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A review of occupant behaviour in residential buildings

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A B S T R A C T

Occupant behaviour has a direct impact on building energy consumption. A better understanding of human-building interactions enables to describe with higher accuracy the occupant behaviour. This paper addresses occupant behaviour in residential buildings, providing a review of current methods in (1) monitoring occupant behaviour, (2) developing occupant behaviour models, and (3) applying occupant behaviour models in building performance simulations. Occupant behaviour studies with focus on residential buildings are presented including both challenges and potential for improving building energy performance.

1. Introduction

Energy use in buildings is influenced by six parameters according to the International Energy Agency - Energy in the Buildings and Communities Program (IEA-EBC) Annex 53: (1) climate, (2) building envelope, (3) building energy and services systems, (4) indoor design criteria, (5) building operation and maintenance and (6) occupant behaviour [1]. While several researchers have explored most of these parameters, studies on occupant behaviour are more recent. Moreover, occupant behaviour has been attributed to differences encountered between predicted and actual building performance. Building performance simulations are a highly efficient and low cost alternative for analysing and optimising building design and systems, and it is of fundamental importance that accurate input on occupant behaviour are available. Building performance simulations implemented with occupant behaviour models have the potential to provide output results in close agreement with actual energy use in buildings. Therefore, enhancing the understanding of occupant behaviour is paramount for the assessment of its impact on the overall building performance.

Occupant behaviour is defined by human-building interactions related to energy use, i.e., it can be described by occupancy and the control of devices and systems, such as window control, blind control, lighting system control and heating, ventilation, and air conditioning system control. In the IEA-EBC Annex 66, the relation between occupant behaviour and energy consumption is attributed to the occupants' pursuit of environmental comfort [2].

Occupancy and interactions with devices in building are influenced by variables in three main categories: environmentally-related, time-related and random. The environmentally-related variables include a physical aspect related to the building characteristics and location. Solar orientation, envelope, building layout, and local climate are some examples of environmentally-related factors. The time-related variables comprehend the occupants' routine. In that manner, occupancy and interactions with devices in buildings are influenced by time of day and day of week. Psychological variables were rarely considered in occupant behaviour studies due to difficulties associated with quantifying and monitoring them.

The increased presence of technology and automated systems in buildings has led to even closer interactions between occupants and the built environment, emphasizing the importance of occupant behaviour representation in building performance simulations. For instance, the concept of smart homes uses the Internet of Things to control the automation of system such as hubs, thermostats, home alarm and sensors, security cameras, door locks, dimerization of lighting. The information of occupant behaviour is essential in the success of this concept, since it depends on learning the preferences and routine of the user. The implementation of the human-in-the-loop concept in building innovation allows occupants to participate as active controllers and passive sensors [3].

A common configuration among building performance simulations is to assume a deterministic characteristic for occupant behaviour, representing it, for example, by static schedules. Nonetheless, actual occupant behaviour proceeds stochastically, where occupancy and actions evolve over time and do not follow a repetitive schedule. In this regard, several studies have focused on developing stochastic models for occupant behaviour, and implemented it in building performance simulations.

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The development of occupant behaviour models was based on results from monitoring in-use buildings. Monitoring occupant behaviour approaches can be distinguished by their proximity to the user. For instance, monitoring through questionnaire application requires a direct contact with the occupant, and the collected data is embedded with a certain subjectivity that reflects this proximity. Whereas monitoring with equipment allows the researchers to distance themselves from the occupant, diminishing the subjectivity of the monitored results, however adding uncertainty related to the equipment.

Different modelling techniques have been used to develop a range of occupant behaviour models, varying in complexity, which can be grouped into static schedules, rule-based models, and stochastic models.

Most studies on occupant behaviour focused on office buildings. Residential buildings are characterised by a diversity of occupancy hours and activities, which can represent an increase in the complexity of monitoring and modelling the occupant behaviour. Nevertheless, the higher behavioural diversity in residential buildings also represents a vast opportunity to explore the influencing variables that trigger occupant behaviour and to improve the accuracy of occupant behaviour inputs in building performance simulations. The application of stochastic models of occupant behaviour in building performance simulations provides important insights on how different apartment units perform with accurate human-building interaction input. This information could enable the optimisation of building designs and systems in order to maximise energy efficiency and occupant comfort.

This paper presents an overview of occupant behaviour related to residential building performance simulation. Occupant behaviour was addressed with regard to monitoring to obtain relevant information, developing occupant behaviour models and the application of these models with building performance simulations. The methods available were reviewed herein with a focus on residential buildings.

