set-point considered in a deterministic way as a fixed input value and being dependent on the comfort category. Finally, both window opening and closing and heating set-point adjustments were described through probabilistic models as logistic functions by combining the so called "hybrid models". Specifically three kinds of hybrid models were implemented into IDA Ice, and five scenarios of the research were defined.

2.2.1 *Scenario zero: Deterministic model*

- Window opening: deterministic
- Heating set-point adjustments: deterministic

In order to get an indication of the performance of the four probabilistic models developed and their ability to reproduce occupant behavior interactions with building envelope and system control, a first *reference deterministic*

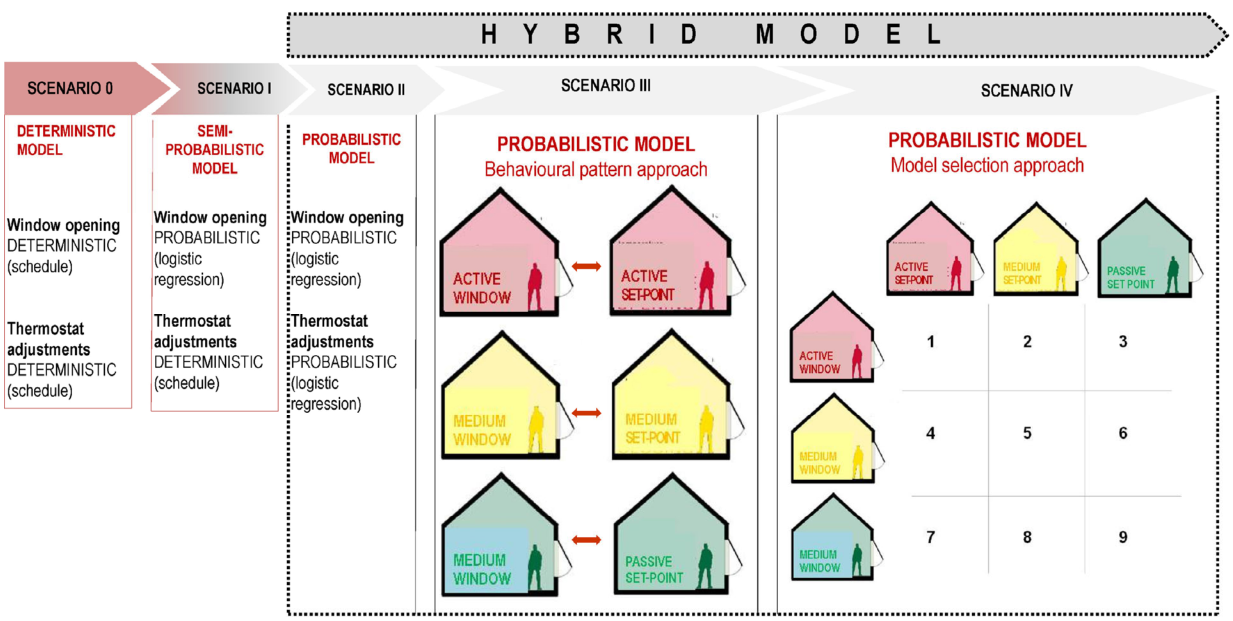

Fig. 3 Graph explaining the methodology of the research

model was implemented. This simulation model considered standard window and thermostat controls, by using deterministic inputs for both variables. Results of this fully deterministic model were considered as singular, since no probabilistic distribution of the output was needed, and subsequently compared with probabilistic model results.

2.2.2 *Scenario I: Semi-probabilistic model*

- Window opening: probabilistic
- Heating set-point adjustments: deterministic

The probability of opening and closing windows was inferred for a behavioral model, regarding naturally ventilated dwellings. Scenario I model was implemented by using variables and coefficients statistically treated (Table 5) as published by Fabi et al. (2012a). In this scenario, heating set-point was treated as a deterministic input.

2.2.3 *Scenario II: Hybrid probabilistic model*

- Window opening: probabilistic
- Heating set-point adjustments: probabilistic

We integrated a probabilistic simulation model considering both the influence of occupant behavior on window opening and closing and heating set-point adjustments. A probabilistic control of thermostats was added to the previous model whereby variables and coefficients statistically treated have been used (Andersen et al. 2011).

The probability of turning up/down the thermostat was inferred for three separated behavioral models based on the number of interactions with system controls and named as active, passive and medium user type (Table 6) as published by Fabi et al. (2012b). Window opening was modelled as in Scenario I.

2.2.4 *Scenario III: Hybrid probabilistic model—Behavioral pattern approach*

In the attempt to model probabilistic both the users interaction with windows and thermostats as related to users' level of interaction, a model of window opening for active, medium and passive users was implemented (Bakkær Sørensen 2012). As described in Table 7, the probability of opening and closing windows is affected by diverse variables and coefficients for different levels of users' interactions.

Table 5 Variables and coefficients for window opening/closing probability

Variable	Time	Open window Coefficient	Open window Magnitude	Close window Coefficient	Close window Magnitude
Intercept in spring – bedroom		−23.83		−1.93	
	Night	−23.04		−0.84	
	Morning day	−24.06		−1.22	
	Afternoon	−24.32		−1.00	
	Evening	−24.47		−0.38	
Intercept in spring – living room		−10.58		−5.31	
	Night	−9.80		−4.22	
	Morning day	−10.82		−4.61	
	Afternoon	−11.08		−4.39	
	Evening	−11.22		−3.77	
Intercept in summer – bedroom		−24.72		−0.77	
	Night	−23.94		0.32	
	Morning day	−24.96		−0.06	
	Afternoon	−25.22		0.16	
	Evening	−25.36		0.77	
Intercept in summer – living room		−11.47		−4.15	
	Night	−10.69		−3.06	
	Morning day	−11.71		−3.45	
	Afternoon	−11.97		−3.23	
	Evening	−12.12		−2.61	
CO_2 concentration	Bedroom	1.87	5.07		
	Living room	0.00023	0.62		
Indoor temperature		16	215		
Solar radiation		50	342		
Outdoor temperature				−0.15	−4.07
Outdoor relative humidity				−0.02	−0.04
Indoor relative humidity	Bedroom			0.04	1.56
	Living room			0.10	4.34

Table 6 Variables and coefficients for Active, Medium, Passive users thermostat turning up/down probability

ACTIVE USERS				
		TURNING UP		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−4.29	—	—
Time of the day	Morning	3.66	1.00	3.66
	Noon	3.45	1.00	3.45
	Afternoon	3.42	**1.00**	3.42
	Evening	2.14	1.00	2.14
Indoor relative humidity		−0.09	50.12	4.27
Outdoor temperature		−0.14	36.30	5.23
		TURNING DOWN		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−3.51	—	—
Solar radiation		−0.02	849.00	16.52
MEDIUM USERS				
		TURNING UP		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−7.64	—	—
Outdoor temperature		−0.23	36.30	8.29
Wind speed		0.37	10.70	3.96
		TURNING DOWN		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−22.84	—	—
Time of the day	Morning	17.68	1.00	17.68
	Noon	16.74	1.00	16.74
	Afternoon	16.26	**1.00**	16.26
	Evening	16.18	1.00	16.18
PASSIVE USERS				
		TURNING UP		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−9.72	—	—
		TURNING DOWN		
Variable		Coefficient	Max–Min	Magnitude
Intercept		−14.28	—	—
Solar radiation		−1.01	10.70	10.78

A new probabilistic simulation model was run, representing different users' frequency of interaction within the same dwelling.

Thus, three models were indicative of active, medium and passive users behavior both for window control and for heating set-point adjustment (active-active, medium-medium, and passive-passive models).

2.2.5 *Scenario IV: Hybrid probabilistic model—Model selection approach*

Starting from the assumption that users' willingness in reaching a certain level of comfort could be different regarding window openings and heating set-point adjustment, each of three behavioral models of window control previously developed was matched in a macro with the three concerning thermostat adjustments. Accordingly, nine models were implemented, covering all possible combinations between them.

3 Results

By switching from a deterministic to a probabilistic approach in dynamic simulation software, high variation in energy consumption predictions was found. Results of the research focused on differences in delivered heat energy consumption between singular values of deterministic simulations and mean values of probabilistic simulations.

3.1 Window openings

In the probabilistic models windows opened accordingly to a probability which was strictly correlated to indoor and outdoor parameters. In living room (Fig. 4), the window opening probability had a bell-shaped curve distribution and presented a peak between June and September in Athens. The maximum value was observed between March and May in Stockholm's simulations. In Frankfurt, the tendency was in between the Mediterranean and Nordic climates, with maximum values ranging from May to September.

Since no fixed air change rate but variable indoor and outdoor parameters drove the probability of opening windows, great variation in ventilation losses between the deterministic and the probabilistic scenarios was found in every climate location. Among other factors, such as transparent building components' air tightness and cracks in opaque building envelope, ventilation rate operated by users was the paramount driver for variation in heat energy consumption in residential buildings.

Figure 5 displays a comparison among results of infiltration and natural ventilation for deterministic simulations (Scenario 0, deterministic input) and for the distribution of a set of 10 simulations (Scenario IV, probabilistic inputs), both for living room and bedroom. Representative results are shown for the Category of Comfort II. In Athens, ventilation losses simulated by using fixed value of ventilation rate was 38 kWh/(m^2·year). On the contrary, the probabilistic distribution of infiltration and natural ventilation ranged from 28 kWh/(m^2·year) to 56 kWh/(m^2·year), with a maximum variation of 47%. In Frankfurt, ventilation losses simulated by using fixed value of ventilation rate was 72 kWh/(m^2·year). On the contrary, the probabilistic distribution of infiltration and natural ventilation ranged from 48 kWh/(m^2·year) to 102 kWh/(m^2·year), with a maximum

Table 7 Variables and coefficients for Active, Medium, Passive users window opening/closing probability

		ACTIVE		MEDIUM		PASSIVE	
		Open	Close	Open	Close	Open	Close
Intercept (hour 0)	Bedroom	−11.9	3.43	−28.75	−18.27	−16.10	−21.19
	Living room	−11.9	3.26	−28.75	−16.16	−16.50	−18.56
Indoor T		0.10	−0.08	0.15		0.14	
Indoor RH	Bedroom	0.02	−0.07	−0.10	−0.19	0.07	
	Living room	0.02	−0.15	−0.10	−0.13	0.07	
CO_2 concentration				1.40	2.24	1.01	1.62
Illuminance		0.28	−0.48	−0.34			
Outdoor T	Bedroom	0.10		0.16	−0.01	−0.04	−0.13
	Living room	−0.09		0.16	−0.09	0.07	−0.13
Wind	Bedroom	0.34	−0.29	0.34	0.47	−0.14	
	Living room	0.34	−0.29	0.34	0.47	0.91	
Outdoor RH		0.01	0.02	0.02	0.01		
Solar radiation						0.19	
Sunshine hours		−0.08		−0.09		−0.08	
Hour 1		−0.02		11.73	−12.06	−13.05	
Hour 2		−0.72		11.07	−0.41	−13.02	
Hour 3		−0.43		11.10	−1.10	−13.00	
Hour 4		0.97		15.21	−0.49	−12.98	
Hour 5		2.48		15.32	1.86	2.02	
Hour 6		**3.0**		15.85	2.80	3.28	
Hour 7		2.81		**16.07**	2.89	**4.62**	
Hour 8		2.49		15.99	3.47	4.11	
Hour 9		2.12		15.57	3.21	3.22	
Hour 10		1.69		15.03	3.45	3.06	
Hour 11		1.85		14.37	**3.68**	3.23	
Hour 12		1.67		14.64	3.21	2.71	
Hour 13		1.46		14.90	3.30	2.36	
Hour 14		1.51		14.98	3.01	2.40	
Hour 15		1.59		14.74	3.20	2.90	
Hour 16		1.93		14.84	3.43	2.67	
Hour 17		1.90		14.20	3.17	2.79	
Hour 18		1.38		14.15	3.02	1.69	
Hour 19		1.0		14.48	2.89	1.92	
Hour 20		1.2		14.42	3.11	1.91	
Hour 21		1.8		14.58	2.70	2.03	
Hour 22		2.15		13.50	2.30	1.62	
Hour 23		1.84		12.12	2.05	−13.06	

variation of 42%. In Stockholm, ventilation losses simulated by using fixed value of ventilation rate was 89 kWh/(m^2·year). On the contrary, the probabilistic distribution of infiltration and natural ventilation ranged from 53 kWh/(m^2·year) to −133 kWh/(m^2·year), with a maximum variation of 49%.

3.2 Heating set-point adjustments

Simulated thermostat set-points during heating season (from 15 September to 15 June) in living room and bedroom were analysed for each scenario.

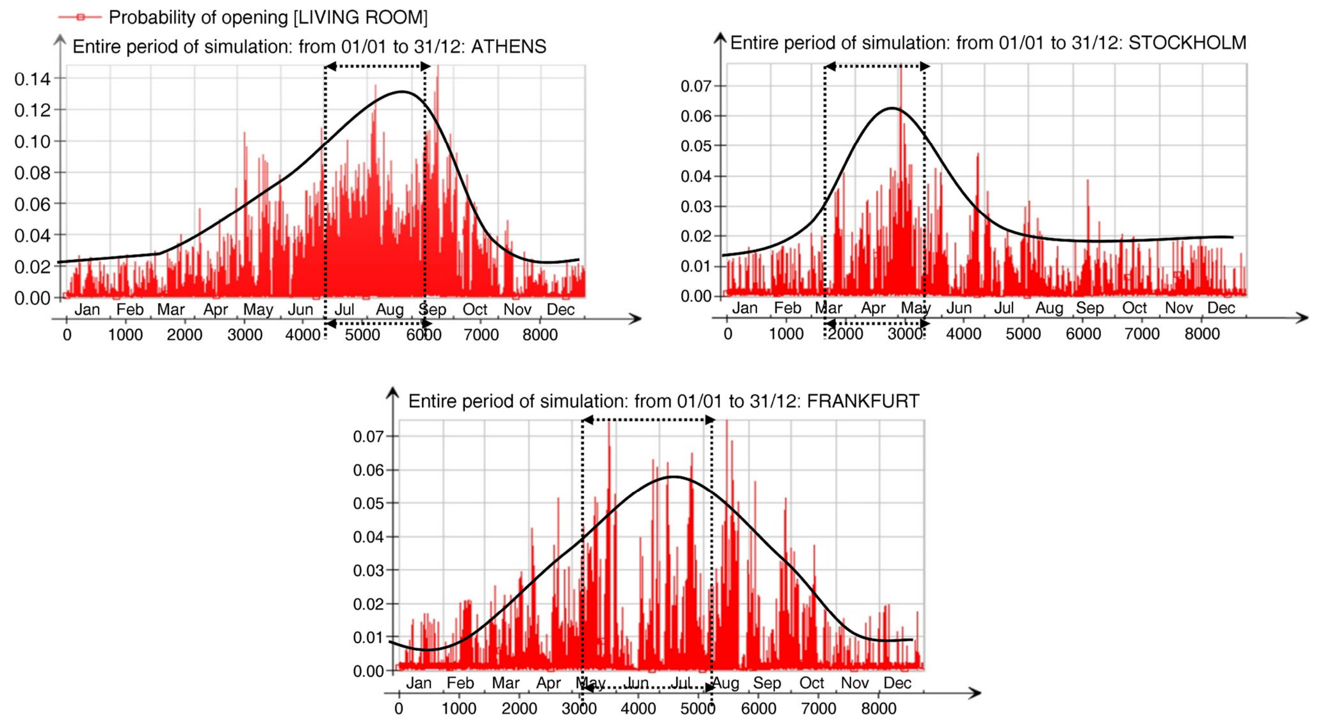

Fig. 4 Probability of window opening in living room. Results for Athens, Frankfurt, Stockholm

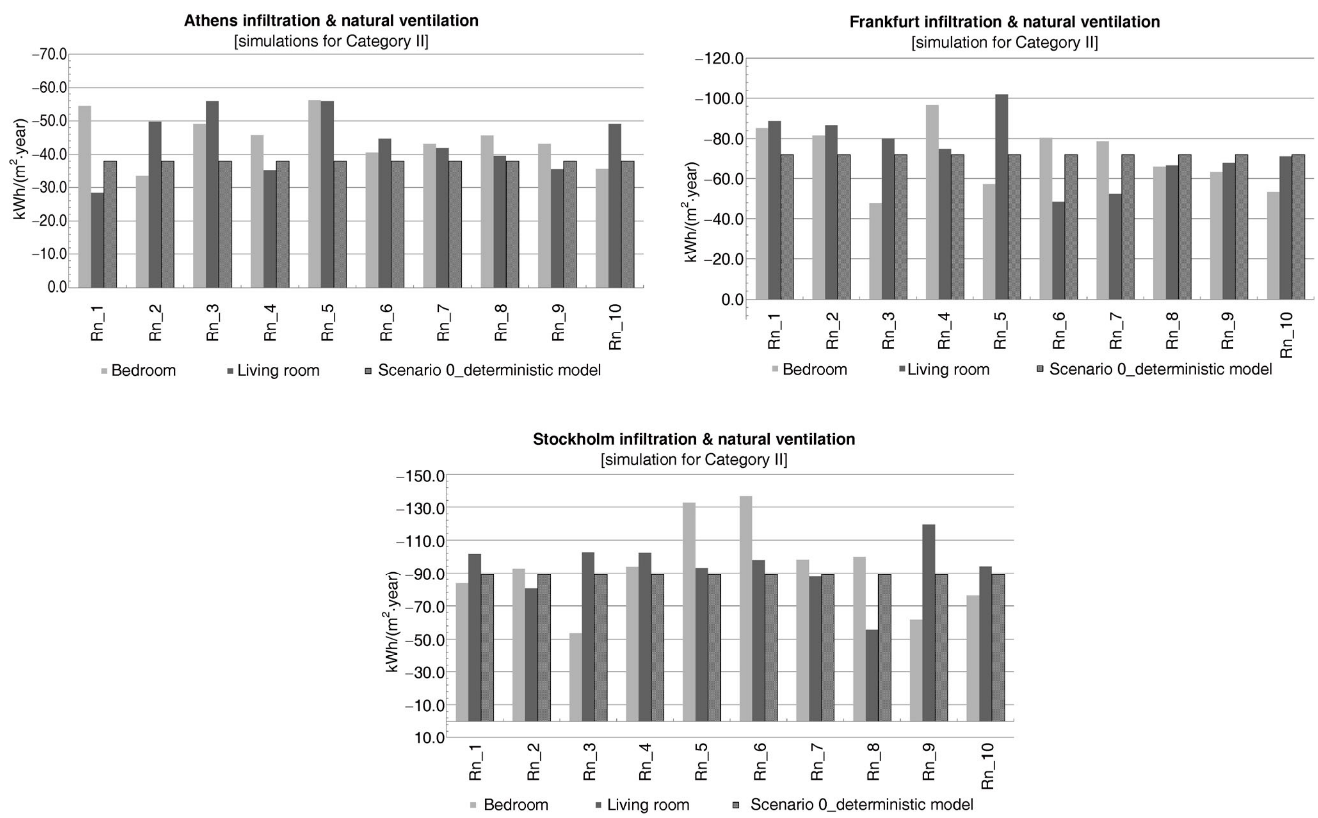

Fig. 5 Simulated infiltration and natural ventilation for deterministic simulations (singular value) and for the distribution of a set of 10 simulations (probabilistic inputs)

In scenario 0, a heating set-point of 18℃ was considered acceptable for the comfort category III, according to the deterministic approach of European standard EN 15251:2007. However, from the simulated occupant behavior (inferred from field measurements) it was evident that if occupants have the opportunity to choose the heating set-point, they tend to prefer temperatures above 21℃ (Category I), both in living room and bedroom. As a consequence, simulations based on category III in EN 15251, resulted as the greater underestimation in heating consumption, when compared to probabilistic results (Fig. 6).