1.1. Review framework

This review paper focuses on how to collect relevant information on occupant behaviour and to incorporate it into building simulation. The main subjects addressed were: (1) monitoring occupant behaviour in residential buildings; (2) developing occupant behaviour models; and (3) applying occupant behaviour models in building performance simulation.

1.2. Literature search

A literature search was conducted to gather information on the main subjects related to occupant behaviour in building performance simulation. The search was based on scientific publications from the past 10 years, using Scopus as the main database. This period was selected due to a significant increase in studies on occupant behaviour from 2006 onwards (Fig. 1). The partial results for papers published in 2018 were omitted in Fig. 1.

The keywords used in the literature search were "occupant behaviour" and "building simulation", since the objective of this paper was to review studies related to all of the stages required to implement occupant behaviour in building performance simulations. The first search in Scopus yielded 357 articles and reviews written in English. A filter was then applied since not all of the papers were relevant to this review. For example, the following search had to include the filter "and not evacuation", to remove the papers regarding occupant evacuation in buildings due to fire hazard. The final search yielded 328 papers; yet, not all of them were available as full texts. The reading of the full papers allowed the ones most relevant to this review to be selected.

Of the publications identified, the 10 most cited papers are listed in Table 1, including the number of citations according to the search in Scopus database [4–13].

Within the most cited papers, only three referred to residential buildings (No. 4, 6 and 7 in Table 1). Overall, occupant behaviour was more often studied in office buildings. Although residential buildings represent a high energy demand and a high potential for energy savings, difficulties related to monitor occupant behaviour in these type of buildings may accentuate a knowledge gap. The review papers encountered through the literature search reinforced this uneven distribution, often focusing in office buildings. In view of that, this paper provides a review exclusively based on residential buildings. The framework for this review was established on the findings of the literature search, from which it was observed that the studies on occupant behaviour highlighted three main aspects: monitoring occupant behaviour, developing occupant behaviour models and applying occupant behaviour models in building performance simulations. It was also noted that the modelling studies often focus on only one interaction between occupant and the built environment, which can be an indicative of the subject's complexity.

2. Monitoring occupant behaviour

Monitoring occupant behaviour comprehends the collection of suitable information on occupancy, window and blind control, lighting system control, cooling and heating systems control and appliances use.

In general, occupant behaviour has been monitored for different purposes, from the identification of typical patterns for a specific behaviour to the development of stochastic models for occupancy and interactions with building devices. In addition, exploring the influence of occupant behaviour on building energy consumption and identifying factors that influence occupant behaviour are among the main purposes to conduct a monitoring campaign. While the purpose of the monitoring usually focus on one specific behaviour, the method of data collection can retrieve information on multiple behaviour. The monitoring of occupant behaviour conducted by previous studies often included occupancy along with an interaction with building devices, e.g. window, blind, lighting and HVAC systems.

The identification of typical patterns or a range of patterns has been used to implement building performance simulation with suitable static input on occupant behaviour. Patterns of window control in a residential building in Chile were obtained through monitoring results from a questionnaire application [14]. The window control patterns configured ventilation strategies used in summer and winter by the occupants. The monitoring of occupant behaviour conducted by Andersen et al. [15] resulted in patterns for the control of window, shading, lighting and heating systems in Danish dwellings. The patterns obtained by logistic regression allowed identifying external environment variables that influenced the occupant behaviour. In another study, the results from a long monitoring of heating system control in four houses were used to explore the influence of occupant behaviour on building energy consumption by comparing the monitored results from occupied and unoccupied houses [16].

The study conducted by Fabi et al. [17] investigated the influencing variables of occupant behaviour. The variables were classified into internal and external and their influence on occupant behaviour was referred as a trigger to a reaction, e.g. closing a window. Conditioning rules that synthesize the relation between an influencing variable and an interaction with a building device are an alternative to implement building performance simulations with information on the triggers of occupant behaviour. A rule-based control was used by Bălan et al. [18] in the simulations of

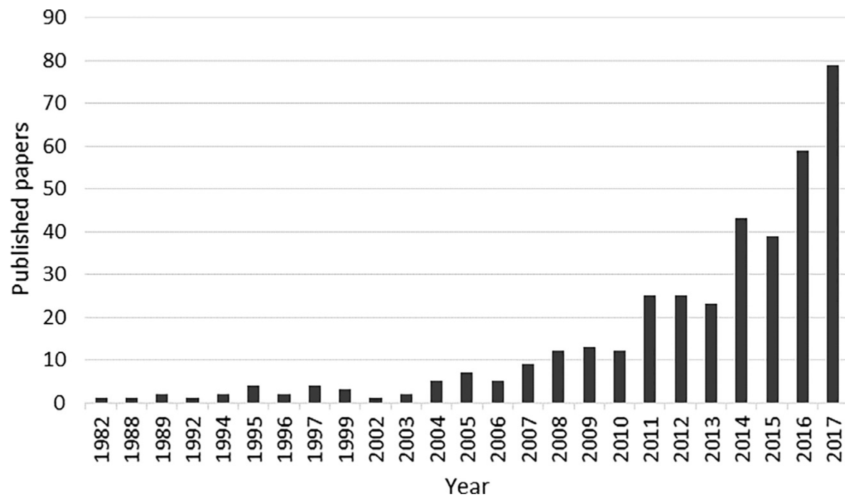

Fig. 1. Distribution of published papers per year in Scopus database.

Table 1
The ten most cited papers identified in the literature search (updated 16/03/2018).

No.	Paper title	Authors	Year	Journal	Cited by
1	A generalised stochastic model for the simulation of occupant presence	Page et al. [4]	2008	Energy and Buildings	283
2	User behavior in whole building simulation	Hoes et al. [5]	2009	Energy and Buildings	272
3	Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings	Rijal et al. [6]	2007	Energy and Buildings	251
4	A high-resolution domestic building occupancy model for energy demand simulations	Richardson et al. [7]	2008	Energy and Buildings	226
5	The dark side of occupants' behaviour on building energy use	Masoso and Grobler [8]	2010	Energy and Buildings	209
6	A systematic procedure to study the influence of occupant behavior on building energy consumption	Yu et al. [9]	2011	Energy and Buildings	191
7	A high-resolution stochastic model of domestic activity patterns and electricity demand	Widén and Wäckelgård [10]	2010	Applied Energy	188
8	Interactions with window openings by office occupants	Haldi and Robinson [11]	2009	Building and Environment	171
9	On the behaviour and adaptation of office occupants	Haldi and Robinson [12]	2008	Building and Environment	143
10	A roadmap towards intelligent net zero- and positive-energy buildings	Kolokotsa et al. [13]	2011	Solar Energy	139

the thermal model of a house, where the influence of occupancy was determined as a secondary heat input, therefore impacting the internal load.

A review of the variables that influence occupants' interactions in order to describe occupant behaviour was proposed in [19]. In the assessment, as previously carried out by Peng et al. [20], the variables characterised three categories of occupant actions: environmentally-related, time-related and random. According to this classification, the first type of interactions between occupant and building devices relates to a quest for environment comfort. Time-related interactions represent the routine and habits of the occupants. Random interactions cannot be synthesised with association rules, since a direct relation to external variables is not present. The influencing variables (also denominated as drivers) related to window and blind control were the focus of multiple occupant behaviour studies. The explanatory variables that lead to the opening and closing of windows in Danish residential buildings were identified, separately, by Andersen et al. [21]. While, in study conducted by Calì et al. [22], the focus was only the opening of windows.

In the studies conducted by Fabi et al. [23] and by Fabi et al. [24], monitoring occupant behaviour had the purpose of verifying the accuracy of models developed for window control and thermostat control. The comparison between actual monitoring results and building simulation results showed that the models were able to reproduce general tendencies of occupant behaviour.

Nevertheless, the development of mathematical models is the most frequent purpose for monitoring occupant behaviour. In that manner, Section 3 is dedicated to review the methods used in the creation of occupant behaviour models.

In order to achieve each purpose of monitoring the occupant behaviour, different methods were employed. The monitoring approaches were divided by Yan et al. [25] into three main groups: observational studies, surveys and interviews, and laboratory studies. This proposed division reflects in the techniques used to monitor occupant behaviour. For Guerra–Santin and Tweed [26], the monitoring approaches are classified into: physical monitoring and occupant investigation. Physical monitoring is based on equipment used to track occupancy and actions in the building while occupant investigation is based on the application of questionnaire surveys, diaries, observation and interviews. A simpler division would be to group the studies according to whether or not equipment was used to monitor occupancy and interactions with building devices.

2.1. Physical monitoring

The physical monitoring comprehends the methods of monitoring occupant behaviour with equipment. In addition, this category includes a segment relating to adaptive behaviour monitoring, in which information on both the occupant behaviour and the environmental conditions is collected to investigate the relation between the two sets of information.