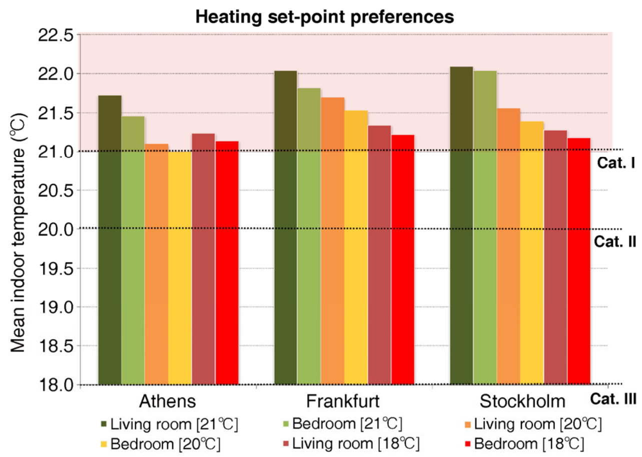

Fig. 6 Heating set-point preferences. Mean value for living room and bedroom

3.3 From deterministic to probabilistic approach in modelling

Figure 7 displays a comparison among results of heating delivered energy for deterministic simulations (Scenario 0, deterministic input) and for the distribution of three sets of 10 simulations (Scenario IV, probabilistic inputs). Representative results are shown for Category of Comfort II. In Athens, heating delivered energy simulated by using fixed values of ventilation rate and heating set-point was 47 kWh/(m^2·year). On the contrary, the probabilistic distribution of heating delivered energy ranged from 46 kWh/(m^2·year) to 68 kWh/(m^2·year), with a maximum variation of 45%. In Frankfurt, heating delivered energy simulated by using fixed values of ventilation rate and heating set-point was 153 kWh/(m^2·year). On the contrary, the probabilistic distribution of heating delivered energy ranged from 160 kWh/(m^2·year) to 206 kWh/(m^2·year), with a maximum variation of 36%. In Stockholm, heating delivered energy simulated by using fixed values of ventilation rate and heating set-point was 212 kWh/(m^2·year). On the contrary, the probabilistic distribution of heating delivered energy ranged from 212 kWh/(m^2·year) to 267 kWh/(m^2·year), with a maximum variation of 26%.

Figure 8 shows how the deterministic approach (Scenario 0) generally underestimated the heating consumption, when compared to probabilistic predictions taking occupant behavior into account (Scenario IV). The largest impact in delivered energy variation from deterministic to probabilistic simulations was simulated for category III in Athens (61%), Frankfurt (47%) and Stockholm (35%). Maximum variation resulted in Mediterranean climate (Athens) for Category I (24%), Category II (47%) and Category III (61%).

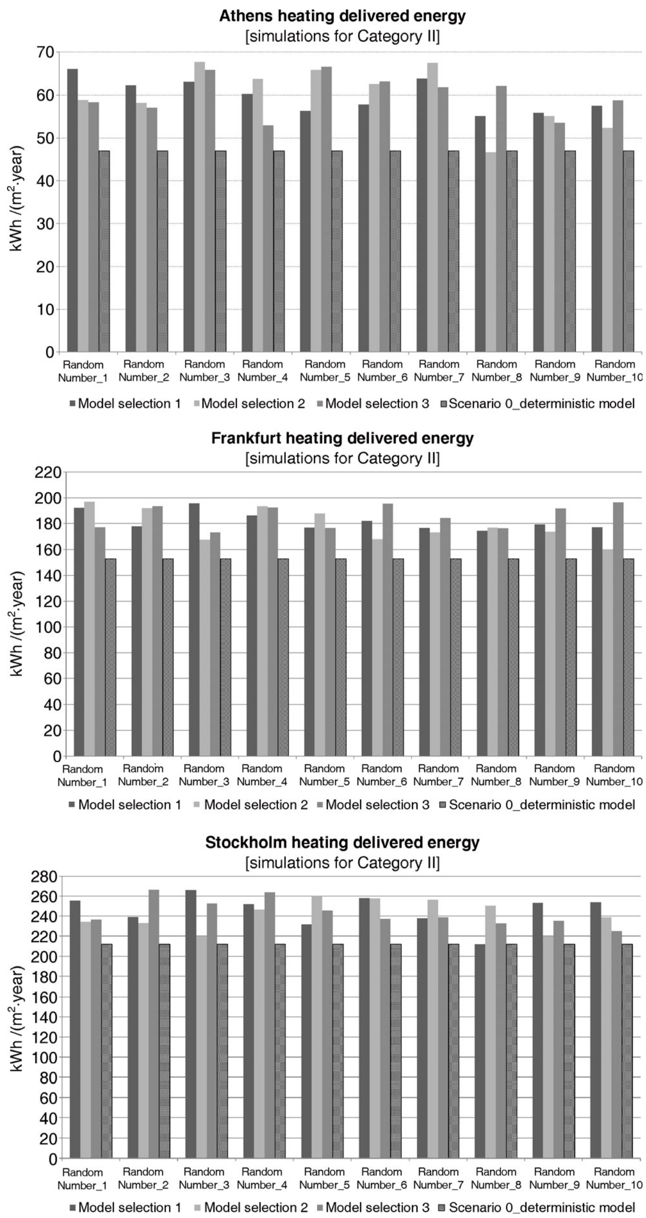

Fig. 7 Simulated heating delivered energy for deterministic simulations (singular value) and for the distribution of 3 sets of 10 simulations (probabilistic inputs)

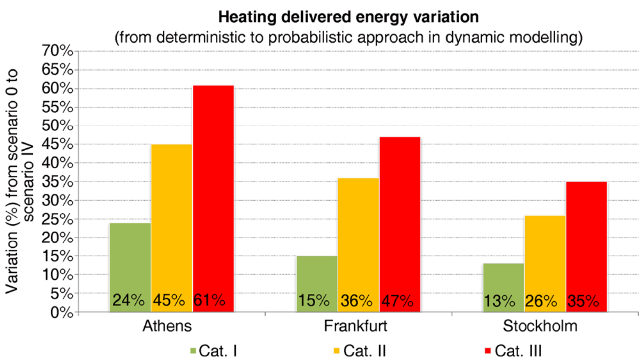

Fig. 8 Heating delivered energy augmentation from deterministic to probabilistic approach in modelling

4 Discussion

Results of this research gave confirmation to the hypothesis that occupants behavior in buildings is to be regarded one of the key reasons of discrepancies between predicted and actual energy consumption in dwellings. Some building occupants are very much aware of their energy bills (heating and electricity) and tend to act in ways to reduce their bill rather than to maintain a high level of comfort. In contrast, energy-unconscious occupants liberally interact with control system in order to improve comfort conditions in their homes.

Findings of this research underlined that occupants interactions within building envelope and control systems are strictly interrelated to the pursuit of personal comfort, the perceived indoor environmental quality and therefore global energy performance of the buildings.

The research presented in this paper cannot be regarded as concluded. On the contrary, analysis methods, developed models and results should rather be taken as starting points for future research aiming at a further understanding of the occupant behavior leverage on thermal comfort and energy consumption in buildings. Specifically, validating these models with new data set coming from different geographical areas is highly advisable in order to strengthen the applicability of human based models to cultural and climatic differences. Moreover, implementing more statistical variability of user control over indoor environmental conditions, such as blind adjustment, electric systems and domestic hot water usage, is strongly appealed in the aim of a better prediction of total energy use in buildings.

In this paper, we have investigated the influence of nine different probabilistic behaviour patterns (combinations of active, medium and passive operation of windows and thermostats). Haldi (2013) discussed how different occupants could be assigned different model coefficients, to model the fact that different occupants will have different behavior patterns. In that sense, the nine behavior patterns could be regarded as models of nine specific persons. However, since the models were inferred from data from 15 different dwellings including more than 40 residents, the models could also be regarded as a representation of nine standard behavior patterns, covering the variation observed in the 15 dwellings.

5 Conclusions

The energy consumption of dwellings in which occupants control (window opening and heating set-point adjustments) was simulated by probabilistic functions, was up to 61% higher than when the control system was simulated in a deterministic way by fixed schedules. The maximum variation in heating performance prediction, due to a switch from deterministic to a probabilistic modelling approach was recorded for Athens. This discrepancy could be attribuited to users interaction specifically within windows opening. In the Mediterranean climate naturally ventilated buildings tend to get over heating during warmer periods and consequently users tend to open windows more often. This interaction necessarely leads to an increase of ventilation losses.

Maximum impact in the step from a deterministic to a probabilistic approach in simulation was found for the comfort category III. Significantly, the probabilistic models of occupants behavior (infered from field measurements) led heating set-points and ventilation rate to the highest comfort condition, often close to category I. This confirms that a gap between deterministically predicted and actual heating consumption in dwelling is partly due to occupants interaction with control systems, performed in order to restore a comfort condition in indoor environments.

The presented paper applies an innovative "best practice" approaches and develops new models on human energy behaviors. The positive effects of major innovations of this paper can benefit building energy performance during the whole-building life cycle:

- Design phase: predicting actual building energy use more realistically. The improved simulation model implemented in IDA Ice with new behavioral modules will support decision making in the early design stage.
- Operation phase: using predictive models and algorithms of occupant behavior embedded in users device and control technologies to supply advice to users through "smart" communication.
- Building retrofit: evaluating the impact of occupant behavior on different building technology solutions.
- Building management: allowing building energy flows, control systems, appliances usage and comfort level mapping.
- Building codes and policy: advancing building standards development by quantifying variation of energy savings of technologies related to occupant behavior.

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SIMULATING

Gap between predicted and actual building energy consumption

Is there sufficient benefit in quantifying OB in building energy simulations?

PAPER 8
S. D'Oca, S.P. Corgnati, V. Fabi, R.K. Andersen.
Effect of thermostat and window opening occupant behavior models on energy use in homes
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PAPER 9
S. D'Oca, S.P. Corgnati.
Insights into the variability of energy consumption due to adaptive occupant behaviors in offices.
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Insights into the variability of energy consumption due to adaptive occupant behaviors in offices: a simulation study

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Insights into the variability of energy consumption due to adaptive occupant behaviors in offices: a simulation study

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Insights into the variability of energy consumption due to adaptive occupant behaviors in offices: a simulation study

Abstract

Occupant behavior (OB) is now commonly established as one of the main contributors to variability in buildings' energy use. However, adaptive occupant-building interaction scenarios in offices are still limited understood and over-simplified, leading to the 'credibility gap' of actual building energy performance. Recent advances in building energy simulations have seen the switch from a deterministic to a probabilistic approach in describing and modeling occupant behavior in buildings. Probabilistic models of occupant adaptive behavior on 1) window opening, usage of 2) shadings, 3) heaters and fans and 4) artificial lighting system selected from recently published literature have been implemented into the building simulation program (BSP) IDA ICE. The heating, cooling and lighting energy performance of an office reference-building representative of the European building stock is been simulated. A comparative analysis of the results is performed, with respect to simulations implementing deterministic behavioral inputs and schedules, to provide insights into the variability of building energy performance due to adaptive energy-related behaviors of the occupants. Synthetic energy variability indicators are proposed to measure the robustness of different building envelope configurations (massive and light) and climate conditions (Mediterranean and Continental) over the selected energy-related adaptive occupant behaviors. Outcomes of this study are aiming to support building designers, architects and engineers, to design building that are –on the one hand – less sensitive to "energy-unconscious" occupant adaptive behaviors, and to profit – on the other hand – from the energy reduction potential of "pro-environmental" adaptation mechanisms.

Keywords

Adaptive occupant behavior (OB), stochastic models, energy performance, building simulation program (BSP), robustness.

1. Introduction

In 2010, buildings consumed nearly half of the total amount of energy used in Europe, despite EU energy savings directives and building experts' challenges [1]. Indeed, as Bordass stated in 2001 [2], real-life building performance still often undermines design expectations, leading to a "credibility gap" of building energy performance [3]. This occurrence alludes to the defeat of predictability when design expectations and actual building consumption outcomes diverge considerably. This highlighted discrepancy is due to several factors. Existing dynamic building simulation programs (BSP), improved in the last 10 years, exceed the static size of the simplified calculation methods through always more accurate descriptive inputs for building envelope characteristics, plant systems, controls and climate conditions. However, BSP is still unable to replicate the stochastic dynamics that govern energy-related behaviors within buildings. Bordass [3] advocated such credibility gaps arise not so much because occupants behave erroneously, but because the assumptions used during the design phase are not sufficiently informed by what occurs during the operation phase of the buildings. Energy models are simulated based on fixed spatial organization and occupier's usability; more often, building designs do not accommodate or anticipate the inevitable environmental adaptations of real occupants. As a matter of fact, building plant and control systems are used differently from the assumptions made in the design phase.

Different research studies over post-occupancy evaluation of buildings energy performance have shown occupants' behaviors have paramount influence over energy consumption in both domestic and non-residential buildings [4; 5; 6; 7; 8]. Hong et al. [9; 10] introduced the most recent advances and current obstacles in quantifying the impact of occupant energy-related behavior on building energy use. In this context, Gunay et al. [11] framed two main categories of occupant energy-related in office buildings recognized in literature: 1) adaptive actions and 2) non-adaptive actions, with respect to the indoor environment.

The principle that underlies the adaptive category indicates that '*'if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort''* [12]. This principle implies that if people are uncomfortable, they will take actions, which they think will improve their comfort. If the action is effective, they will reduce or avoid discomfort. When using the adaptive model in the design of a building [13], occupants are expected to 1) adapt the environment to their needs or 2) adapt themselves to the environment. These adaptive actions can be divided respectively into 1) changes that alter the *environment* to make it more comfortable, such as to turn on/off the heaters and fans, to open/close a window, to turn lights on or off or to adjust the solar shading and into 2) changes that adapt the *occupant* to the prevailing environment, such adjusting clothing, adjusting body posture and consuming hot or cold drinks (Figure 1)

Figure 1. Adaptive and non-adaptive behaviors having an effect on building energy performance (comfort and consumption).

Actions related to the first classification will be investigated in this study. Differently, non-adaptive actions are related to people presence and movement into indoor spaces. Such aspect is out of the scope of investigation of the proposed study.

Because occupants are not a passive receiver of the building they occupy, adaptive interactions with building controls need to be taken into account when designing the building. However, current building energy performance simulations are commonly based on predefined occupancy schedules, which are not able to capture the actual energy-related behavior of building's users, which is by nature subjective, variable and uncertain. This deterministic approach to user's behavior provides static and fully replicable solutions, which cannot fit the field studies' results. Advancements in the standardization of a probabilistic approach in building energy simulations have been initiated by the EBC IEA project Annex 53 [14] and pursued by Annex 66 [15] project with the aims to establish a quantitative simulation methodology to model occupant behavior in buildings, and to understand the effect of occupant behavior on building energy use and the indoor environment.

1.1 Implementation of stochastic behavioral models in building simulation programs

Different methods to integrate occupant behavioral models into BPS was classified by Yan et al. [16]. The methodological approach categorized as "User customized code" relies on stochastic behavioral models built upon the statistical analysis of real occupant interaction within the building controls. This method is based on the black box models or data-driven models. In this case, the input (regression variables) and output variables (response) are known and measured, and the objective is to estimate the system parameters and to describe the mathematical model [17]. A large number of parameters influencing users' interaction with building control systems are monitored and ranked in term of variance and magnitude to determine which one contributes to most sensitivity to the embedded level of uncertainty of human behavior. Both input and output are hence considered as a probabilistic distribution of values, in contrast with the exact and single values provided by the static definition of schedule usage [18].

Behavioral interactions with building and systems, based on measurements of real occupant behaviors, started to be virtualized by means stochastic models reflecting human's variability and hence implemented in building simulation programs to improve the outcome of actual simulation of building energy consumption. For a comprehensive literature review, please refer to [14; 19].

Several adaptive occupant behavioral models based on field measurements in real buildings have been implemented into the BSP IDA ICE [20]. Thanks to its extensible equation-based modeling nature, which makes it straightforward to quickly expand the software controls with external models, probabilistic equations describing users' interference with various type of controls can be implemented at the advanced level.

Results of such advanced simulations have been broadly published in the literature [21-24]. All these studies demonstrated implementation of stochastic user-driven adaptive controls – such as window opening, thermostat adjustments, blind usage - typically led to higher energy consumption when compared to simulations using fixed occupant-related schedules based on minimum standard requirements and thresholds. To mention some, D'Oca et al. [22] found the energy consumption of dwellings in which occupants' controls for window opening and heating set point adjustment were jointly simulated by probabilistic functions, increased up to 61% than simulations in which such human control systems interaction was simulated by deterministic schedules. Moreover, Fabi et al. [23] carried on a simulation study on the combined effects on energy demand of occupant interaction with windows and heating controls, in a residential high performing building. Results highlighted a significant influence of occupant's behavior on the building energy demand, which increased up to 36% in comparison to simulations in which the occupants' interaction with the controls was regulated by fixed schedules.

In these studies, multiple behaviors were simulated simultaneously, impeding isolating the intrinsic influence of a specific adaptive behavior individually, but also yielding to a larger energy impact than each behavior might allocate on its own. Also, while studies on the residential sector are quite diffuse, simulation studies on the impact of adaptive energy-related behavior in office buildings are still quite uncovered.

1.2 Robustness of building design

One strategy to enhance energy efficient behaviors in buildings is to engage users towards conservative consumption patterns. Several research since the '70 engaged to the challenge of modifying occupant behavior in buildings [25, 30]. This strategy proposes solutions, which are independent from the building types and characteristics, but mainly leverage on the cognitive and physiological aspects of human behavior. A different approach begins in the design stage of the buildings, by leveraging on the study of building envelope and system control solutions, which are able to guarantee the intended building energy performance, independently from the occupant's adaptive behaviors.

In this view, the concept of building robustness was firstly introduced by Palme et al. [31], and later discussed by Hoes et al. [32]. O'Brien et al [33] discussed robustness of building design does not imply occupants are not allowed to interact with building controls or only mechanical provisions of the indoor environmental quality levels are delivered. Rather, this concept supports the development of buildings, which are “occupant-proof” [33], meaning “less sensitive” to occupant behavior adaptive actions. Apart from conceptualizations, a study conducted by Karjalainen [34] demonstrated that the effect of “careless” occupant behavior on energy consumption can be margined, when robust design solutions are employed. These include technological applications such as occupancy detection for lighting control of lighting, design of window overhang to limit the solar radiation energy entering the space, adoption of thermochromics windows to dynamically adjust to changing levels of sunshine and limit the solar energy entering the room (O’ Brien [33]).

2. Methodology

Aim of this paper is to provide insights into the variance of building energy performance due to individual energy-related adaptive behaviors including 1) window opening, usage of 2) shadings, 3) heaters and fans, and 4) lighting system, with respect to the heating, cooling and lighting usage in typical office building representative of the European building stock, having fixed building morphology and plant system characteristics [25].

Probabilistic models of the four occupant-adaptive behaviors selected from recently published literature [26-28] have been implemented into the BSP IDA ICE.

By isolating other paramount influencing factors on energy consumption, such as building orientation, morphology and plant system characteristics, a comparative analysis of the energy simulation results is performed to provide insights into the variance of final building energy performance due to individual adaptive occupant energy-related behaviors.

Synthetic variability indicators are proposed to measure the impact of the selected energy-related occupant behaviors on heating, cooling and electricity energy consumption and robustness with respect to dissimilar building envelope configurations and climate conditions.

The methodological approach to the presented study is specified in the following sections.

2.1 Case study

An office Reference Building (RB) representative of the European building stock [35] is chosen as a case study. The RB is a naturally ventilated office with a radiator for heating and a fan system as a cooling device. The standard floor plan is characterized by a typical sideways cellular office distribution (Figure 1). The study focuses on two cellular offices of the RB for which a variation in orientation and characteristic of the building envelope (thermal mass and transparency) might play a weighty influence on energy consumption:

1 **Zone A:** facing south, having light envelope (low thermal mass), and extended window area

2 **Zone B:** facing east, having a massive envelope and a reduced window area.

Building characteristics are described in Table 1 while detailed features of the two opaque envelope configurations are given in Table 2. For both zones, characteristics of the transparent components are described in Table 3

Figure 2: Typical Floor Plan of the chosen Reference Building and indication of the two simulated zones.

Table 1: Building characteristics of the two simulated zones.

Table 2: Opaque envelope characteristics of the two simulated zones.

Table 3: Characteristic of the transparent components of the Reference Building.

2.2 Building energy model

The RB is implemented into the IDA ICE [20] to simulate the energy performance into two typical European climates. To do so, the energy models of the RB are located in a Continental climate – Frankfurt (HDD: 2174, CDD: 548) and in a Mediterranean climate – Athens (HDD: 730, CDD: 1894). Every thermal zone of the building is mechanically heated and cooled, with heating and cooling set-point (21°-25°) referred to the comfort category I for cellular offices described in Standard EN 15251 [39].

Concerning heating, each thermal zone has a waterborne radiator with constant heating set-point of 21°C and a dead-band of ±2°C. Every zone is provided with a fan coil for cooling having set-point of 25°C and a dead band of ±2°. Maximum heating and cooling power are varying according to room size and exposure (Table 4). Heating and cooling season are set differently based on climate location, ad described in Table 5.

Table 4. Heating maximum power of the water radiator and cooling maximum power of the cooling device

Table 5. Heating and Cooling seasons for climate locations

Plant system's schedules follow the occupancy schedule during the working days (from Monday to Friday).

Office occupants are modeled with a density of 0.06 people/$m^{2,}$ an average metabolic activity of 0.9 MET and a clothing level varying between 1 clo: (22nd September – 20th June) and 0.5 clo (21th June – 21th September) [35].

Artificial lighting is providing 10 W/m^2 of internal gains and follows settings of a typical office building: lights are on from 7:00 to 19:00 every working day, with no link between switching on and off operations and luminance.

Office equipment are emitting 15 W/m^2 and are scheduled to work at full load from 7:00 to 19:00 every working day, while a baseline of 5% is considered to work overnight and during the week.

Operation on windows is not allowed in this configuration of the model, and a fixed air change rate of 0.5 ACH every hour is assumed provided by wind dependent infiltration, as defined by the EU Standard 15251[39].

A configuration of external shadings operation is defined in the model, accordingly to which external shading are never drawn by the occupants.

2.3 Occupant behavior stochastic models

Behavioral interactions with the building and plant system typical for an office building are virtualized individually by means stochastic models selected from existing literature with respect to:

1) Window opening: Haldi and Robinson [36]

2) Shading usage: Haldi and Robinson [37]

3) Heaters, fans, and artificial lighting turning on/off: Nicol el al. [38]

2.3.1 Window Opening

Based on seven years of continuous measurements in the Solar Energy and Building Physics Laboratory (LESO-PB) in Lausanne, Switzerland, Haldi and Robinson [36] developed and tested a stochastic model of the window opening to predict the probability of opening or closing a window. Fourteen south-facing cellular offices of the LESO building were monitored from December 2001 to November 2008 and the probability of actions on windows is inferred via univariate and multivariate logistic models, model based on a discrete-time Markov process and continuous random process. Guided by the preliminary observation that actions on windows mostly occur when occupants arrive or leave their office, different transition probabilities between the states of a window have been inferred from actions on arrival, at departure and during occupancy, as proposed by the mentioned study by Herkel et al. [40]. Values of the regression parameters used for each sub-model are shown in Table 6.

Table 6. Regression parameters for the Markovian transition probabilities.

2.3.2 Shading

Based on continuous measurements of the same office building observed for Haldi and Robinson [36] explored the link between the action of lowering external shading and indoor and outdoor temperature. Values of the regression parameters for the chosen single logistic regression model [Eq. 1] are shown in Table 7.

$$\text{logit}\,(P_{10,\text{int}}(T_{\text{out}})) = a + b_{\text{out}}\,T_{\text{out}} \qquad \textit{Eq.1}$$

Table 7. Regression parameters for the single logistic regression

2.3.3 Heater, Fans, and Lighting

Nicol et al. [38] analyzed a database of survey data detailing the subjective comfort of building occupants in five European countries (UK, Sweden, Portugal, Greece, and France) and Pakistan. Nicol then used logit functions to develop a predictive, stochastic model for human interactions with building systems: windows, lights, blinds as well as heaters and fans. The probability of turning on the heaters and running fans, as well as turning on the artificial lights, is expressed as a function of mean outdoor air temperature, as [Eq. 2]:

$$\ln\left(\frac{p}{1-p}\right) = a + b_{out} \cdot T_{out} \qquad \textit{Eq.2}$$

The results are displaying UK buildings, European buildings, and Pakistan buildings. Where, specifically for Europe buildings, selected regression parameters are described in Table 8.

Table 8. Regression parameters for the single logistic regression

2.4 Models implementation in IDA ICE

A simulation study has been developed, based on the implementation of some user customize codes in the building simulation engine IDA ICE. The methodological approach is explained as composed of three main steps, as follows:

I. Implementation of probabilistic models of occupant behavior written as an NMF language, as inputs in the dynamic energy simulation program.
II. Run of a set of probabilistic simulations in the BSP
III. Comparison of the energy consumption resulting from the average of probabilistic simulation results, with outcomes of simulations adopting deterministic behavioral input values, and evaluation of the variation in simulated results.

The variation in simulated results is assumed as a proxy for the impact of occupant driven operation of control over the building energy performance. Implicitly, this variation entails the concept that occupant behavior must be regarded as one of the key parameters causing discrepancies between predicted and actual energy performance (energy consumption and comfort level) in buildings.

2.4.1 Deterministic behavioral input in IDA ICE

Table 9 shows an example of how deterministic behavioral inputs embedded as NMF native formats are typically handled to model operational controls in IDA ICE. With respect to natural ventilation, standard schedules plus PI (Proportional-Integral) control assumes occupants to open windows if the indoor temperature exceeded a certain value (25°C ± 2°C) and the outdoor temperature was lower than the indoor temperature. Such standardized behavioral control input is described as in D'Oca et al. [22].

Table 9. Example of IDA ICE deterministic native NMF input syntax for opening windows using schedules

2.4.2 User custom code, user function

To implement behavioral models into IDA ICE, mathematical equations described in terms of NMF formal language, need to be converted into deterministic signals for the different system controls. Accordingly, the calculated probabilities are compared to a random number changing dynamically every five minutes. Within this time frame, if the simulated probability is higher than the random number, the adaptive action would occur. Then, the control action would not change until a new likelihood of change happens to be greater than the matching random number. Hence, by switching the random number list in the simulation program over a series of time, a probabilistic distribution of energy consumption of the building models is simulated.

Table 10. Example of IDA ICE User Customized Code written in NMF syntax, for opening windows

Table 10 shows a custom user code, written in the NMF native input language, to simulate a probabilistic behavioral model in IDA ICE. The example relies on the probability function described in Andersen et al. [21].

Multivariate logistic regressions were used to infer the probabilistic controls of the indoor environment. These formulas describe a relationship between the change in window, thermostat, blind and lighting system state and a set of independent predictors used when the outcome is binary, that is when there are only two possible accounts (0 or 1) in the case: open/close windows, turn up/turn thermostats; drawn/not drawn blinds, switch on/switch off lights.

The outcomes of the models were probabilities of an action occurring within the next 10 minutes (since the independent variables were measured at 10-minute intervals). To determine the state of the windows and heating set-point, the probabilities were compared to a random number that was generated at 10-minute intervals. An action occurred in the simulation if the calculated probability was higher than the random number. The building component would stay in the same position until the probability of state-transition become higher than the matching random number.

Since operational controls were modeled stochastically, simulations implementing the same probabilistic control present dissimilar results. This mean a probabilistic distribution of results, instead of single deterministic value, needs to be considered as representative of actual energy consumption simulation.

Although simulation results of probabilistic behavioral inputs emerged quite discordant to energy models relying on deterministic schedules, tiny variation emerged among outcomes of the same set of probabilistic simulations after changing 10 times the combination random number probability of action. To verify this tendency, a set of 20 and 30 simulations was run for each of the selected models, resulting in no significant improvement regarding variation among simulation results. No evident benefits emerged in running each model more than 10 times since (a) small variation (from 10% to 12%) among results distribution was found between the sets of 10, 20 or 30 runs and (b) one IDA Ice yearly simulation implementing probabilistic inputs for window and thermostat operation lasted up to 2 hours.

In a view of this fact, we assumed the stationary nature of building simulations implementing advanced behavioral schedules, considering n=10 simulations as a representative for evaluating the occupant behavior intrinsic variability. This trend for stochastic behavioral models implementation in IDA ICE has been already corroborated by previously correlated studies [21-24].

1. Results

The average values resultant from the sets of simulations implementing the four behavioral models were compared to the outcomes of the deterministic simulations making usage of standardized occupant control inputs.

Indicators of the simulated variability of building energy consumption due to the occupant behaviors on each of the four adaptive opportunities are highlighted in Figure 4. Variation is isolated as a function of outdoor climate (Mediterranean and Continental) and building envelope configuration (massive and light). Results show probabilistic models of occupant behavior generates a mean variation of 22% from deterministic assumptions in building energy simulations. This percentage confirm trends of corroborated studies in the literature [42, 43]. Moreover, behavioral adjustments of the indoor environment emerged responsible for a twofold variation effect compared to standardized simulated energy performance. On the one hand, a reduction of energy use for dynamically managing the solar heat gains entering the building is observed – with specific regards to usage of window blinds. On the other hand, increments in energy consumption for the usage of heating and fans (up to 73% in light envelope buildings) and natural ventilation (up to +49% in continental climates) emerged.

Light envelope buildings emerged more vulnerable to energy variation due to manual operation of environmental control systems (+31% in simulated energy consumption), than massive buildings (+13%). The same trend has been highlighted for continental (+28%) and Mediterranean climatic conditions (+16%).

Figure 4. Variation in simulated Total Delivered Energy from Deterministic to Stochastic models Figure 4. Variation in simulated Total Delivered Energy from Deterministic (No Control) – Stochastic models

Figure 5 illustrates the user operation of heaters and fans led to the greater variation in energy consumption, with respect to simulation implementing deterministic trigger operational inputs. Light building envelope models increased the simulated energy consumption up to 79% when located in Continental climate, and around 68% if in Mediterranean climate. Massive envelope buildings demonstrated being more robust with respect to occupant's manual operation of heating and fans, both in Continental (+29%) and Mediterranean climates (+53%). In turn, for the two climatic area simulations, the biggest share of energy consumption variation is represented by heating (Continental) and cooling (Mediterranean) delivered energy. A similar comparable trend emerged for the manual operation of windows. Massive envelope buildings located in Mediterranean climates emerged the most robust configuration with respect to natural ventilation behaviors. For this definite case, simulations demonstrated energy can be saved, indicatively around 6% of the total delivered energy. Specifically for the manual use of shading, a reduction in the simulated energy consumption emerged for both a Continental climate location (from -7% in light building envelope buildings to -4% in massive building envelope buildings) and Mediterranean climate location (from -18% in light building envelope buildings to -7% in massive building envelope buildings).

Figure 5. Variation in simulated Total Delivered Energy from Deterministic to Stochastic models for Continental and Mediterranean Climate

Moreover, these variability indicators are considered as proxies of the robustness of climate condition and building envelope design with respect to some identified comfort adaptive opportunities, having an impact on the final energy consumption. In order to isolate the effect of occupant behavior with respect to the building energy consumption, a correlation analysis of the building energy balance of two adaptive control scenarios have been performed (Figure 6).

Figure 6. Energy balance correlation simulation implementing Deterministic and Stochastic adaptive control inputs

In the first scenario, no adaptive control has been considered, and deterministic inputs have been implemented in the building energy model. In the second scenario, stochastic models of adaptive behavior have been applied as control inputs. A linear correlation between the energy balance of these two scenarios has been calculated. The discordance in the correlation coefficient R^2 has then been considered as a measure of the variation in energy consumption due to human interference with building controls (Figure 7).

The energy balance simulated for massive buildings located in continental climates emerged having a strong correlation among the occupant driven and deterministic control scenarios (R^2 =90%). Such little variation corroborates the concept of robustness with respect to occupant behavior in altering building energy performance, as discussed in Fabi et al. and Buso et al. [41, 44]. This is specifically true for the usage of blinds (R^2 =99%), lighting (R^2 =96%) and heating and fans (R^2 =92%) while slightly more attention need to be conveyed to the variation generated by natural ventilation behaviors (R^2 =71%). The weakest correlation in energy balance emerged the one simulated for light envelope buildings located in continental climates (R^2 =71%). Significantly, window-opening behaviors in the presence of big window areas and significant thermic delta from indoor and outdoor temperature during the heating season determine a little correlation (R^2 =59%) to the energy balance simulated by using fixed infiltration and ventilation rates, as suggested by national norms and standards. A very similar trend can be observed for the usage of artificial lighting (R^2 =61%).

Figure 7. R2 correlation of the energy balance simulation implementing Deterministic and Stochastic adaptive control inputs

2. Discussion

For the practical point of view, the main aim of the highlighted variability indicators of simulated building energy consumption is to stress the big issue of the occupants' role in actively modifying buildings' performances in real life operation. Numerical simulations of a reference office building representative of the European building stock were performed along with the BSP IDA ICE. Four stochastic models of adaptive behaviors – window opening, use of blinds, heater and fans and artificial lighting - were selected from recently published literature and implemented as advance inputs into the BSP. Results of the deterministic simulations, taking into account fixed air change rates, automated control over the shading system, threshold values for usage of artificial lights and fixed heating-cooling operation, were compared to average results of sets of simulations implementing the behavioral models individually. The authors aimed at verifying the impact of some identified behavioral models on a reference building having fixed building morphology and plant system under different climates, orientation and building thermal mass conditions. Also, Parys [45] in his study shown that integration of proper user behavior in the building simulation is important. However, most of the existing simulation studies focus mainly on conventional residential buildings and are limited to effects on the building side only.

Despite some simplification has been made during the selection and implementation of stochastic models of occupant behavior into the BSP, the proposed methodology and preliminary results are aiming to support the advancement of contemporary research bridging the credibility gap of building energy performance due to the actual operation of buildings. Results of the simulations are circumstantial to the case study building and implemented models and do not represent the complete set of variability indicators that can be derived from other simulation studies. Nevertheless, they represent a meaningful methodology to be possibly applied to new behavioral data sets and simulation models providing an outcome to the impact of different adaptive behaviors and specific operation and maintenance strategies over building having diverse envelope characteristic and geographical location. In this context, to support the validity of the results of the presented study, future works will focus on implementing into the dynamic BSP other more complex stochastic behavioral models available in the literature, to characterize the most compact, physical meaningful and high-quality set of results that can be derived with satisfactory performance.

Regarding the limitation of the implementation of stochastic models into BSP, by applying single logistic regression, predictions of the probability i.e. of lowering a shades and usage of artificial lights are driven by outdoor temperature, nevertheless more straightforward observations might led to assume occupants are mainly driven by indoor temperature, solar radiance, and illuminance level respectively. Despite the highlighted deficiencies, the models have been used in the study for four main reasons:

1. are the most recent work analyzing occupant adaptive behaviors, with a statistical approach;
2. the logistic regression models can be implemented in IDA ICE;
3. models are based on monitored data that match the office intended use of the adaptive actions investigated;
4. models derive from observations of users from the same geographical area (Europe).

Since occupants' behavior is influenced by social and contextual factors, these two latter aspects give authors warranty of coherent use of the simulated building controls.

Moreover, with respect to the correlation of the usage of lights with the outdoor air temperature, Nicol justified this choice by stressing the likelihood that artificial lights are on during winter months, counting more hours of dark during the daily working time. To confirm this observation, results of the model showed the probability of turning the lights is gradually decreasing with the increasing outdoor air temperature.

3. Conclusions

By isolating other paramount influencing factors on energy consumption, such as building morphology, orientation, and plant system type, a comparative analysis of the energy simulation results was performed to provide insights into the variance of building energy performance due to individual adaptive occupant energy-related behaviors. Synthetic variability indicators were proposed to measure the impact of the selected energy-related occupant behaviors on heating, cooling and electricity energy consumption and robustness with respect to dissimilar building envelope configurations and climate conditions.

Implementation of the four probabilistic models of occupant adaptive behaviors into the BSP allowed virtualizing – by means a comparative analysis with deterministic simulation results – an average impact of 22% of occupant adaptive behaviors over building energy consumption. Behavioral adjustments in the indoor environment emerged responsible for a twofold variation effect compared to standardized simulated energy performance. On the one hand, a reduction of energy use for dynamically managing the solar heat gains entering the building is observed – with specific regards to usage of window shadings. On the other hand, increments for the usage of air conditioning (heating and cooling) and natural ventilation emerged in every climate condition and for both building envelope configurations.

Massive buildings located in continental climates emerged as the most robust building configuration with respect to occupant adaptive behavior. In opposition, light envelope buildings located in continental climates emerged more affected by the occupant driven adaptive operation of building controls. The presented results suggest the design of manual control of environmental conditions and adaptive opportunities can profit from the robustness of building design such as thermal inertia as well from mild climatic conditions and narrower thermal excursions. Conversely, light envelope characteristics and more severe climatic conditions have been demonstrated to be factors associated with buildings, which are more susceptible to occupant's interaction with control systems.

As an example, natural ventilation behavior will have minor negative drawbacks in terms of energy consumption in mild climates, when compared to continental climates, where fluctuation from indoor and outdoor air temperature is higher. Similarly, in massive buildings, where transparent to opaque building envelope ratio is lower, and window area is smaller, natural ventilation will allow smaller air volume entering the space per window opening, having the minor impact of the overall energy balance.

A better description of the building real functioning is not only a scientific problem addressed to improve the prediction accuracy of energy consumption through calculation methods, but also a need of the building designer and policy makers. Indeed, in the daily routine of building energy audits or energy performance certificates, only deterministic simulations are usually put in place. The availability of occupants' behavior-related variation parameters associated with specific building features or climate can give a hint of the actual energy performances of the building object of analysis. In this frame, the purpose of this paper was to quantify to which extent the so-called "credibility gap" of building energy consumption is affected by the adaptive interaction of the users with the building control systems, by isolating other factors influencing the energy performance such as building envelope configurations and climate locations.

In this view, outcomes of this study are aiming to support building designers, architects and engineers, to design building that are –on the one hand – less sensitive to occupant adaptive behaviors when simulated stochastic controls are indicating uncertainty in energy consumption variation, and to profit – on the other hand – from the energy reduction potential of environmental adaptation mechanisms. In fact, enormous amounts of behavioral opportunities are available to act towards the energy mitigation challenge in the building sector. However, despite the burgeoning interest and sensitivity around environmental concerns of actual trends of energy consumption paradigm worldwide, average people ask for comfort in indoor spaces, no matter what the cost nor the consequences of daily routine or habits. Typically, in office building– from CEOs to front-line workers – all employees behave in an unconscious energy-intensive manner, i.e. leaving their PCs and lights on when not in the office, opening a window when arriving the office to provide fresh air, no matter the HVAC system is still running. It becomes tremendously difficult to rewire the human brain to unlearn such energy-wasting patterns of behaviors and to initialize a path towards more "motivated" energy-conserving habits and routines. Furthermore, individual building users are able to act just up to a certain level. This changeover must be scaled up to the building management system level, in order to leverage the positive impacts of behavioral mitigation strategies. The universe of Action (the energy market and building construction sector) and the universe of Norm and Standards (the building operation and management strategies and the regulatory policy arena) need hence to work jointly, to allow people to make this switch run.

Designed energy efficiency measures over decades have been documented as being deviated from reality, relying on assumptions of rationality and determinisms when referring to human behavior. This has led to suboptimal policies in the past; this is the trend that needs to be promoted and nourished with a fresh look into behavioral insights in order to satisfactorily meet a shift in the energy consumption paradigm towards a low carbon future. One of the most popular approaches suggested in the recent literature [36] is to alter the environment in which decision are made so that humans (from building occupants to operators and managers) are more likely to behave (and make choices) that may lead to better (more energy-conscious) outcomes.

Accordingly, in order to meet the 2020 and 2050 decarbonization targets, this study foresees the need to foster dedicated behavioral policies in the building sector (i.e. Energy Performance Occupant Directive EPOD), besides more traditional Energy Performance Building Directive – such as the UE EPBD.

Solutions illuminated by this study supported the concept that energy efficiency in buildings is not merely a technology issue. Conversely, policies and programs pivoting around building science knowledge and applying behavioral models resolutions to building energy performance might yield improvements in program cost-effectiveness, as well as the development of more robust energy conservation strategies. Rigorous testing and evaluation of impacts and outcomes of such strategies must be employed. Going forward, efforts to strengthen and update multidisciplinary and international relationships and networks will be continuously nurtured; both within the research and industry communities, to better drive empirical findings towards the development of behaviorally driven market actions and building management system codes and standards.