The use of equipment to monitor occupant behaviour generates objective inputs, since the method allows a distance between researcher and respondent. The monitoring results derive from the equipment, often represented by sensors. In that manner, the monitoring results can represent the actual behaviour (e.g. time of occupancy) or raw data (e.g. carbon dioxide concentration). In the latter case, in order to indicate a certain behaviour the results need to be interpreted with an algorithm and then, for example, the carbon dioxide concentration can indicate the presence of occupants [27].

Different technology available for monitoring occupant behaviour were categorised by Wagner et al. [28] in: image-based, threshold and mechanical, motion sensing, radio-based, human-in-the-loop, and consumption sensing. In addition, the authors provided metrics for the evaluation of each sensing system.

Image-based monitoring presents a major issue concerning privacy; therefore, it has not been applied to residential buildings. This monitoring approach has only been applied to office buildings, for instance, by photographing the façade in order to monitor blind control [29], and videoing a room for occupancy information [30].

Threshold and mechanical sensing include technologies such as reed sensor, door badges, piezoelectric mats, and infrared beams [28]. In the monitoring of window control, Calì et al. [22] used wired reed switches and permanent magnets. The former was installed in the frames of the window, while the latter was installed on the moveable panel. Combined, the monitoring system was able to collect data on the window's position. Two types of monitoring systems were employed with the purpose of the modelling occupant behaviour regarding window control, and identifying influencing variables that lead to an interaction with this building device.

Motion sensing was extensively used in monitoring occupancy. This technology does not implicate with the same level of concern for privacy, since the identity of the occupants are preserved. This type of sensor collects information on the movement of the occupants. In contrast, a static activity may be interpreted as an absence. An accurate reading also requires a clean line of sight, which can be complicated for certain layouts.

Radio-based sensing had been explored due to the dissemination of smartphones. Using WiFi, Bluetooth or Global Positioning System (GPS) it is possible to count and locate occupants in a building. According to Yang et al. [31], to count the number of occupants and to locate the occupants in the indoor space of the building are the main objectives of sensors used in monitoring occupancy. In an experimental monitoring conducted by Zhou et al. [32], information on air conditioning system control was collected using a sensing terminal, a WiFi gateway and an app on occupant's phones. They were able to monitor not only the turning on/off of the air conditioning system, but also temperature and relative humidity of the room. The equipment was installed in three bedrooms. The monitoring results were used on the development of recognition rules of the occupant behaviour.

The human-in-the-loop monitoring focus on collecting information from occupants interactions with technology, which includes thermostats settings, light and dimmer switches, motorised blinds control, an even Internet data. The latter presents privacy concerns in regards of the security of sensitive information.

Monitoring occupant behaviour through consumption sensing is based on the interpretation of energy consumption. In that manner, Time-Use Surveys results have been largely used to infer on occupancy and appliances use in buildings. These large datasets are especially useful when investigating occupant behaviour on a wide scale. A TUS was conducted in residential buildings in the United Kingdom retrieving information with 10 min resolution about the presence of active occupants, along with energy use and load profiles. The UK TUS results was used by Richardson et al. [7] to produce synthetic occupancy with a first-order Markov chain. The resulting model was able to generate stochastic occupancy profiles. Likewise, Chiou et al. [33] used a large-scale monitoring study conducted in the United States to develop models on occupant behaviour, in particular, energy use. The results from the American Time-Use Survey were used through bootstrap sampling to capture activity patterns. In another study, results from the Belgian Time-Use Survey were used by Aerts et al. [34] to develop an occupancy probabilistic model for residential buildings. Monitoring results from a Time Use Survey that gather information on occupancy, appliance use and door opening for UK households in a 10 min resolution were used by Blight and Coley [35] to create weekly profiles in a thermal model for a Passivhaus.

All available technologies for monitoring occupant behaviour present some uncertainty, which can be related to the positioning of the equipment or even to a limitation of its accuracy. Monitoring occupant behaviour with equipment requires attention to the maintenance of the equipment and to the position of cabling. Visible cabling may influence occupant behaviour, as it reminds occupants that their actions are been monitored. Wireless sensors offer an option to reduce the influence that wiring and position have on the occupant behaviour [36]. These type of sensors can be connected to a distribution network to collect data from different nodes in the same building. In addition, triangulation, that is, the comparison of data gathered from different methods, was described by Guerra-Santin and Tweed [26] as a way to overcome some of the uncertainties associated with monitoring with equipment.