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Figure

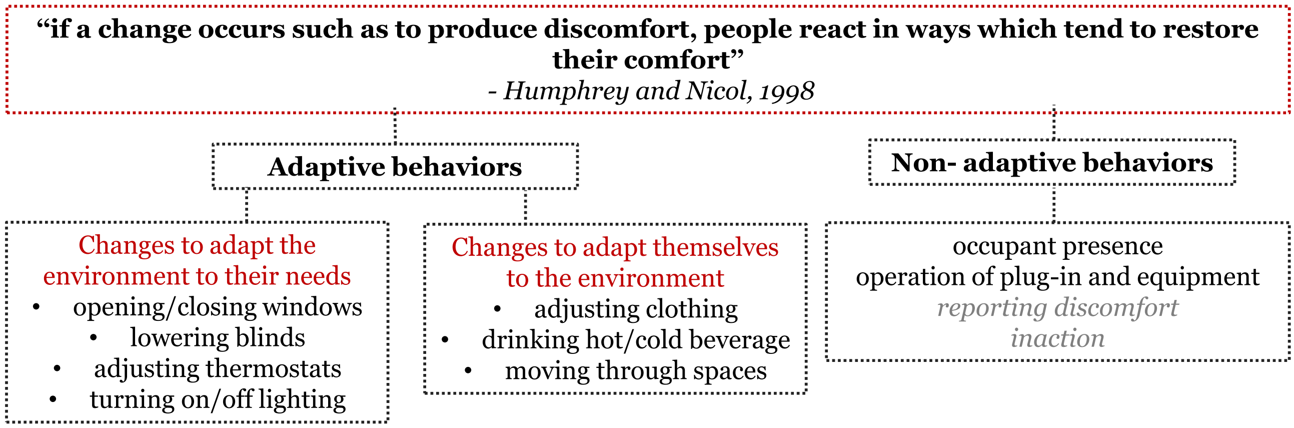


Figure 1. Adaptive and non-adaptive behaviors having effect on building energy performance (comfort and consumption).

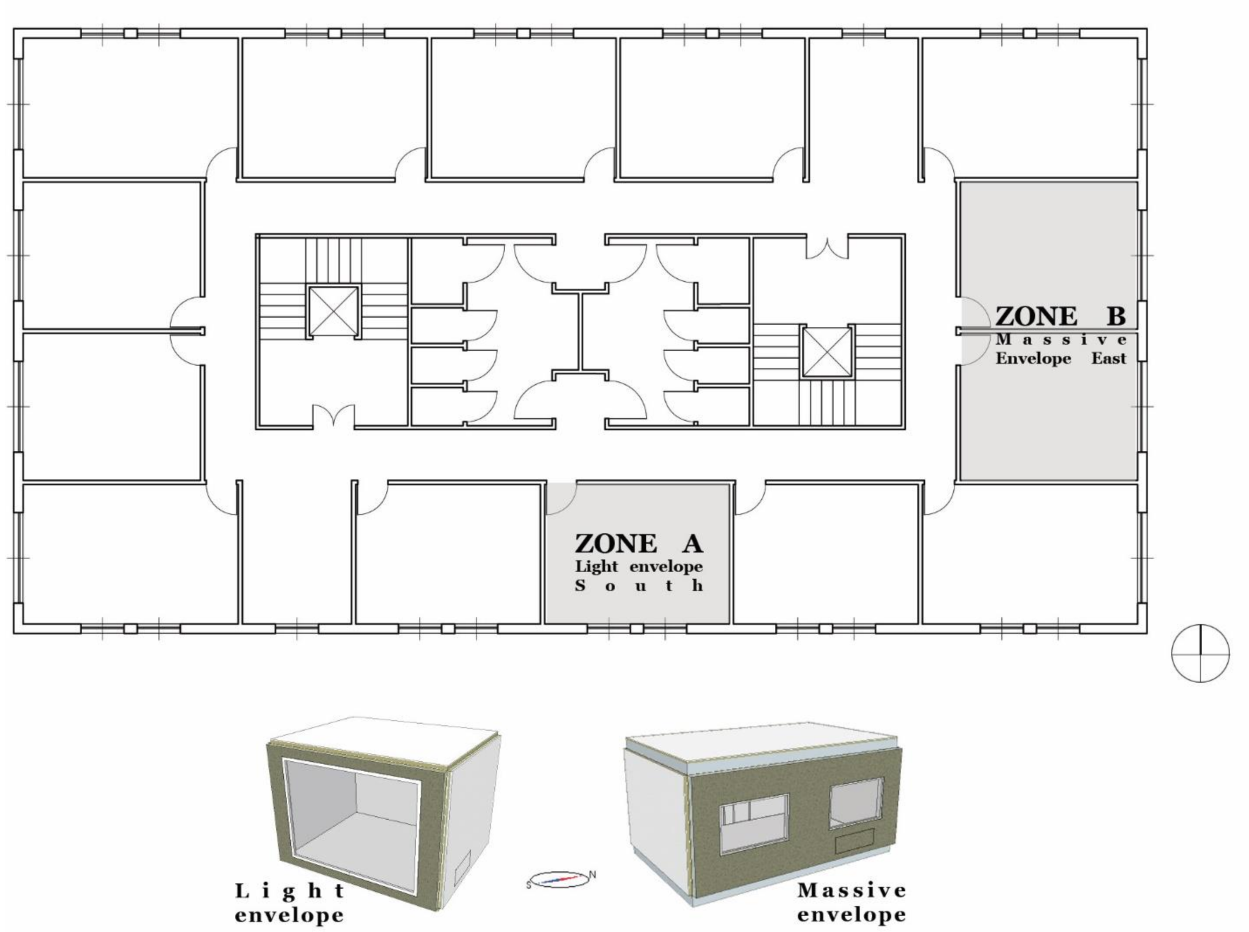


Figure 2: Typical Floor Plan of the chosen Reference Building and indication of the two simulated zones.

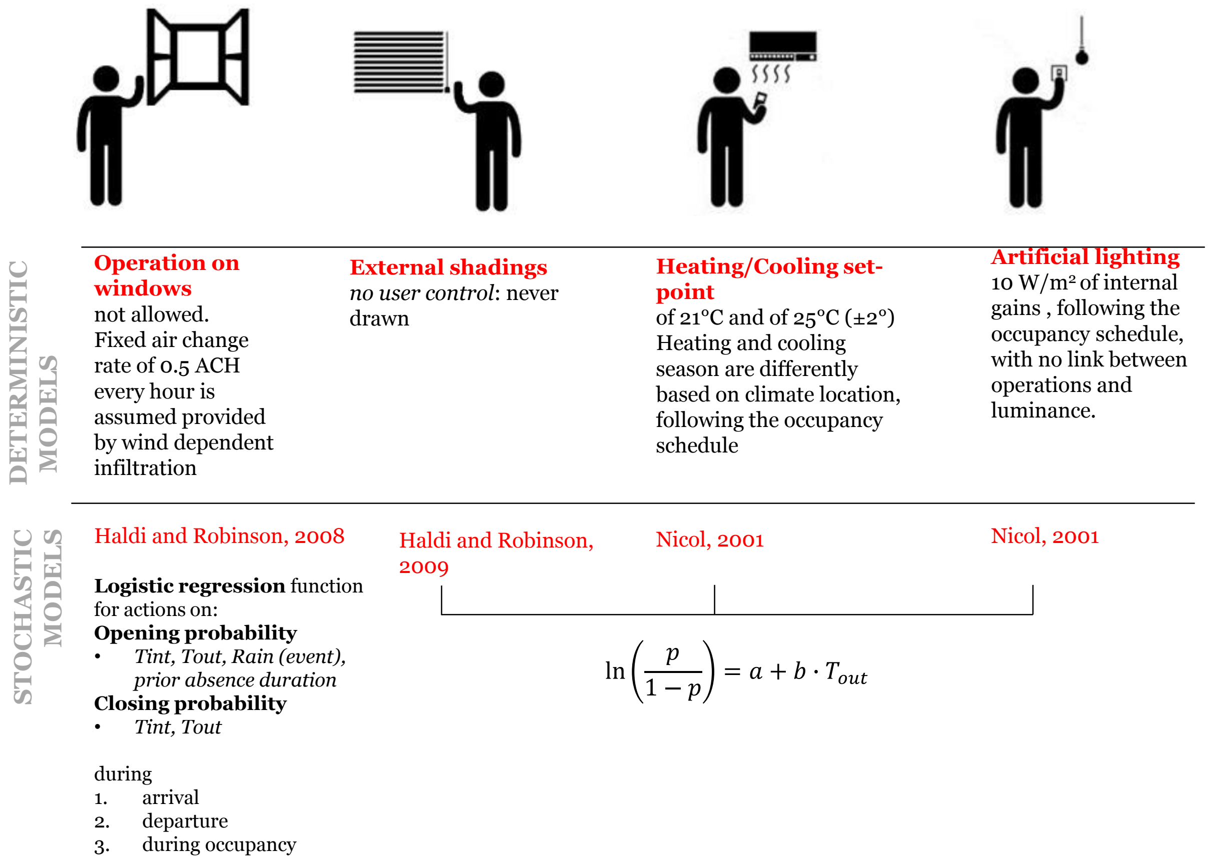
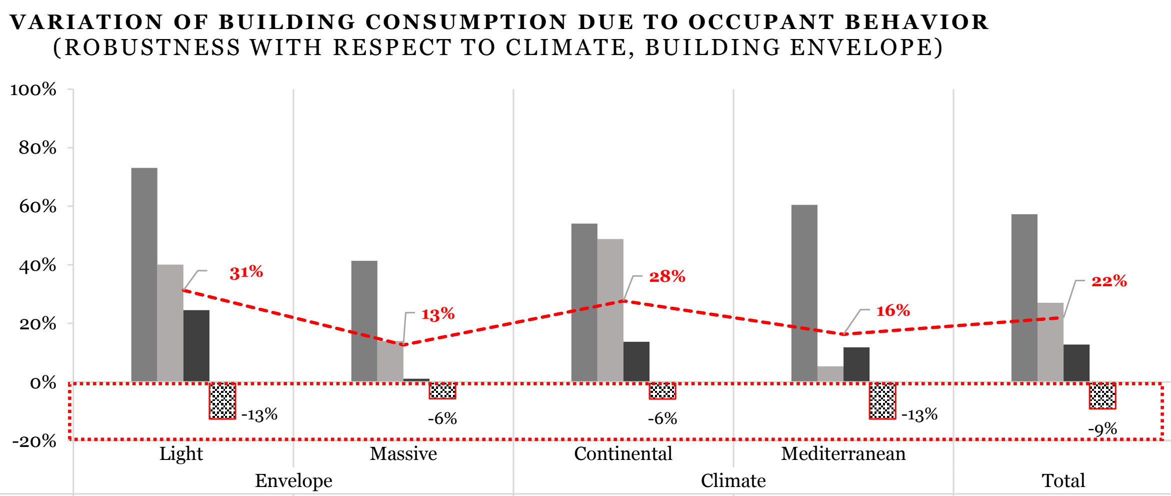
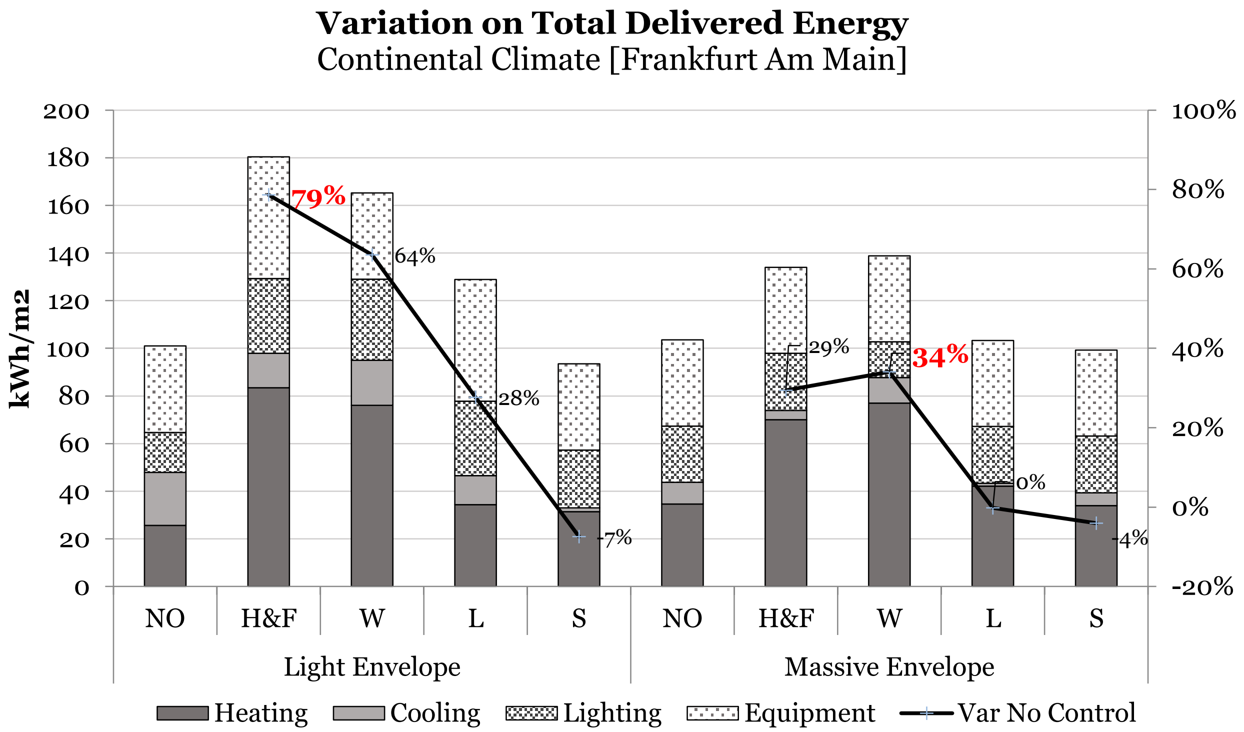


Figure 3: Selected behavioral models for the adaptive opportunities simulated in the building energy model



	Light	Massive	Continental	Mediterranean	Total
Heaters&Fan	73%	41%	54%	60%	57%
Window	40%	14%	49%	5%	27%
Lighting	24%	1%	14%	12%	13%
Shading	-13%	-6%	-6%	-13%	-9%
Mean	31%	13%	28%	16%	22%

Figure 4. Variation in simulated Total Delivered Energy from Deterministic to Stochastic models Figure 4. Variation in simulated Total Delivered Energy from Deterministic (No Control) – Stochastic models



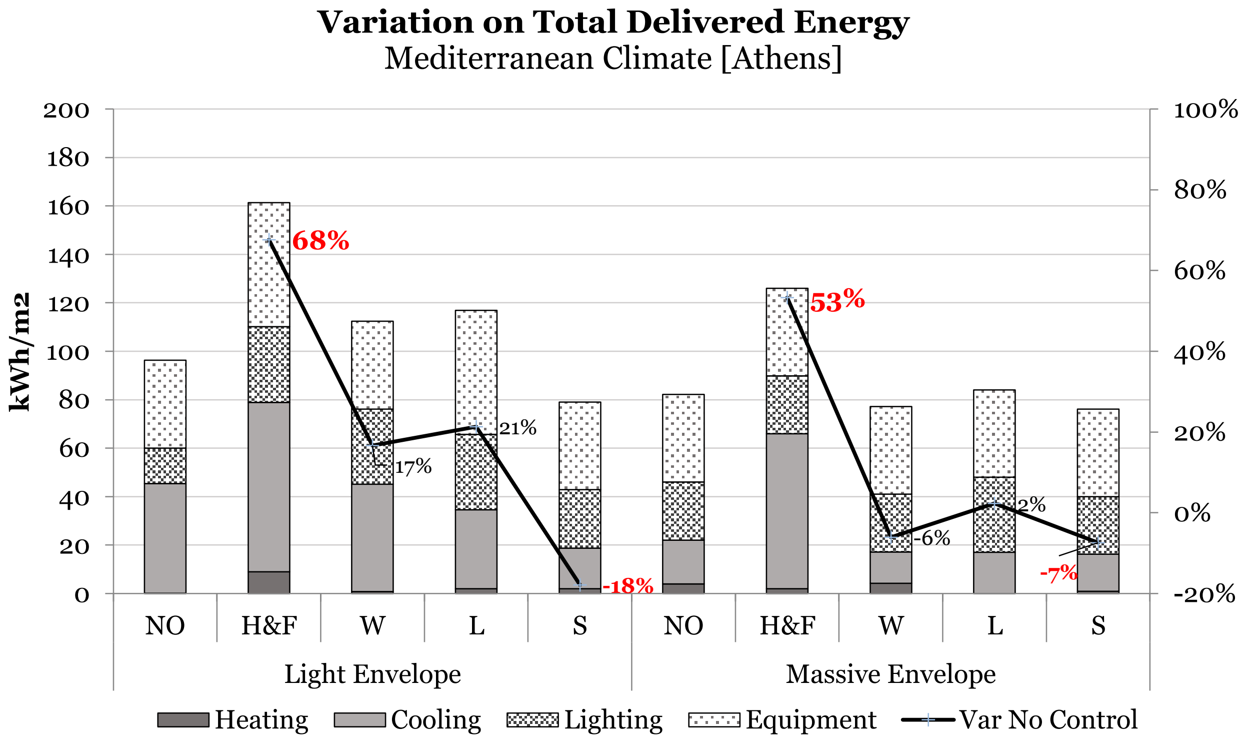


Figure 5. Variation in simulated Total Delivered Energy from Deterministic to Stochastic models for Continental and Mediterranean Climate

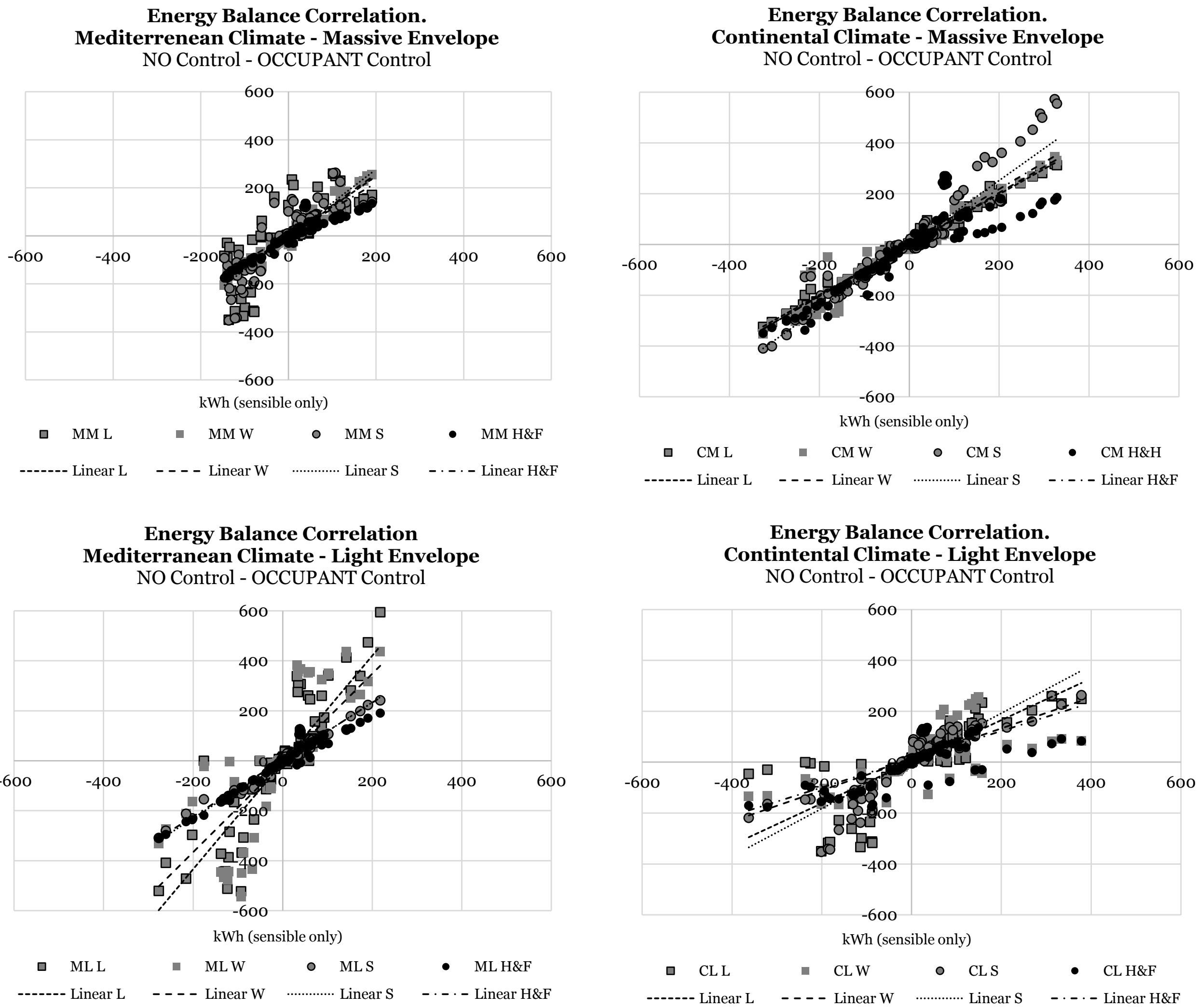


Figure 6. Energy balance correlation simulation implementing Deterministic and Stochastic adaptive control inputs