In order to improve the accuracy of monitoring results, some studies employed a mixed approach, combining different equipment or implementing with questionnaire application. Occupant behaviour related to window and air conditioning control in residential buildings were monitored by Wilde et al. [37]. The approach combined questionnaire application and equipment. The questionnaire gathered information on the habits of interactions with building devices, such as windows, air conditioning system and electric fans. In addition, magnetic proximity sensors were used to monitor the state of a window, varying from open and closed. Equipment was also employed to monitor indoor and outdoor environment conditions. Monitoring results were obtained for both living room and master bedroom of the households. In a study by Hong and Rashed-Ali [38], the information on occupant behaviour was collected using multiple sources, such as building energy codes, census data and survey. The study's proposal was to compare energy consumption in two houses in China and US. Residential energy use patterns were needed to conduct building simulations, for the dominant housing typologies for each country: single-family detached house and multi-family, multi-story residential buildings. For that matter, a survey was applied to complement information retrieved from Chinese building code and a report on residential energy consumption. The survey included questions about heating and cooling system control, lighting system control, appliances use and hot water use. Equipment were used by Andersen et al. [39] to monitor indoor environment conditions in five apartments, while information on outdoor conditions were collected through a close weather station. In addition, a questionnaire was applied to complete information collected during the monitoring campaign. The questionnaire focused on occupant behaviour regarding heating system control, appliance use and occupancy. The monitoring results were used to develop occupancy profiles that were latter applied in building performance simulations. The mixed mode approach conducted by Guerra-Santin et al.

[40] combined the monitoring of objective and subjective data. The objective data were measured, and included indoor and outdoor environment conditions, energy consumption, lighting level and movement. The subjective data comprehended the answers provided by the occupants about occupancy, thermal comfort, heating system control and attitudes toward energy savings. Sensors and meters were used for monitoring the objective data. The subjective data were gathered in the same period through questionnaire application and interviews. In studies on adaptive behaviour, a set of monitoring techniques is often used to collect data on both occupant behaviour and environmental conditions. A questionnaire survey on window control in Danish dwellings followed by measurements of environmental conditions was conducted by Andersen et al. [21]. The objective was to develop a window control model and, therefore investigate the relation between indoor conditions and opening/closing windows. This combination of techniques allowed a complete monitoring of the building.

2.2. Occupant investigation

Occupant investigation, as classified by Guerra-Santin and Tweed [26], defines methods to monitor occupant behaviour based on self-reported data. Some of the methods used in this approach included questionnaire surveys, diaries, observation, and interviews. Occupant investigation is recommended for collecting information on intention and motives for the interactions between occupant and building devices, due to the active participation of the occupants during the monitoring. In addition, occupant investigation may collect information not measured by equipment, such as thermal sensation, clothing level [28].

The application of questionnaires is the most frequent method used in occupant investigations' studies. The application of questionnaires allows the occupant behaviour to be monitored in a low-intrusion manner and to collect information on multiple levels, including personal motivation for specific actions [41]. Occupant behaviour was monitored in three complexity levels by Chen et al. [42]. The monitoring results provided inputs on occupant behaviour for different purposes, according to its complexity level. The monitoring campaign was conducted by questionnaire application followed by interviews on residential buildings in Changsha, China. In the first level, information on occupancy was collected regarding the quantity of occupied hours, along with appliances use. In the more complex level, hourly fraction of the nominal occupancy was collected with information on window and shading control. In addition, the latter level was complemented with a year monitoring of appliances use in a selected household.

Surveys were defined as a cost effective method for monitoring occupant behaviour in large samples [28]. Although the focus of the questionnaire application is collecting quantitative information on occupant behaviour, the use of open-ended questions may also gather occupants' perceptions and preferences regarding buildings device. In contrast, the absence of equipment during the monitoring of occupant behaviour reflects in a lack of contextual information (e.g., environment conditions). In that manner, a mixed mode approach was employed by Jeong et al. [43] to monitor occupant behaviour using measurements of indoor and outdoor conditions along with a questionnaire application. The monitoring campaign was conducted in 20 apartments in Seoul and it focused on window control. The environment conditions measurements provided information to analyse influencing variables of opening and closing the dining-room window. The questionnaire gathered information on the daily activities, the motives for window control and the thermal sensation on a seven-point scale. From the results, a relation was found between window control and the daily activities of the occupants. Interviews with dwellers to collected data on their daily activities and lifestyles were conducted by Cuerda and González [44]. The interviews include semi-open questions about the dwellers' habit and their interactions with building devices controls, such as heating and ventilation systems. In addition, information on the presence of the occupants and their use of spaces within the apartment were gathered. The qualitative information on occupant behaviour was triangulated with monitoring results from a wireless energy meter, which retrieved information on energy consumption from appliances in individual apartments. The monitoring results were used to develop occupancy patterns in a 24 hours profile for working days and a 48 hours profile for weekends.