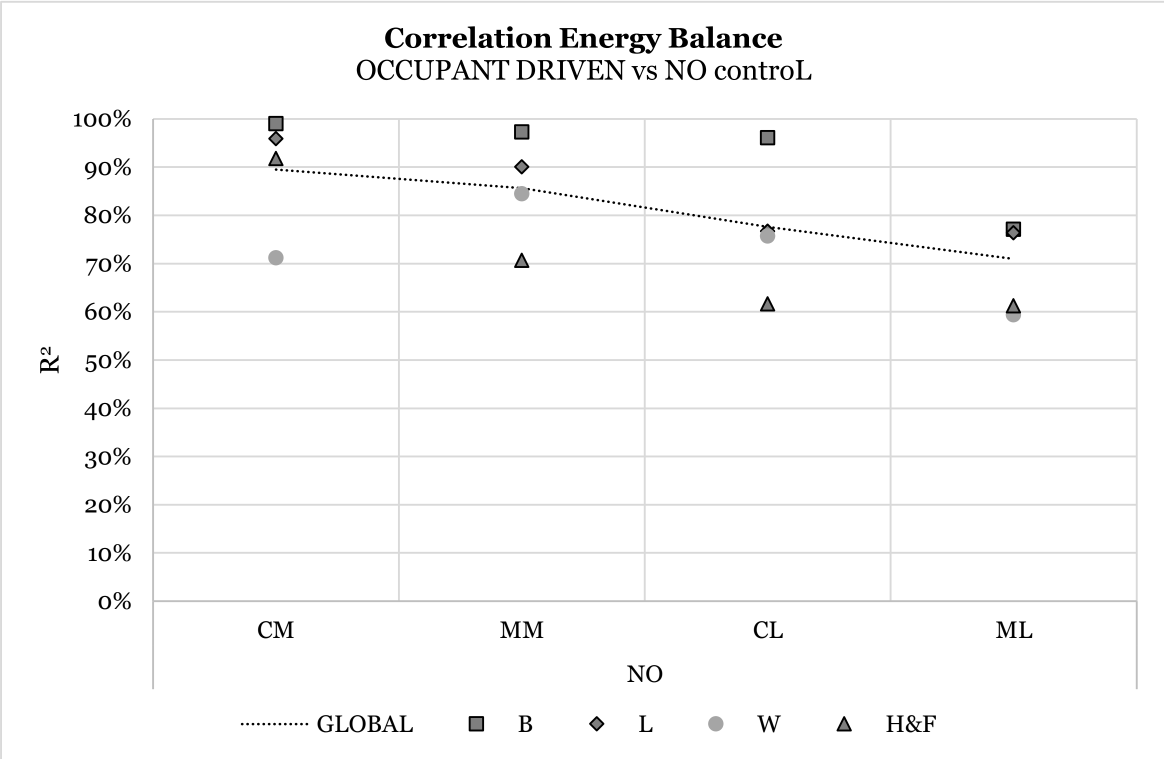


Figure 7. R2 correlation of the energy balance simulation implementing Deterministic and Stochastic adaptive control inputs

Table

Table 1: Building characteristics of the two simulated zones.

	Light Envelope	**Massive Envelope**
Orientation	South	East
Area [m^2]	24	40
Length [m]	6	8
Depth [m]	4	5
Height [m]	3,5	3,5
Windows area	7,02	7,2
Window Opening	2%	5%

Table 2: Opaque envelope characteristics of the two simulated zones.

Thermal Mass		**Light Envelope**	**Massive**
External wall	surface mass [kg/m^2]	52	130
	U [W/m^2K]	0,31	0,32
Internal wall	surface mass [kg/m^2]	45	94
	U [W/m^2K]	0,90	1,20
Internal floor	surface mass [kg/m^2]	169	853
	U [W/m^2K]	1,92	1,96

Table 3: Characteristic of the transparent components of the Reference Building.

Type of component	Triple pane glazing, 4-12-4-12-4
U [W/m2K]	1,9
Solar transmittance	0,6
Solar Heat Gain Coefficient	0,68

Table 4. Heating maximum power of the water radiator and cooling maximum power of the cooling device

	Heating Max Power [kW]	**Cooling Max Power** [kW]
Zone A	3,15	2,5
Zone B	6,3	2,5

Table 5. Heating and Cooling seasons for climate locations

	Heating Season	**Cooling Season**
Frankfurt	1 October – 1 March	31 May – 30 October
Athens	1 November – 31 March	1 April – 31 October

Table 6. Regression parameters for the Markovian transition probabilities.

Type	Parameters	Opening probabilities	Closing probabilities
Arrival	a (intercept)	-13,7	3,95
	tin	0,308	-0,286
	tout	0,0395	-0,05
	abs,prev	1,826	
	R	-0,43	
Intermediate	a (intercept)	-11,78	-4,14
	tin	0,263	0,026
	tout	0,0394	-0,0625
	pres	-0,0009	
	R	-0,336	
Departure	a (intercept)	-8,72	-8,68
	tin		0,222
	tout,dm	0,1352	-0,0936
	abs,next	0,85	1,534
	GF	0,82	-0,845

Table 7. Regression parameters for the single logistic regression

Types	Parameters	Lowering probabilities
Blinds	a (intercept)	-3,54
	tout	0,139

Table 8. Regression parameters for the single logistic regression

	Turning on heaters	Running fans	Turning on lights
a = intercept	2.73 ± 0.18	-3.80 ± 0.25	2.47 ± 0.18
b = gradient	-0.322 ± 0.017	0.110 ± 0.014	-0.058 ± 0.018

Table 9. Example of IDA ICE deterministic native NMF input syntax for opening windows using schedules

```
((OPNCTRL :N "Window1" :T WINDOW :D "Window")
  (:PAR :N X :V 0.5)
  (:PAR :N Y :V 0.25)
  (:PAR :N DX :V 4)
  (:PAR :N DY :V 3)
  (:PAR :N OPENING-CONTROL :V PI-CONTROL+SCHEDULE)
  (:RES :N OPENING-SCHEDULE :V "Schedule people ORB")))
```

Table 10. Example of IDA ICE User Customized Code written in NMF syntax, for opening windows

```
CONTINUOUS_MODEL Logistic
ABSTRACT
"Logistic regression. p=exp(a+bx1+cx2+...)/(1+exp(a+bx1+cx2+...))
where a is the offset, b,c ... are coefficients and
x1, x2, ... are variables/insignals
Sends result to multiple output links"

/*  Updates: 110921 rka, bounds added to denominator, OutSignal and polyn */
EQUATIONS
   polyn := SUM i = 1, n_in
             InSignal[i]* Coeff[i]
            END_SUM + OffSet;

   polynom := IF polyn > 700 THEN
                700
             ELSE
                polyn
             END_IF;

   denominator := IF 1+EXP(polynom) < 0.00001 THEN
                    IF 1+EXP(polynom) > -0.00001 THEN
                      0.00001
                    ELSE
                      1+EXP(polynom)
                    END_IF
                  ELSE
                    1+EXP(polynom)
                  END_IF;

  OutSignal = IF EXP(polynom)/(denominator)<0 THEN
                  0
             ELSE
                IF EXP(polynom)/(denominator)>1 THEN
                     1
                ELSE
                     EXP(polynom)/(denominator)
                END_IF
             END_IF;
LINKS

  FOR i = 1, n_in
```

ENGAGING

LACK OF EFFECTIVE SOLUTIONS AND INSIGHTS TO LEVERAGE ENERGY SAVING POTENTIAL OF OB

HOW TO ENGAGE OB INTO OPTIMIZED CONTROL FORMULATION IN BUILDINGS?

PAPER 10 — **S. D'Oca**, S.P. Corgnati, T. Buso.
Smart meters and energy savings in Italy: Determining the effectiveness of persuasive communication in dwellings.
ENERGY RESEARCH & SOCIAL SCIENCE – 2014

PAPER 11 — **S. D'Oca**, S.P. Corgnati, A.L Pisello, T. Hong.
Introduction to an occupant behavior motivation survey framework.
Proceeding of Clima2016 Conference – Aalborg, Denmark 2016

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Smart meters and energy savings in Italy: Determining the effectiveness of persuasive communication in dwellings

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ABSTRACT

To secure a sustainable energy development in the residential sector, attitudes and human behavior need to be modified toward more efficient and conscious energy usage. The goal of this research is to assess evaluations and to test the effectiveness in reducing domestic electricity consumption. The aim of the smart monitoring system we evaluate is to provide households with a user-friendly tool that improves awareness of energy behavior in homes, enabling better management via the visualization of consumption and persuasive tailored information on domestic electricity use. In our study, the system was tested on 31 Italian families selected among volunteers all over Italy, participating to the first trial phase from October 2012 to November 2013. A combination of persuasive communication strategies such as graphical real-time and historical feedback based on real data and comparison tools to encourage competitiveness against "similar" households were provided to users through a domestic user-friendly interface. In addition, personalized energy saving prompts were sent via web-newsletters to trial users. The study concludes that energy related persuasive communication is effective in reducing electricity consumption in dwellings on average −18% and up to −57%.

1. Introduction

Extended literature studies [1–5] confirm occupant behavior to be setting the direction for contemporary researches aiming to bridge the gap between predicted and actual energy consumption in residential buildings. Since the stochastic nature of occupant behavior, the mutual influences between human-building-environment cannot be described in a simplistic way, rather it requires appropriate methodologies and techniques able to comprehend, describe and reproduce the leverage of occupant behavior on building operation. In a view of these facts, Stern [6] firstly highlighted a growing interest around the enhancement of an integrative, trans-disciplinary science of human–energy interaction.

Moving toward a model to understand household behavior, the human decision to behave in a certain way is driven by a wide range of internal and external factors [7]. Specifically, in the area of domestic energy consumption, there is a need to take into account the physical, social and cultural factors that influence and/or constrain user's choices and behaviors, such as age, gender, social class, income, geographical position and political differences, aside from information provisions and economic incentives. Moreover, a study conducted in 2003 by Shove [8] shown the domestic energy consumption is influenced by dominant conceptions of comfort, cleanliness and convenience. Interesting examples can be found in the field of domestic energy consumption where, in spite of successive campaigns, the take-up of energy efficiency measures has been disappointing and behaviors have often become more energy-intensive. The most widespread explanation relies on lack of information of the leverage of occupant behavior on energy consumption variations. Human attitudes and behaviors are driven by a complex interaction process: for this reason an interdisciplinary understanding is a pre-requisite for any strategy aimed at changes. Thus, disciplines such as sociology, social psychology, anthropology and building physics are increasingly cooperating for providing findings into behavioral patterns of energy consumption in households.

1.1. Electricity consumption in the residential sector

In 2003 the International Energy Agency (IEA) estimated [9] that, even with a continuation of all existing appliance policy

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measures, the appliance electricity demand in the residential sector will grow by 3000 TWh/year by 2030. Accordingly to a later 2007 projection of the EU Commission [10], the final energy net electricity demand in the European residential sector will grow by 2030 by 3800 TWh/year. The most update 2009 projection lowers the tendency by 3600 TWh/year by 2030.

In a view of these facts, although significant improvements in energy efficiency have been achieved in home appliances and lighting, the average electricity consumption in the EU-25 households has been increasing by about 2% per year during the last 10 years [10]. Some of the reasons for such increase in the residential sector electricity consumption are associated with a higher degree of basic comfort and level of amenities (particularly in the new EU member countries) and also with the widespread utilization of relatively new types of loads whose penetration and use have experienced a very significant growth in recent years.

The introduction of energy labels, implemented with EU Directives in the last ten years, has produced a positive trend in the sales of more energy efficient appliances. Consumers have responded positively to this mandatory information scheme enabling comparison of energy-efficiency of various appliance models through the ranking into the proper energy class (A–G). The introduction of even better energy classes (A+ and A++) and the broadening range of appliances labeled are thought to produce even greater electricity savings. Nevertheless, due to technological limitations in further reduction in energy consumption, nowadays white goods and appliances have reached an asymptote in enhancement of energy efficiency.

Smart electricity meters and home energy communication and management systems are shown as powerful tools for modeling residential end user electricity demand patterns as well as testing ability and potentiality to reduce or adjust domestic consumption. Results of several studies [11–13] underlined that the energy saving potential by improving occupant behavior through persuasive communication is on the average among 15%. In this context, the evolution of the electric power system to include home energy communication and management systems offers more flexibility to energy customers and creates new challenges and needs for energy providers, distributors and appliances utilities. Also, with the aim of better aligning electricity generation and demand, this study is stressing the paramount role of domestic energy users both as passive energy consumer and active energy prosumers (producers and consumers). In this view, the employment of home energy systems in the residential sector is demonstrated as capable to reduce energy bills by shifting peak consumption and managing peak demand [14]. Various optimization strategies and methodologies are proposed for the efficient coordination of domestic appliances. Studies are conducted at the academic, industry and government level both by international and national organizations. A study conducted by Sarah Darby in 2008 [15] presented an interesting literature survey of the persuasive methods that result in positive energy behavioral change.

1.2. *Energy saving potential by improving occupant's behavior in dwellings*

The electricity energy consumption is rapidly increasing in the last years due to the use of a higher number of electric appliances, reflecting the higher economic status of the householders and their lifestyles. Nowadays, consumption becomes an act of pleasure beyond satisfying basic needs: consequently, our changing lifestyle has dramatic impact on world energy demand. Many serious worldwide problems accompany the increase of electricity use such as global warming, urban heat island, environmental pollution, CO_2 emissions and degradation. Common citizens rarely care about these inconveniences and are often not aware that the energy they consume in their daily domestic activities is so closely related to the climate change issue. Moreover, occupant behavior at home can enormously vary based on different energy related behavioral patterns: accordingly, Andersen in 2012 [16] demonstrated that energy consumption in almost identical dwellings may increase up to a scale of 3. Hence, reducing energy-demand is an important task to face with, not only worldwide, but also at a household level is some way.

With the aim of reducing energy consumption in the residential sector Wood and Newborough [17,18] advanced three general routes to pursue in the residential sector:

i. replacing the existing housing stock with low energy buildings designed primarily to minimize heating and cooling loads;
ii. developing and achieving widespread replication of low-energy domestic equipment (e.g., appliances, lighting)
iii. promoting and achieving "energy-conscious" behavior among householders.

Another possibility, mentioned by studies conducted by Ueno et al. [19,20] is to induce energy saving potential by providing household members with information on actual domestic energy consumption. While the former two technical routes require much money (high capital intense investments) and time (long term results achievement) to accomplish energy improvement, a change of behavioral pattern by energy-saving education of users can save energy without almost any additional investment in infrastructure (low capital intense investments); moreover, the energy-saving effect can appear quickly (short term results achievement).

1.3. *Empowering domestic user awareness by energy consumption displays*

The concept of displaying energy consumption to domestic consumers in order to promote energy saving behaviors has been suggested since 1970s [21]. Nowadays, home automation technologies allow displaying energy information with the aim of educate, motivate, incentive and persuade domestic users toward energy saving behaviors. Field studies on environmental behavior conceptualized persuasive strategies, pointing out that energy consumer may be influenced by antecedent (general) and consequent (feedback) information. Antecedent strategies announce the availability of positive or negative consequences through information, prompts, demonstration and commitments. Such supply information describes practical ways for reducing energy consumption and could be in the form of brochure, notice, booklet posted through the door, TV programs or Internet sites. Several field studies (Dennis et al., Winnet et al.) [22,23] reported that significant energy savings can be achieved by providing antecedent information about methods of energy conservations. However, antecedent information has proven to be less effective in accomplishing behavioral changes than consequent information.

Consequent strategies provide feedback of positive or negative consequences through prompts, real time visualization, and tailored information. Van Houwelingen and Van Raaij [24] found that the most effective feedback is that which more immediately follows an action. Moreover, Stern [25] argued that it is not the time step differences between days, weeks and months that is important to communicate to users, but that the feedback appears immediately after an action that attempts the goal of energy saving. Stern also stated that the most effective energy information is that which captures the attention of the audience, gains involvement and is credible and useful in the user situation.

However, Wood and Newborough [17] underlined that an adverse effect can often occur in persuasive communication studies, so called Fallback effect. The Fallback effect has been defined by Wilhite and Ling [26] as "the phenomenon in which newness of a change causes people to react, but then the reaction diminishes and the newness wears off". Coherently to this statement, a study conducted by Hayes and Cone [21] found that information alone, such as a poster describing ways to reduce electricity consumptions of individual electric appliances, has temporary effect in reducing electricity consumption.

Interestingly, Stern [25] suggested that the conclusion of research on the responsiveness of consumers to general energy-saving information is heavily affected by the Hawthorne effect. As stressed by Seligman and Darley [27], since subjects are aware that they were taking part in an energy study, people exposed to feedback are performance affected and the average reduction in energy usage could be mystified and not realistic.

1.4. Motivating users to energy saving behaviors through feedback information

From the literature concerning feedback information [27–31] little clarity emerges on how best to achieve energy saving potential in households. A study conducted by Harkins and Lowe [32] gave evidence to the fact that if users are given a goal to reach they feel a sense of satisfaction of achievement from reaching that goal. Achievement goals or benchmark may contribute significantly to perform in a wide range of social, academic and cognitive behaviors.

Moreover, if users are shown how much energy they are using compared to their peers, they may well get satisfaction from knowing they are doing better than others. For this reason, the display design could seek to exploit the competitive need to win by putting the householders in a kind of energy race. By giving them information about how much energy they use compared with statistical average for other group of households having similar domestic profile (household members, age, size of the dwellings, etc.) they may experience significant motivational opportunity, feeling they are winning or losing at being energy efficient.

Regarding the feedback display's form, it is important to evidence how units have strong influence on the consumer as they effectively dictate the comprehension, giving relevance and measurability to the energy use. Using the kWh as display unit would be the most obvious choice among technicians for identifying electricity energy use. However, understanding of this unit is limited for energy users: the majority of the common population does not understand energy units and experiences difficulties in defining a kWh and in estimating how much energy will be needed for different end-use event. Moreover, people may not understand the relevance of the amount of energy they are using to the effect it has on environment.

Economic effects shown to energy users could display how much money they are spending as they use their appliances. Wood and Newborough [18] showed evidence that this could be effective only if the savings are large. However, in most cases, the monetary savings will be small as a proportion of total spend per total unit time. Accordingly, displaying energy in units of money could be ineffective of even unhelpful for motivating and maintaining energy saving behavior. People might consider their energy expenditure as a small part of their total spending, minimizing the perception of the domestic energy use as trivial or unimportant.

Environmental effects shown on display would represent different indirect effects that an energy user might have on the environment such as CO_2 emission avoided by means improvements in energy domestic behavior.

2. Method

Goal of the research is to assess evaluations and to test the effectiveness in reducing domestic electricity consumption of the Italian smart monitoring system Energy@home for residential buildings. The Italian Energy@home project [33] aims to endow householders with a cost–effective tool that improves energy behavior awareness by means of real-time energy monitoring and persuasive feedback communication system, allowing users to better understand electricity usage and manage more efficiently their electric energy loads at home. The project envisions a communication web platform that can provide users with information on their household consumption directly on the display of smart appliances, on the smart phone or on their computer by means graphical user/friendly interfaces, based upon information exchange and persuasive feedback information related to real monitored electricity usage in the home domain.

The Energy@home kit includes several devices involved in the residential energy management [34]. A brief description of the home kit is provided in Fig. 1 and listed below:

i. The Electronic Meter, is responsible for providing certified metering data. The meter is interfaced via a new-generation device called Smart Info, able to gather data via wireless coming from the meter and from the household appliances;
ii. The Smart Appliance (Indesit washing machine), is able to communicate via ZigBee among the Home Area Network;
iii. Five Smart Plugs, able to collect metering data and to implement a simple on/off control on the plugged energy loads other than Smart Appliances;
iv. The Home Residential Gateway, which acts as the central coordinator of the entire home. It allows data exchange between the devices operating in the Home Network, in the Home Area Network, and in the Internet.
v. The Customer Interfaces are all the devices used by the customer to monitor and configure his/her energy behavior. Typical Customer Interfaces are personal computers, smart phones, ad-hoc displays, entertainment systems, in-house monitor.

3. Calculation

A trial test of the Energy@home system was conducted from October 2012 to November 2013.

In this first trial phase, the Energy@home kit was installed in more than 50 test households, selected among volunteers all over Italy. Each trial user was named as "Hag" and coupled with an identification code. In each of the 50 test households, both global electricity consumption (data gathered from the smart meter) and electricity consumption of single appliances (smart appliance and smart plugs) were recorded with a two minutes time-step. Several potentialities of the system were tested (i.e., system switching on and off, appliances and plug testing in different rooms) in trial-households. For this reason, only consistent electricity loads gathered in 31 selected trial-households, were considered for the analysis. A combination of persuasive communication strategies such as graphical real-time and historical feedbacks and comparison tools to encourage competitiveness against "similar" households were provided to users through the domestic user-friendly interface of the Energy@home kit.

Fig. 1. The Energy@home home kit description.

3.1. *Capture actual domestic energy consumption by means constant monitoring*

Electricity pattern loads were clustered for a set of 12 trial users having 4 households family composition, selected among the 31 representative trial users, which were actively testing the system over the time period the newsletters were sent. Only 12 trial users were selected based on electricity data consumption availability and consistency and their pattern loads were clustered to be shown into the tailored newsletters. Moreover, these trial users were selected based on the criteria of being exposed for the first time to energy visualization in order to test the effectiveness of reducing energy consumption by providing them with tailored information regarding actual energy load in their homes, when compared to other similar users.

Pattern loads for family types may be further clustered based on number and age of the household members or family habits dependent on daily routine (number of hours spent at home/work from each householder), leading to wider group scenarios. As a matter of fact, energy related behavior are not only dependent from the number of households, rather factors such as age of components, number and type of electrical equipments normally used as well as presence of electrical heating systems (such as fan coils, heat pumps, air conditioners) and electrical boiler for domestic hot water production may heavily affect domestic energy consumption and pattern loads.

For each of the 12 monitored trial users, an average 24 h pattern load identifying household typical behavior regarding global electricity consumption was created and a weekly mean value of the average daily pattern load was deduced (Fig. 2). Pattern loads were basically distinguished from working days (from Monday to Friday in Fig. 3) and weekends (Saturday and Sunday in Fig. 4), since daily routine may vary with great influence on electricity energy uses.

In Fig. 3, the weekday average daily pattern load presents an obviously extra consumption curve for Monday. This is significant for the Italian case study, since many commercial activities close on this weekday having inevitably local impacts on domestic electricity consumption patterns. Electricity consumption pattern load variation from weekday to weekend is highlighted in Fig. 5. The black dotted line in Fig. 5 indicates the average consumption of 12 trial users during weekdays. The pattern follows the typical daily routine of a working family during working days:

- peak in consumption between 7:00 and 10:00;
- standby consumption during the central part of the day;
- drastic rise in consumption from 17:00 to 20:00;
- high but stable consumption between 20:00 and 24:00;
- fall down of consumption in the night hours.

The gray dotted line in Fig. 5 indicates the average consumption of 12 trial users during weekends. The pattern follows the typical daily routine of a family during weekends:

- no peak in consumption due to wakening-time activities
- rise in consumption above 9:00 (late wakening) with a peak around 11:00 (generally associated to house cleaning and cooking activities)
- high but semi-stable consumption during the whole day until 24:00 with a deeper valley around 18:00 (nap time)
- fall down of consumption in the night hours.

3.2. *Cluster trial users into family type*

The relatively small sample of trial users (12 trials were analyzed) did not allow the authors to group users taking into account more than one variable. The selected variable to cluster users into "family types" was the household composition (2–6 family members). However, in order to coherently evaluate the energy profiles of families in each family type, volunteers were also asked about information on family habits and type and number of electricity equipment home installed. Information were gathered by means a web questionnaire created in Google Drive so that similar users living in similar houses can be identified. Google Drive provides a useful tool for gathering data: from the respondent standpoint questionnaire survey form is simple to understand and fill, whilst gathered data are automatically aggregated into a standard report easy to export into Excel files. Link to the web questionnaire [35] was sent by e-mail to trial-users, asking them to answer to simple and non-intrusive short questions, mainly listed below:

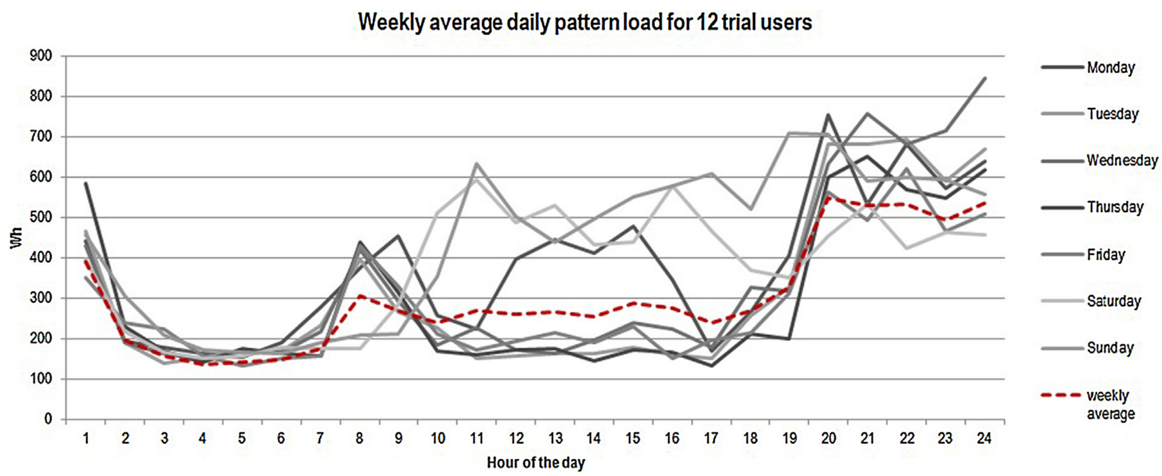

Fig. 2. 4 households family type weekly average daily pattern load for electricity consumption.

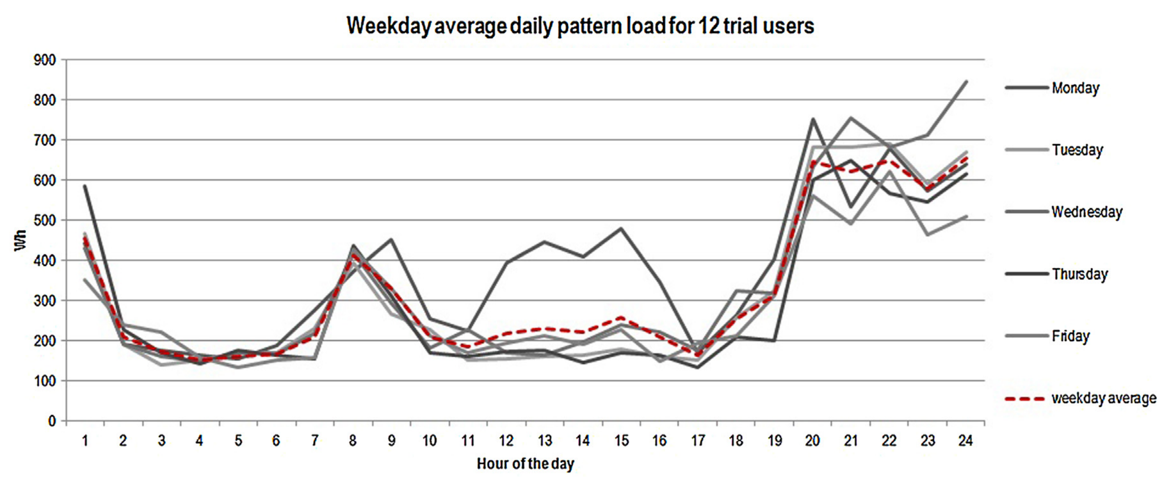

Fig. 3. 4 households family type weekday average daily pattern load for electricity consumption.

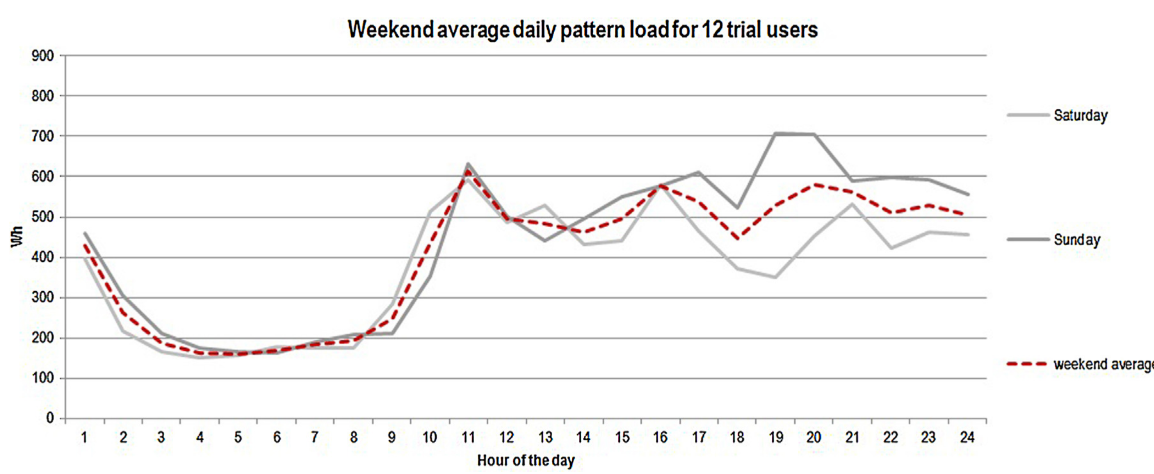

Fig. 4. 4 households family type weekend average daily pattern load for electricity consumption.

- Number of identification of the trial-user
- Location of the trial-user
- House information, such as building type, orientation, size, age of construction, state of maintenance
- Electrical plant system information
- Domestic household information, such as number and age of persons in the family, level of education, activity and un-occupied period
- Appliance usage information, such as number and kind of owned appliances, time and period of usage.

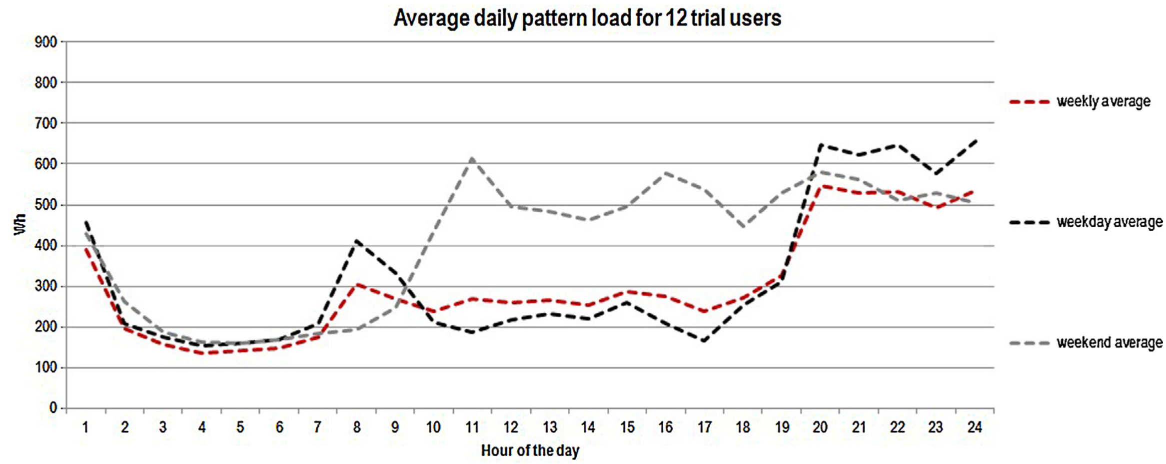

Fig. 5. 4 households family type average daily pattern load for electricity consumption.

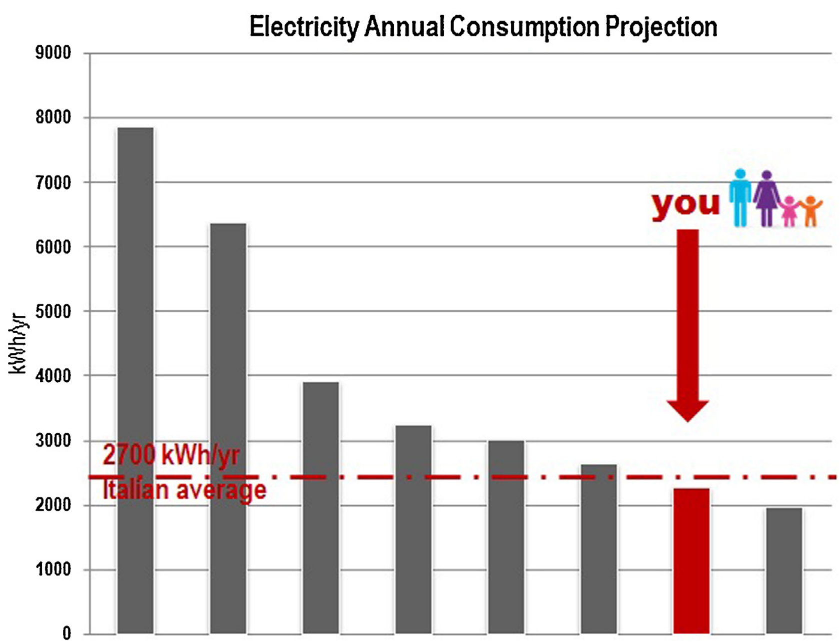

Fig. 6. Electricity annual consumption projection with reference to a trial user having family composition of 4 households.

3.3. *Compare monitored energy loads to benchmark (vertical and horizontal) values*

Among the clustering methods, the comparison of the users' current electricity consumption to reference values emerged to be effective. Reference values (benchmark) may derive from existing studies providing average national values (vertical benchmarking), or from past energy consumption monitoring data (horizontal benchmarking) related to specific users' (family type) profiles, of the user itself. Reasonably, if benchmark setting were to be used, the boundary of the stated benchmark must be carefully considered. Likewise for goals, if a target is too easy the effects could be limited, while unrealistic goals can cause distress.

Useful vertical benchmarks related to typical domestic energy consumption in Italy are provided by the National Agency for electricity and gas energy consumption (AEEG, Agenzia per l'Energia Elettrica e il Gas) [36] and by the Italian National Institute of Statistics, ISTAT [37].

- The average electricity energy consumption for an Italian family (4 households and installed power of 3 kW) is settled by AEEG as 2700 kWh/year.
- The correlated average energy consumption is settled by AEEG as 516 €/year.
- The average Italian electricity energy consumption procapite is settled by ISTAT as 1200 kWh/procapite

The creation of horizontal benchmarks for typical energy consumption of homogeneous groups of users (family type), reveals to be the compromise between the general and averaged benchmark value provided by national surveys, and the very specific one given by the monitoring of individual energy consumption pattern load. Moreover, several literature studies [38–40] gave evidence to the fact that even similar family types, both in terms of building and household characteristics, may behave following dissimilar trends, making unfeasible the creation of coherent and effective benchmarks.

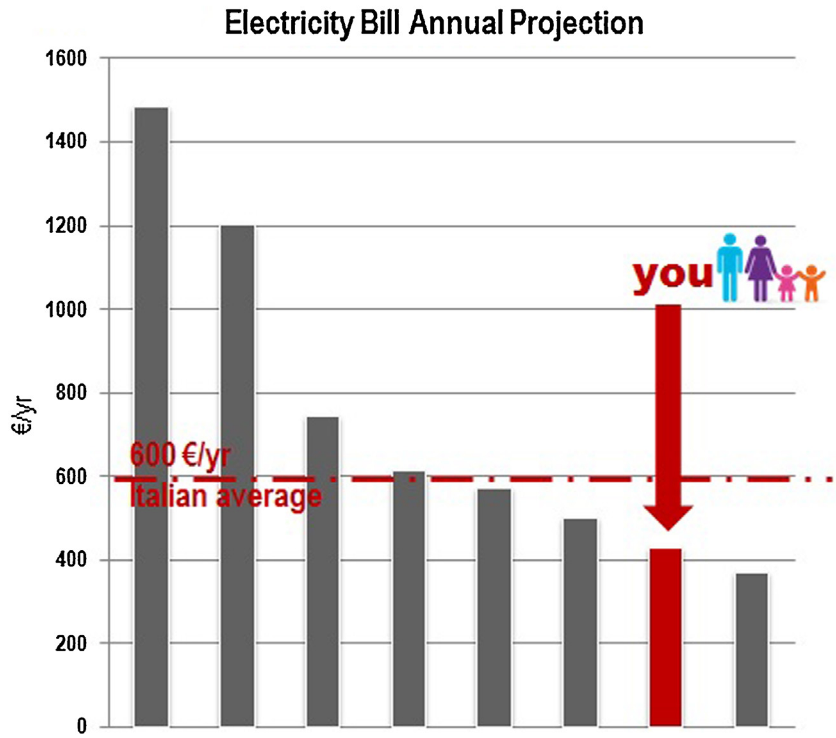

Fig. 7. Electricity annual bill projection with reference to a trial user having family composition of 4 households.

For every trial user, a projection of the electricity annual consumption (Fig. 6) and annual electricity bill (Fig. 7) as well the procapite consumption (Fig. 8) was made. The following coefficients were used:

- 0,19 €/kWhel fixed rate for domestic electricity consumption (1st October 2013) [36]
- 0,422 kgCO_2/kWhel for emissions related to electricity production in Italy (2011) [41]

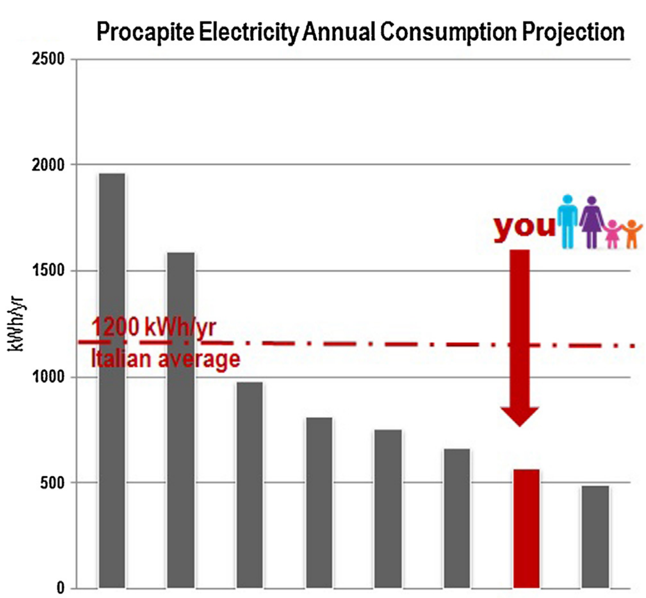

Fig. 8. Procapite electricity annual consumption projection with reference to a trial user having family composition of 4 households.

Average values were highlighted and comparison to the national annual average electricity consumption (2700 kWh/year corresponding to 516 €/year) accordingly to AEEG and for the procapite national annul average electricity consumption (1200 kWh/procapite year) accordingly to ISTAT was provided.

3.4. *Provide energy visualization and feedbacks to occupants through tailored newsletters sent via e-mail*

A good way to persuade consumers toward energy saving behaviors emerged from literature is showing users how much energy they have used in one situation. This information was used to compare how much they used in a subsequent week or how much energy used a trial user having same household characteristics. This comparison made trial users aware they were using more or less energy than usual or than similar households and therefore, motivating the desire to better control energy consumption. With the aim of successfully motivate energy consumers, besides the continuous feedback provided by the real-time interfaces of the Energy@home kit, a total number of 9 web-newsletters were sent to 10 trial users (via e-mail) in order to prompt users with a specific information, in the period from 27/03/2013 and 17/7/2013 (Table 1).

Based on the analysis of the average daily pattern loads for electricity consumption, for every family type (Fig. 6), threshold values were settled based on typical consumption pattern ranging from "energy saver", "on the average", up to "energy intensive". Not a singular value but a range of positive and negative values around the average was considered significant for clustering the typical consumption pattern for similar household compositions. Specifically, a Buffer Acceptability Range (BAR) composed by three bands was created on a daily basis (Fig. 9), regarding the whole week (Monday–Sunday).

- The yellow band corresponded to "average" consumption

Table 1
List of 9 web-newsletters sent to 10 trial users.