Monitoring results from self-reporting occupant behaviour are subject to bias related to the respondent. The subjectivity of collecting information directly from the occupant relates to issues noted by Yan et al. [25]. In responding to a questionnaire or an interview, the occupant may misrepresent the behaviour also due to lack of memory, when requested to fill in schedules related to their behaviour through seasons or for the whole year. The Hawthorne effect and social desirability bias were reported to influence the answers provided by the occupants [28]. In the former, the respondent may mask the behaviour with the awareness of being observed. In the latter, the answers provided may represent a desirable behaviour other than the actual one.

In order to overcome the bias and misinterpretation, the question must be carefully developed, prioritising full sentence structure, direct words and multi items [28]. The latter refers to increasing the granularity in order to improve the understanding, for example, inquiring about thermal, visual and acoustic comfort separately instead of using only one question regarding environmental comfort.

A questionnaire application was employed by Andersen et al. [15] to monitor occupant behaviour in Danish dwellings, previously selected in order to represent the housing stock. The questionnaire inferred about the present state of the building devices (window, shading, lighting and heating systems) and the control of these building devices during the previous two weeks. The questionnaire was available both online and on paper, depending on the internet access of each respondent.

A questionnaire survey was used by Feng et al. [45] to monitor window and air conditioning control in living rooms and bedroom of residential buildings. Over 500 answers were obtained for opening and closing windows. The monitoring results were used to develop typical patterns from the large sample.

In comparison with office buildings, monitoring occupant behaviour in residential buildings presents additional challenges, often related to privacy issues and involvement of occupants. Monitoring occupant behaviour in residential buildings must employ methods that preserve the identity of occupants and secure sensitive information. Monitoring with equipment must have additional attention to its position, as a visible equipment may influence the occupant behaviour.

In residential buildings, occupants present a higher variety of activities, which adds complexity to the monitoring campaign. For instance, equipment such as motion sensors were sufficient when monitoring activities in office buildings, distinguishing between presence and absence of occupant. However, a broader range of metabolic rates from occupants' activities in residential building must be monitored using multiple states. An alternative ternary state proposed by Widén et al. [46] added a variation between present and active, and present and inactive. In addition, occupancy and interactions with devices in residential buildings occur in several spaces. In contrast, occupant behaviour in office buildings is often constrained to a single space. Monitoring occupants' movements in dwellings is a complex aspect to be explored in future studies on occupant behaviour in residential buildings.

With the exception of Time-Use Surveys, monitoring results in residential buildings were restricted to few occupants. The difficulties of conducting large scale monitoring campaigns in residential buildings include low response rate for questionnaires application, low agreement in installing monitoring equipment, difficulty in access the equipment for maintenance.

In order to overcome privacy concerns and increase the involvement of occupants in monitoring in residential buildings, the selected methods must be ethically supported. Ethical standards in occupant behaviour studies are fundamental to both protect the respondents (i.e. privacy, rights and benefits) and to provide scientific validity to the study [28].

Regardless of the monitoring approach, the monitoring results have a direct relation to contextual factors, such as building design, culture, and climate. These contextual factors are implicit in the dataset as noted by Yan et al. [25] and remain an unsolved issue in monitoring. The link between monitored occupant behaviour and contextual factors prevents the extrapolation of monitoring results to different contexts.

3. Developing occupant behaviour models

Occupant behaviour models were classified in the literature by their main features. Thus, they can be divided according to their object of study, as carried out by Stazi et al. [19], where the models were grouped into: occupancy and interactions with devices of building (e.g. window, blind, thermostat). The complexity of the models was considered by Gaetani et al. [47] to classify the approaches into: fixed schedules, data-based models (non-probabilistic), stochastic models (probabilistic) and agent-based models.

The increasing model complexity has led to the proposal in [47] of a fit-for-purpose modelling approach, in which several factors are considered in the selection of the appropriate modelling technique. The selection must take into account factors related to the simulation object, the aim of the simulation, performance indicators, interaction between object and user, and climate. This approach was proposed in response to a tendency to include all available information and overload the model.

According to Yan et al. [25], the identification of the model problem should precede the development of the occupant behaviour model, in order to adequately adjust the model complexity. In addition, the model resolution should be defined regarding the precision in which the timing of events, physical scale and occupancy will be modelled. The model objective must lead to the appropriate modelling approach and model complexity.

Most of the modelling techniques merge the data obtained from monitoring occupant behaviour during the model development and thus the resulting occupant behaviour model represents an average occupant within the data collected. In contrast, a modelling method proposed by Haldi et al. [48] used a generalization in the estimation of probabilities in order to account for occupants diversity in the stochastic model.

Fixed schedules are a simple form of integrating occupant behaviour information in building performance simulations. The schedules are obtained by statistical analysis of monitoring results. Clustering analysis, for example, have been used to identify typical patterns for occupant behaviour, which were latter used as input in building performance simulations [34,49,50].

Multivariate logistic regression was a recurrent technique used in rule-based models to retrieve information on the relation between occupant behaviour and time or environmental conditions. When using logistic regression, the resulting coefficients were analysed to identify the main influencing variables of a certain behaviour. The sign, size and scale of the coefficients were evaluated. Moreover, rule-based models remain dependent on the original dataset, i.e., they are extrapolated from the monitoring results. Thus, rule-based models are not able to create new patterns of behaviour, they only synthesize the known behaviour.

Stochastic models are developed based on the probability of a change in a state. For instance, the state can be represented by the presence of an occupant, an open window, an air conditioning system turned off. Markovian processes were highly employed in the development of occupant behaviour models. For this method, the transition probabilities are dependent on the current state of the process.

Occupancy and interactions with devices in building present a relation to occupants' routine, demonstrating a time-dependency. In order to model this time-dependency, a Markovian process called time-inhomogeneous Markov chains were frequently employed. In a time-inhomogeneous Markov chain, the time spent in a given state has an exponential distribution and a random characteristic. The time spent in a given state does not influence the future state; however, it adds a memoryless property to the modelling process. Modelling occupant behaviour based on a Markovian process aims to comprise the stochastic characteristic of occupancy and interactions in order to be implemented in building performance simulations. Nevertheless, stochastic models still have an accuracy limit, especially when referring to collective activities. In stochastic models, occupants' activities are presented independently. Therefore, activities usually conducted by multiple occupants at the same time may occur separately (e.g. having dinner) [51]. Stochastic processes present the possibility of modelling occupant behaviour with several influencing variables related to environmental conditions and time. However, the reality of occupant behaviour includes an even broader range of influencing variables. For Johnson and Starke [51], the probability of an occupant engaging in an activity includes: the time they last engaged in the activity, the time they usually engage in the activity, and what activities are the other members of the household engaged in.

The following sub-sections address different methods to developing occupant behaviour models, which were grouped according to their object of study.

3.1. Occupancy

Studies on occupancy are fundamental for understanding occupant behaviour, since several interactions with devices of building are dependent on the presence of occupants. For example, the action of opening a window involves the presence of an occupant in the room who adjusts the device accordingly to thermal and visual preferences.

The development of an occupancy model demands information on this behaviour, which was often provided through monitoring results from Time-Use Surveys. The use of large samples allowed the models to include high variety of behaviour, therefore, showing their suitability for representing a population. A stochastic model was developed from monitoring results of the UK Time-Use Survey, which indicated, in a ten-minute resolution, the number of active occupants in the household. This information was interpreted as a state in a first order Markov chain used by Richardson et al. [7]. Monitoring results from a Swedish Time-Use Survey were used by Widén et al. [46] to model occupancy in a ternary state: (1) absent, (2) present and active, and (3) present and inactive. A model for occupancy and appliances use was created by Chiou et al. [33] using the American Time-Use Survey results. A stochastic model for occupancy and activities based on a French Time-Use Survey was developed by Wilke et al. [52]. The main difference of this model is related to the association of starting probabilities with 41 dummy variables that show individual characteristics of the occupants.

Stochastic models for occupant behaviour often employed a binary state description (e.g. the presence or absence of occupants).

The ternary state proposed by Widén et al. [46] provided an alternative by differentiating a present and active occupant from a present and inactive one. In that manner, a change in a state would also indicate a change in metabolic rate and, consequently, the thermal load. A three state occupancy were also used by Aerts et al. [34] in the development of a probabilistic model. The development of the occupancy model used monitoring results from a Belgium Time-Use Survey, in a 10 minutes resolution.