9 newsletters sent to 10 trial users								
15/02/2013	01/03/2013	15/03/2013	27/03/2013	05/04/2013	23/04/2013	21/05/2013	09/07/2013	17/07/2013
Prompts on global energy consumption	Prompts on energy consumption with reference to family type	Prompts on stand-by energy consumption	Suggestion of actions to reduce stand-by energy consumption	Prompts on refrigerator energy consumption	Which is the most energy consuming appliance?	Prompts on smart washing machine energy consumption (Part I)	Prompts on smart washing machine energy consumption (Part II)	Visualization of changes in energy consumption load

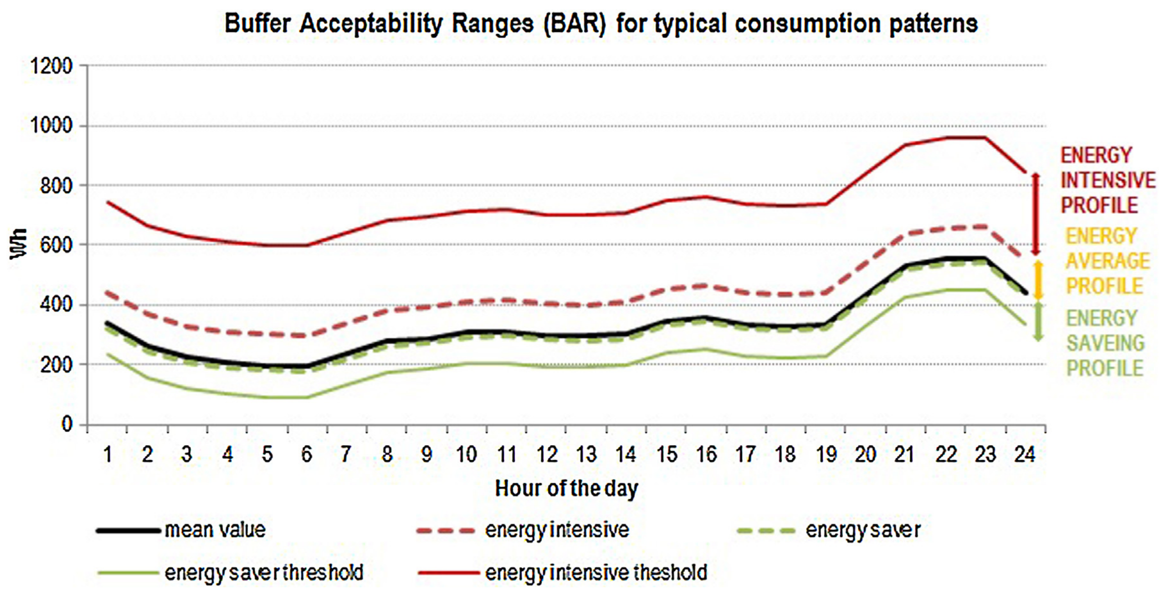

Fig. 9. Buffer acceptability ranges (BAR) for typical consumption patterns ranging from "energy saver", "on the average" up to "energy intensive".

- Two more bands were defined to identify a valid range of "energy intense" (red band) and "energy saver" (green band) typical consumption.

For every hour of the day, higher and lower limits were defined around the mean value by adding and subtracting the standard deviation to the average values.

The Buffer Acceptability Range for typical consumption pattern profiles was therefore used as self-reference value (horizontal benchmark) for the weekly average electricity energy consumption of each specific family type. Daily average pattern loads of each of the trial users were overlapped to the BARs in order to provide users with tailored information regarding their typical consumption pattern. The study therefore highlighted for how many hours of the day the electricity consumption of each trial user was bounded into as "energy saver", "average" or "energy intensive" behavioral pattern (Fig. 10).

It is believed that there is a social driver at work in the presentation of energy use in comparative fashion. If households realize they use more energy than their peers, it is assumed they will be motivated to reduce consumption.

Based on the former mentioned analysis, easy-to-understand graphs were provided to users, with the aim to:

i. enable them to evaluate their own improvements (or worsening), on a weekly basis, during the monitoring period and compare them with those of similar households (Fig. 11)
ii. boost competition between trial users involved into a kind of ≪social-energy race≫, driving users toward always more energy saving behavioral profiles (Fig. 12)

4. Results

Main purpose of this study was to evaluate the energy saving potential by improving household occupant's behavior through energy-saving education and rise in user awareness in energy use. In this aim, the study observed whether the suggested changes were actually implemented and discerned actual energy saving, also in terms of economic and environmental impacts.

Comparison between electricity consumption at the beginning of the monitoring period and an arbitrary date of ending period (31st October) was performed for each of the 31 selected trial users. Outcomes of the research demonstrate that the Energy@home system is an effective tool in reducing electricity energy consumption at home on the average among -18%. Results (Fig. 11) demonstrated that more than 73% of the testing-users (23 over 31) achieved energy savings, after installing the Energy@home system Significantly, "best case" trial user managed to lower the electricity energy consumption up to -57%. Moreover Fig. 13 shows 26% of the test-users (8 over 31) did not manage to reduce their energy loads and consumed more energy up to 32%. Households happened to increase their electricity consumption even if exposed to the Energy@home real-time monitoring system and feedback messaging. Some reason can be attributed to the fact that, on the short term, residential occupant behavior is ruled by habits and routines which are hard to break and more persistent exposure to

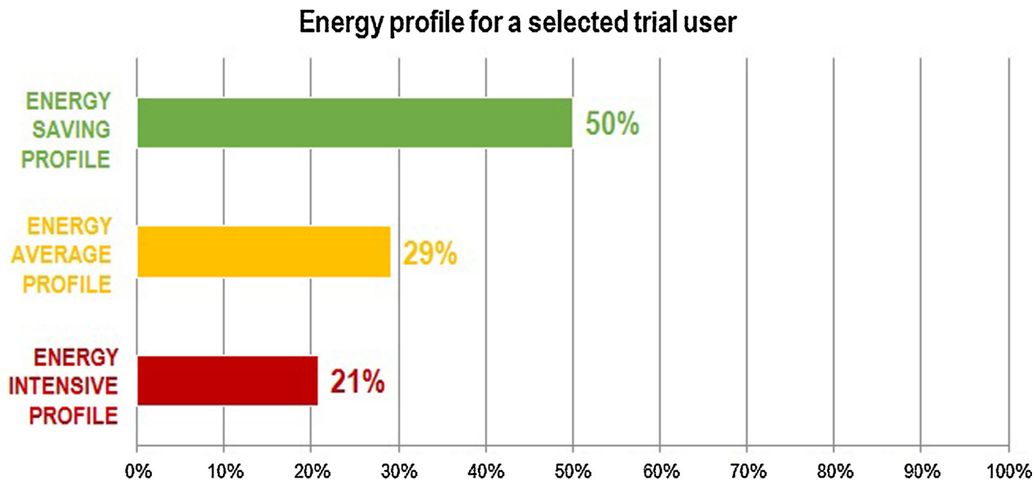

Fig. 10. Target of energy profile with reference to a trial user having family composition of 4 households.

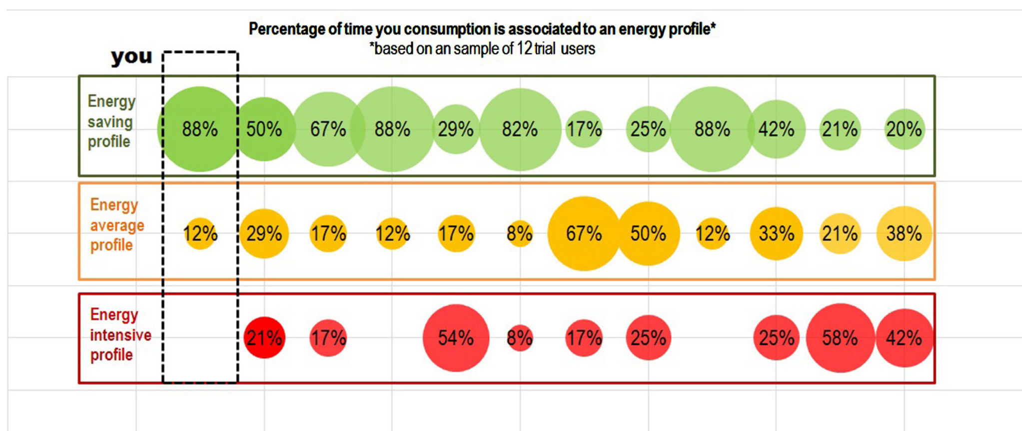

Fig. 11. Comparison of energy consumption profiles for 12 trial users having family composition of 4 households.

Fig. 12. Energy race among a cluster of 12 trial users having family composition of 4 households.

the system may be needed. In this view, authors find interesting to further investigate the possible relationships among household composition and the tendency to energy consumption intensification despite the exposure to energy saving programs.

A total number of 9 web-newsletters were sent to 10 trial users (via e-mail) in the period from 27/03/2013 and 17/7/2013. The effectiveness of these newsletters in reducing energy consumptions was calculated as the variation in energy consumption trends with respect to reference average values. Average values of the seasonal energy consumption was calculated. Moreover, in the time step between the dispatches of two newsletters, an average value of energy consumption was calculated.

The effectiveness of the first newsletter in reducing electricity consumption was calculated as the variation in energy consumption

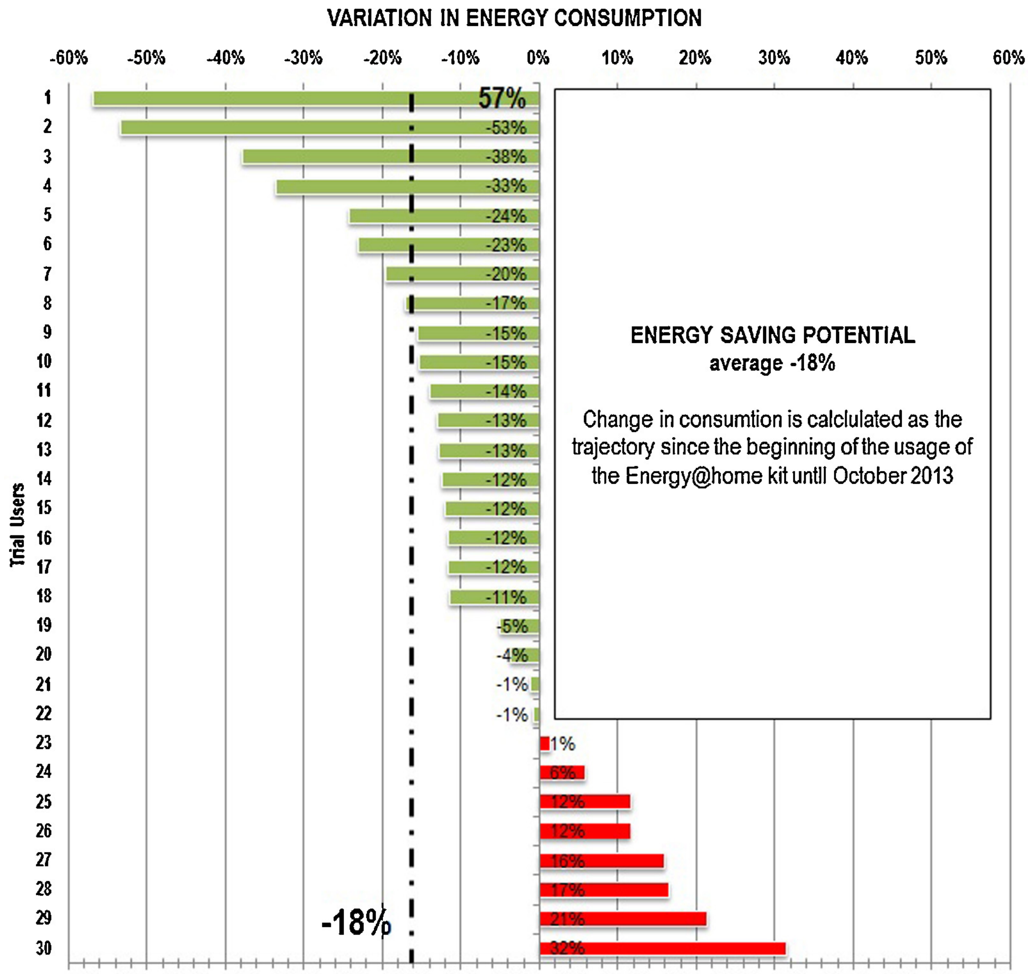

Fig. 13. Global energy saving achieved during the trial testing phase of the Energy@home system.

trends with reference to the seasonal average for 10 monitored trial users.
The effectiveness of the following newsletters in reducing electricity consumption was calculated as the variation in energy consumption trends with reference to the average energy consumption in the time step between the dispatches of two previous newsletters for 10 monitored trial users.

In order to give evidence of the newsletters that enabled trial users in achieving the greatest energy savings on energy consumption variation, results were expressed in terms of energy, economical and environmental savings (Fig. 14). The most effective newsletter was the one sent on the 27/03/2013. This newsletter provided trial users with tailored information on their stand-by consumption, prompting them with suggestion on actions to perform in order to reduce the stand-by energy consumption in their households. This newsletter allowed trial users to save up to 1131 kWh of electrical energy, equivalent to 214 € in terms of economical savings and correspondent to avoid the emission of 477 Kg CO_2 in the atmosphere, in terms of environmental savings. The less effective newsletter was the one sent on the 15/02/2013. This newsletter provided trial users with tailored information related to their global energy consumption.

5. Discussion

Goal of the research was to assess evaluations and to test the effectiveness in reducing domestic electricity consumption of the Italian smart monitoring system Energy@home for residential buildings. Results from literature underlined that the energy saving potential by improving occupant behavior at home is on the average among 15%.

The Energy@home system is an effective tool in reducing domestic electricity energy consumption on the average among 18%. Results demonstrates that more than 73% of the testing-users achieved energy savings, after installing the Energy@home system in their homes. Significantly, "best case" trial user managed to lower its electricity energy consumption up to −57%.

The persistency of this kind of persuasive communication on energy saving has not been tested. Nonetheless, from several recent works in related fields [19,20] it emerged that high level of education, interest in environmental topics and energy related research issues are parameters that positively influence the potential of long term effectiveness of real time energy monitoring, visualization and feedback in the residential sector. In the specific case study, authors find interesting to investigate the persistence of the proposed persuasive communication messaging methodology in further studies.

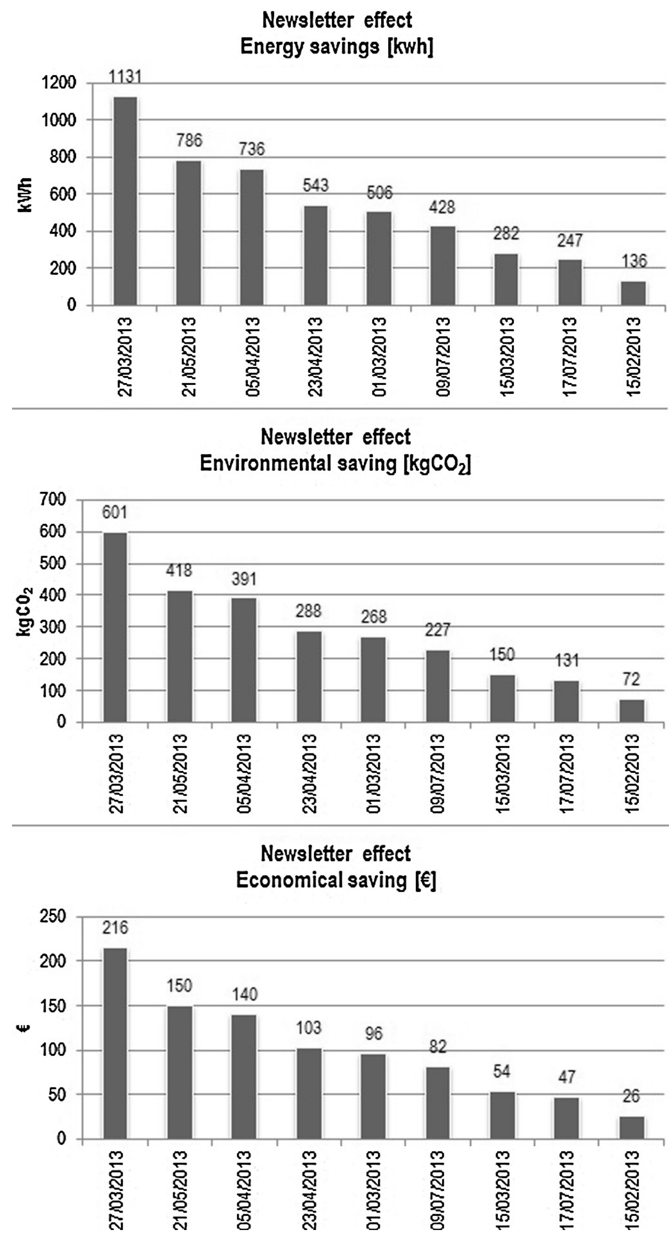

Fig. 14. Global savings (energy, economical and environmental) per newsletter.

The effect of climate seasonal changes has been considered and isolated when evaluating the effect of tailored newsletter in reducing electricity energy consumption. The effect of other outside disturbing parameters such as time of the day, order and type of information sent in the newsletters or side correlations among information sent – just to mention some – has not been considered in this study. Nevertheless, it is worthy of interest for a deeper understanding on human centered studies and behavioral programs to determine the effectiveness of persuasive communication.

The Energy@home system is designed and intended as a permanent domestic tool to improve user awareness on household electricity consumption on the long run. It is plausible to assume that persistence of energy saving may benefit from long term exposure to real time energy consumption visualization, feedback and prompts.

Energy consumption in the household sector is tremendously influenced by occupant behavior. It is in authors' knowledge that simple vertical and horizontal benchmarking may led to oversimplification and uncertainty to estimate energy savings compared to baseline energy usage. Nevertheless several studies and behavioral programs (such as Opower [41], Enernoc [42] in the United States and Eviz [43,44] in Europe) focusing on peer comparisons demonstrated that showing domestic consumers information on the energy consumption of their neighbors is one of the most widely used and effective methods to encourage the adoption energy saving measures and decline energy use intensity. In a view of these facts, horizontal and vertical benchmarks were only used as motivational stimuli to drive energy saving behaviors among testing users. Energy savings were then calculated by comparing household energy consumption during the Energy@home messaging and feedback testing phase.

The method used in this paper had the aim to demonstrate the effectiveness of persuasive strategies, personalized energy feedbacks and real time prompts in reducing electricity energy consumption at home, applied to the specific Energy@home case study. Nevertheless, it is in authors' knowledge that the 31 households testing sample is not relevant to justify the effectiveness of the system at the whole national level. Further research developments and broader sample tests are required in order to identify the robustness of the proposed methodology and analyzed system to improve customers' energy saving opportunities and potential in residential buildings.

Specifically in Italy, accordingly to a study conducted by the European Environmental Agency in 2011 [45], thermal loads account for more than 84% of the domestic energy consumption breakdown (68% for space heating, 9% for water heating and 6% for cooking), whereas only 16% of domestic energy consumption is used on the average for lighting and electrical appliances usage. For this reason, there is a strong need to integrate thermal load monitoring also into the Energy@home kit, in order to perform a comprehensive monitoring of the whole energy use of the domestic energy consumption.

6. Conclusions

A test of the effectiveness of Energy@home System was presented in this paper. The study aimed at enhancing the user awareness related to domestic energy uses and hence the energy efficiency of the whole house system. Main achievement of the research project are listed below:

i. Capture actual domestic energy consumption by means real-time monitoring
ii. Cluster trial users into household family types
iii. Compare monitored energy loads to benchmark (vertical and horizontal) values
iv. Provide information, prompts and feedbacks to occupants through real time user-friendly interface visualizations and tailored newsletters sent via e-mail
v. Observe whether the suggested changes are actually implemented and discern energy saving, also in terms of economical and environmental impacts.

Outcomes of the research demonstrate that the Energy@home system is an effective tool in reducing domestic electricity energy consumption on the average among −18%. In the Italian scenario, whether this energy saving would be achieved by 29.2 million Italian electricity domestic consumers, in one year a total amount of 2128 Million € can be saved, equivalent to 71.6 € saved in the electricity bill and corresponding to avoiding the emission of 5.8 Million tons of CO_2.

Nonetheless the persistency of this kind of persuasive communication on energy saving has not been tested in this study, the results are significant to show how improved occupant behavior can be seen as a zero-cost (or low-cost) investment to enhance the energy saving potential in residential buildings. Indeed, simple and low cost solutions which can be provided to a large amount of people may offer a higher aggregated result than higher cost solutions provided to only a few (i.e., renovation packages in energy building retrofits).

A goal for future domestic energy control devices is therefore to became a cost–effective and reliable tool able to raise user awareness regarding total energy uses in residential buildings and hence to guide users toward more energy saving behavioral profiles. Moreover, the project is a further step toward the development of the so-called "smart grid" in the Italian electricity market, which would allow continuous real-time two-way information exchange between utilities and home appliances. Final aim is to enable domestic electricity customers to manage in a more smart way their energy loads and consumption patterns depending on power supply and prices, hence enhancing the energy efficiency of the entire house system.

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LACK OF EFFECTIVE SOLUTIONS AND INSIGHTS TO LEVERAGE ENERGY SAVING POTENTIAL OF OB

HOW TO ENGAGE OB INTO OPTIMIZED CONTROL FORMULATION IN BUILDINGS?

PAPER 10 **S. D'Oca**, S.P. Corgnati, T. Buso.
Smart meters and energy savings in Italy: Determining the effectiveness of persuasive communication in dwellings. ENERGY RESEARCH & SOCIAL SCIENCE – 2014

PAPER 11 **S. D'Oca,** S.P. Corgnati, A.L Pisello, T. Hong.
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Introduction to an occupant behavior motivation survey framework

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Abstract

An increasing body of research is underlying the need to foster energy behaviors and interaction with technology as a way to achieve energy savings in office buildings. However, engaging office users into more "forgiving" comfort-adaptive behavior is not a trivial task, since neither consequences nor benefits for changing behavior have visible or tangible effects on them personally. Since the 70's, survey studies in the field of building science have been used to gain better understanding of multidisciplinary drivers of occupant behavior with respect to comfort and energy requirements in buildings. Rather than focusing on individual behaviors – and influencing factors – purpose of this survey research is to provide quantitative descriptions on the collective and social motivations within the complexity of different social groups in working environment, under different geographical context, culture and norms. The resultant questionnaire survey emerges as a combination of traditional and adaptive comfort theories, merged with social science theory. The questionnaire explores to what extent the occupant energy-related behavior in working spaces is driven by a motivational sphere influenced by i) comfort requirements, ii) habits, iii) intentions and iv) actual control of building systems. The key elements of the proposed occupant behavior motivational framework are grounded on the Driver Need Action System framework for energy-related behaviors in buildings. Goal of the study is to construct an additional layer of standardized knowledge to enrich the state-of-the-art on energy-related behavior in office buildings.

Keywords: energy-related occupant behavior, questionnaire survey, motivation, DNAs framework, office buildings

1. Introduction

In Europe and US, about 40% of the total primary energy consumption derives from building construction and operation. Specifically, more than 60% of this amount depends on the energy consumption for heating, cooling, ventilation and lighting, meaning a huge proportion of world energy consumption is spent to maintain comfortable and healthy inhabited environments. As demands for low energy consumption is constantly increasing, architects and engineers are facing great challenges of saving energy while maintaining or even improving current comfort levels for occupants. The implications of occupants' behaviors seeking for comfort conditions in indoor environments are undoubtedly essential for building energy requirements.

Recent advancements in energy researches have brought about more awareness of the importance of the human dimension as part of the energy system. Achieving energy conservation emerged as a double challenge, partly technical and partly human. Energy consumption may vary largely due to how occupants interact with system controls (thermostats, lights, equipment, etc.) and the building envelope (windows, blinds, shades, etc.) to adapt themselves to the thermal and visual environment.

There is a growing body of research underlying the need to foster energy conscious behaviors and interaction with technology as a way to achieve energy savings [1-4]. Results from a simulation study to evaluate the impact of occupant behavior on energy use of private offices [5] demonstrated that occupants with wasteful work-style consumed up to 90% more energy than standard users, while austerity work-style occupants used half of the energy of the standard occupants. Accordingly, the development of energy conservation technologies is a necessary but incomplete step toward energy efficiency goals and net zero energy buildings. However, it is a challenging task to develop reliable scenarios of the impact of occupant behavior on final energy usage due to the stochastic nature of human behavior [6].

It is shown that users allowed to interact with control systems are more satisfied with their own working environments [7], since they became more *forgiving* to adapt themselves to the variation of indoor climate conditions and to tolerate greater fluctuations in acceptable temperature ranges [8]. In this context, leading building occupants in workspaces towards comfort-adaptive energy-saving behaviors can be seen as an effective and low-cost investment [9] to reduce energy consumption by up to 30% [5]. This can be achieved by maintaining comfort condition and increasing satisfaction and productivity [10]. Yet, in office buildings, engaging users into more "forgiving" indoor climate conditions [11] – sometime at the expenses of indoor environmental quality and comfort – is not a trivial task. Differently from the household context, neither consequences nor benefits for changing behavior (i.e. saving money from the energy bill) have visible or tangible effects on them personally. For this reason, it is necessary to achieve a deeper understanding of the *motivation structure* towards the concept of "forgiveness" and comfort-adaptive (and energy-saving) behaviors within the complexity of different social groups in working environment.

The future of occupant behavior studies remains a multidisciplinary and controversial field [12], since comfort condition and energy use is recognized not merely related to physical parameters but also factors. In order to fully understand occupant behavior based on facts rather than hypothesis, there is a need for discovery of a layer of social, contextual and group interaction constructs related to individual motivations, which overlap the four key components of the human-building interaction: i) the Drivers of behavior, ii) the Needs of the occupants, iii) the Actions carried out by the occupants, and iv) the building systems acted upon by the occupants [13]. Motivation emerged as a key unlocking parameter for behavioral change, as largely discussed in the field of behavioral science theory [14, 15]. As described in the Theory of Planned Behavior [16], motivations are driving behavior, and can be assumed as a proxy to describe actual behavior. Questionnaire studies conducted in the field of behavioral studies [17-18], also confirmed motivation can be assumed to be the immediate antecedent of behavior. Building occupant behavior research commonly focuses on direct observations such as sensor or other non-self-report data. In contrast, social science research generally deals with self-report data or latent variables such as motivations, beliefs, perceptions, emotions, and attitudes. To the extent that *perceived behavioral control* communicated by the questionnaire respondents is veridical, it acts as a latent variable for actual control and can contribute to the prediction and estimate of the behavior in question. Social science provides quantitative methodological descriptions on how to develop survey researches related to human subjects [19]. Since the 70's, a wide spectrum of building science researches started dealing with the variables of occupants' comfort satisfaction, need, acceptance and energy concerns. Yet, surveys have been widely used to gain a better understanding of occupant behavior and comfort requirements in office buildings, as reviewed in Ackerly et al [20].

2. Methodology

The purpose of this survey research is to provide standardized quantitative descriptions on the motivations driving occupant behavior in office buildings. Rather than focusing on individual behaviors and influencing factors, key results aim to be generalized under collective and social conventions shaped by geographical and climatic contexts, culture and norms.

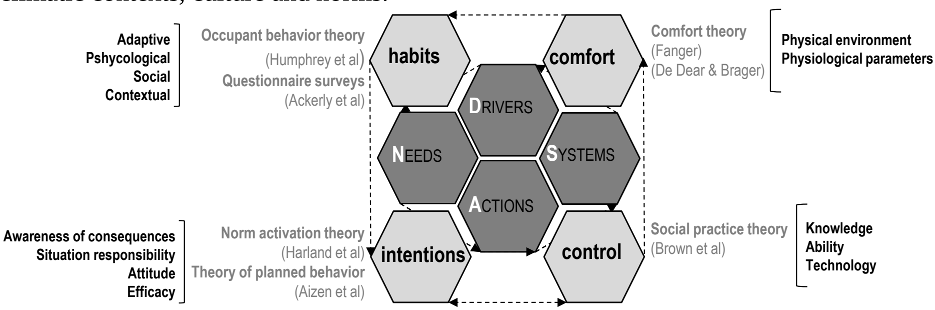

Figure 1. Structure of the OB Motivation Framework

The survey structure is primarily grounded on the DNAS ontology for energy-related occupant behavior in buildings [13]. In this framework, the goal of the study is to create an additional layer of standardized knowledge on energy-related behavior in office buildings, to enrich the state-of-the-art. The resultant self-report questionnaire is a combination of key questions emerged in a comprehensive literature review of occupant behavior questionnaire surveys [20], Humphreys' principle of occupant's interaction with control systems in buildings [21], traditional [22] and adaptive comfort theories [23] merged with social science theories [15-18, 24]. The questionnaire explores to what extent the occupant energy-related behavior in working spaces is driven by an individual motivational sphere influenced by i) comfort requirements, ii) habits, iii) intentions and iv) actual control of building systems (Table 1)

Table 2. Structure of the OB Motivation Survey Framework

Section	Context	Focus Area	References
Comfort	physical environment	thermal comfort	Brager et al, 2004 [23]
		visual comfort	
		IAQ	
	physiological parameters	gender	Fanger, 1987 [22]
		age	
Habits	adaptive	past behavior	Ackerly et al, 2012 [20] Humphreys et al, 1995 [21]
	phsychological	response automaticity	
	social	social norms	
	contextual	workstyle routine	
		empolyment role	
		country of origin	
		enviromental factors	
Intentions	awareness of consequences	perceived subjective norms	Onwezen at al, 2013 [15] Ajzen et al, 2001 [16] Harland et al, 2007 [17] Stern et al, 1986 [18]
	situation responsability	perceived social norms	
	attitude	perceived willingness	
	efficacy	perceived effectiveness	
Control	knowledge	perceived control	Brown et al, 2009 [24]
	ability	actual control	
		perceived access	
		perceived impediments	
	technology	perceived achievements	

3. Results

As the first step towards the development of the motivational framework, a field survey structure is settled in order to understand the predictor variables leading occupants to adapt to and to accept more rigid comfort conditions reducing or not relying on the mechanical control systems in offices.

The occupant motivation survey is structured into the following 4 *sections*, corresponding to the framework structure. For each *section*, the questionnaire defines *i)* the *context* of the question and allocates distinct *ii) focus area* categories, and provides background references, as follows:

1. *Comfort* (Table 2)
    a. *Physical environment*: thermal comfort; visual comfort; acoustic comfort; IAQ
    b. *Physiological parameters*: gender; age
2. *Habits* (Table 3)
    a. *Adaptive:* past behaviors
    b. *Psychological*: response automaticity
    c. *Contextual*: workstyle routine; employment role; country of origin; environmental factors
3. *Intention* (Table 4)
    a. *Awareness of consequences*: perceived subjective norms
    b. *Situation responsibility*: perceived social norms
    c. *Attitude*: perceived willingness
    d. *Efficacy*: perceived effectiveness
4. *Control* (Table 5)
    a. Ability: perceived and actual control; perceived access and impediments

For each of the *focus area* categories, the questionnaire allocates iii) *survey questions* and specifies *iv)* the *scale* or the options for the questionnaire responses.

Table 2. Comfort Section: Occupant Behavior Motivation Survey Framework

Context	Focus Area	Survey question	Scale
physical environment	thermal comfort	Grade your typical thermal comfort satisfaction in your working space	ASHRAE 7 points scale
		What's the most frequent cause for thermal discomfort?	§ Air draft § Floor too cold (cold feet) § Too cold during winter § Too hot during summer § Too aggressive heating during winter § Too aggressive cooling during summer § Zones at different temperatures § Cold nearby windows
	visual comfort	Grade your typical visual comfort satisfaction in your working space	dissatisfied/satisfied 7 points scale
		What's the most frequent cause for visual discomfort?	§ Improper office lighting § Excessive office lighting via natural means § Glare on my computer/working plane § Lack of view from outside (eye tiredness)
	IAQ	Grade your IAQ satisfaction	dissatisfied/satisfied 7 points scale
		What's the main cause for indoor air quality discomfort?	§ Stuffy air § Co2 concentration § Bad/strong/offensive odors/scents
physiological parameters	gender	What's your gender?	male/female
	age	What's your age?	cardinal

The questions and scale/options for self-report responses are designed to comply with the principles of specificity (qualitative responses) and generality (quantitative responses) [20]. Insights from social science are borrowed to design a correct order of the questions to avoid biased effects on the answer of the respondents [19].

Table 3. Habits Section: Occupant Behavior Motivation Survey Framework

Context	**Focus Area**	**Survey question**	**Scale**
Adaptive	past behavior	I typically perform these adaptive actions to make myself comfortable because: § feeling hot (summer) § feeling cold (winter) § for airing spaces § for providing natural lighting § for preventing glare § for preventing overheating § for preventing overcooling	§ never § once a week § more than once a week § once a day § more than once a day
		I typically perform these adaptive opportunities in my working space in order to: § restore my comfort conditions § conserve energy	§ opening/closing windows § turning up/drawing blinds/shadings § turning on/off the heater/cooling when feeling too hot/too cold § using flexible dress code
phsychological	response automaticity	Preference of indoor environmental control in your office space	§ Free manual control (operable windows and shading, manual heating and cooling set points) § Automatic mechanical control (mechanical ventilation, automatic shading and heating and cooling set point)
contextual	workstyle routine	What's your workstyle schedule?	full time/part time
	employment role	What's your employment role?	employee, manager, student, professor
	country of origin	What's your country of origin?	nominal
	environmental factors	What's the spatial configuration of your office?	§ Open Space § Shared office (max 4 people) § Shared office with another person § Single office
social	social norms	Do you feel free to dress as you like? Do you have a formalized dress code in your office?	yes/no
		How much does the building management encourage/discourage these adaptive actions/opportunities? § opening/closing windows § turning up/drawing blinds/shadings § turning on/off the heater/cooling when feeling too hot/too cold § using flexible dress code	§ encouraging § don't care § discouraging
		How much does the building management encourage/discourage flexible dress?	§ encouraging § don't care § discouraging

The elements of the questionnaire identify at times a specific action or motivation, by means of qualitative responses. Other times the generality of the questions is increased by aggregation of typical behaviors, by means the adoption of unpaired numerical scales (7 points). These elements constitutes the predictor variables for measuring the impact of motivational drivers over the likelihood of adopting motivation-driven rather than adaptive-unconscious interaction with the building control systems, having impact on energy and comfort requirements.

Table 4. Intention Section: Occupant Behavior Motivation Survey Framework

Context	Focus Area	Survey question	Scale
awareness of consequences	perceived subjective norms	Saving energy in my workspace will cause me to reduce my comfort level	very much/not at all 7 points scale
		Reducing comfort in my workspace will cause me to reduce my productivity	very much/not at all 7 points scale
		Interacting with the control systems to make myself comfortable in my workspace will influence: § Energy consumption § My comfort level § My productivity	§ reducing § any change § augmenting
situation responsability	perceived social norms	I am prone to accept more forgiving indoor environmental condition to conserve energy in my workspace: § to help my company to reduce budget costs for energy provision § to be visible among my coworkers § to be environmentally friendly	likely/unlikely 7 points scale
attitude	perceived willingness	Are you willing to use windows/other devices to make yourself comfortable?	very much/not at all 7 points scale
		Are you willing to use windows/other devices to save energy in your workspace?	very much/not at all 7 points scale
efficacy	perceived effectiveness	Which are in your opinion the barriers to overcome to turn your willingness into a habit?	§ Lack of time § Lack of convenience § Technical barriers due to control system usability issues § Technical barriers due to space layout issues § Comfort issues
		Which are for you the benefits of adopting energy saving behavior in your working space?	§ Visibility among employers § Visibility of my employers/company § Comfort issues
		Which type of reward would you willing to receive, to motivate you towards energy saving behaviors?	§ Being financially rewarded when performing energy saving behavior (peer comparison) § Being praised when performing energy saving behavior (incentives) § Receiving negative messages or criticism when not performing energy saving behavior (naming and shaming)
		How effective are the adaptive actions in helping you to stay comfortable?	very ineffective/very effective 5 point scale

A selection of statistical models typically adopted for survey data analysis (e.g. multivariate analysis, frequency distribution analysis, marginal homogeneity test, Pearson Chi-Square test, Cronbach's alpha test, likelihood ratio test, correlation analysis, single and multiple regression models.) and data mining methods (cluster analysis, decision tree, association rules, etc.) will be applied for the investigation of the predictor motivational variables. The evaluation of the magnitude of different perceived control opportunities will establish new knowledge about the motivational sphere driving decisions of similar profiles of office users' to engage towards the energy-related measures under scope of investigation. A wide variety of survey distribution method and tools are available for survey delivery. To align with the authors' expertise, project goals and budget, the open-access and web-based Google Forms will be used.

Table 5. Control Section: Occupant Behavior Motivational Framework questionnaire

Context	Perceived control opportunity	Survey question	Scale
ability	perceived control	How would you grade your knowledge in terms of? § how is comfort control provided in your workspace § who is responsible for comfort controlling in your workspace	§ very knowledgeable § don't care § not at all knowledgeable
		Who is responsible for controlling?	not at all knowledgeable/very knowledgeable
	actual control	During the last six months, I performed these adaptive actions to make myself comfortable: § opening window when feeling hot § closing window when feeling hot § opening window for airing spaces § turning up blinds/shadings for providing natural lighting § drawing blinds/shadings for preventing glare § drawing blinds/shadings for preventing overheating § turning on the heater when feeling cold (winter) § turning off the heater when feeling too hot (winter) § turning on the cooling/fans when feeling hot (summer) § turning off the cooling/fans when feeling too cold (summer) § removing/adding extra layers of clothing	§ never § once a week § more than once a week § once a day § more than once a day
	perceived access	My authority (I am allowed to) to interact with control systems in my working space is	not allowed/allowed 7 point scale
		My ability (I manage to) to interact with control systems in my working space is	no control, full control 7 point scale
		How satisfied are you with your degree of control/ability to make yourself comfortable?	very dissatisfied/very satisfied 7 point scale
	perceived impediments	What are your main perceived impediments to interact with the control systems?	§ Access § Knowledge § No need § Upset coworkers § Security § Outdoor pollutant

Regarding the sample needed to assure validity and robustness of the survey question, insights from social science provide a formula to determine the survey respondent sample size and response rate acceptability, as a function of population sizes and characteristics at confidence intervals [25]. Another approach is to refer to the average sample number – about 1000 interviewed – of the occupant survey researches published in literature.

4. Discussion and Conclusions

The prospect of comfort theory is still debated as a multidisciplinary and controversial field [12], since comfort condition is not only related to building physical and environmental parameters but also to social constructs reflecting beliefs, values, expectations, and mostly motivation of occupants. The key elements of the proposed occupant behavior motivational framework are grounded on the DNAS framework for energy-related behaviors in buildings [13]. The resultant questionnaire is based on extensive literature review of previously developed occupant behavior surveys [20] and emerges as a combination of traditional [22] and adaptive *comfort* [23] theories, merged with occupant behavior [21] and social science theories [15-18, 24]. Behavioral insights introduce the concept of behavioral *motivation* by means of i) *individual* behavioral beliefs – leading to favorable or unfavorable habits towards the behaviour; ii) *social* pressure and *normative* beliefs – influencing individual intention; and iii) *control* beliefs, giving rise to perceived behavioral control with respect to the actual IEQ control opportunities for the specific office configuration. As a rule, the more favorable the individual habits and intention, the more encouraging the social pressure and norms, and the greater the perceived control, the stronger should be the person's motivation to perform the behaviour in question [16].

In line with this work, outcomes from Shove [1] argue building occupants' motivations, i.e. to adopt more energy conscious behaviors in offices, depends on the diffusion of sustainable beliefs and actions through society. The study establishes that users are generally not aware of their routines and habits, above all in energy field, leading to overrated existing consumption patterns. Hence, Shove [1] concludes that routine behaviors leading to consumption patterns are largely driven by social norms, and are deeply molded by cultural and economic factors. However, the connection of such correspondence remains controversial and quite undiscovered. Bridging this causality gap is one of the scope of the proposed framework and questionnaire.

The starting-point of this work is that human behavior is stochastic by nature and interactions among the several factors that influence occupant's motivations towards consumption practices are dynamic. Influencing factors change over time, rendering individual consumer (occupant) behavior and the process of (energy) consumption practices to some extent irrational, and therefore unpredictable. One of the main conclusions curtailing from this research is that rather than focusing on *individual* behaviors – and influencing factors – research should focus on the rise and alteration of *collective* and *social* conventions shaped by geographical context, culture and norms, driving occupant motivations, as they are crucial in fastening behavioral patterns, with different consequences for building energy consumption and indoor environment comfort. Further advancements of the presented study is the operative rollout of an extensive survey questionnaire campaign in different geographical locations, among the international research community embracing the IEA EBC Annex 66 on "Definition and Simulation of Occupant Behavior in Buildings" [26]. The final aim of this study – in a broader perspective – is to provide a standardized tool to drive effective occupant behavior data collection, to enhance the state of the art on knowledge, methodologies and tools.

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