Occupancy was highly associated with occupants' routine. In that manner, the stochastic methods employed in the development of an occupancy model used artifices to include a time-dependency characteristic. For a first order Markov chain method used by Richardson et al. [7], the present state is dependent on the previous one along with the transitions probabilities of changing a state. In order to add a time-dependency, the present state was determined by a random number, together with transitions probabilities and previous state, configuring a Markov chain Monte Carlo technique. The method was able to generate an occupancy model that differs in each run due to the random number, but presented similar characteristics. A stochastic model developed by Widén et al. [46] employed transitions probabilities obtained through the monitoring results, and since the model was developed as non-homogeneous, the transitions probabilities were not fixed. Therefore, a time-dependency was applied to the occupancy model, as the transitions probabilities would vary with time. The probabilistic model proposed by Aerts et al. [34] considered time-dependency transitions probabilities for both the probability of a change in a state and the duration probability of that state. In general, a probabilistic model considers the previous state to determine the present state. However, the employment of time-dependency transitions probabilities indicates that the present state would be determined by the previous state and the current time.

The modelling methods employed in previous studies focused on the development of a stochastic model for occupancy. In addition, schedules and patterns for occupant behaviour were also obtained from modelling occupancy with different approaches. A bootstrap method was used by Chiou et al. [33] to create a model for occupancy and appliances use from the American Time-Use Survey results. The bootstrap method used the mean and standard error of the mean as estimators of the population at each batch run. The estimators obtained from the multiple batches were used to describe the behaviour of the population in form of schedules for occupancy and activities related to appliances use. An occupant behaviour schedule model was created by Taniguchi et al. [53]. The schedule was generated from monitoring results from a Japanese Time-Use Survey, and it interspersed routine and non-routine behaviour. According to this differentiation, the schedule model referred to a series of daily behaviour (i.e. routine behaviour, such as sleeping) followed by sporadic behaviour. A first-order non-homogeneous Markov chain process was applied by Diao et al. [49] to behaviour patterns previously obtained from monitoring results of the American Time-Use Survey. The behaviour patterns for occupancy and appliances use were the result of a clustering analysis, which considered the k-modes as a distance-based method to divide the objects. Differently from other studies, the stochastic modelling method used synthesized results and not the actual monitoring results. A probabilistic model was developed and used by Carlucci et al. [54] to evaluate the energy performance of multifamily residential building in China. The information on occupants' state was used to compose different types of families, accordingly to the probabilistic distribution of family members. The occupancy behaviour associated with each family member was grouped to create an occupancy profile for all the occupants of an apartment. The development of the model employed data from a survey conducted in Japan, since the Chinese data were not available. The imported data included the probability distributions of the duration of activities, beginning and ending time for activities.

Occupancy models were explored in order to represent other interactions between occupants and devices in buildings. A correspondence between the occupancy model and lighting power demand was developed by Widén et al. [46]. The association of different power demands for each occupancy status and number of occupants allowed the model to incorporate both occupancy and lighting control. In a following study, Widén and Wäckelgård [10] associated the occupancy model with nine activities related to electricity end-uses. The stochastic model was able to generate load patterns regarding these activities. Transitions probabilities were also obtain from the Time-Use Survey. The comparison between the transitions probabilities and a random number generated in each time step determined if a change in status occurred.

3.2. Window and blind control

The development of models for window control often explored the results from an adaptive monitoring. Moreover, the relation between environmental conditions and the action of opening and closing a window were investigated. The probability of opening and closing a window was explored by Andersen et al. [21] using multivariate logistic regression. The probabilities were inferred based on results from an adaptive monitoring in 15 dwellings in Denmark. Several explanatory variables were evaluated, including environmental conditions (such as outdoor/indoor temperature, solar radiation, wind speed, outdoor/indoor relative humidity), as well as type of room, time of day and day of week. The variable regarding CO_2 concentration and outdoor temperature influenced the most the opening and closing of a window, respectively. The modelling method developed by Fabi et al. [55] comprehended a continuous adaptive monitoring from which patterns were retrieved by means of statistical analysis. Following the implementation of these patterns in building simulations, a method was proposed using probabilistic distribution for the energy consumption results, and not a single value as commonly obtained. The results showed that common patterns were encountered even for dwellings with different characteristics regarding ownership and ventilation type. The CO_2 concentration, outdoor temperature and indoor illumination are the main variables in the window opening probability while the outdoor temperature and indoor illumination were the most important variables for the window closing probability. In another application of logistic regression, Calì et al. [22] employed the method separately for each window monitored. The monitoring results included four years of window control and environmental variables for five rooms in a multifamily residential building. The application of the statistical method individually for each window allowed identifying the most frequent influencing variables. The method considered the probability of a change of window state. The time of day was the explanatory variable highlighted for both events of opening and closing a window. A multivariate logistic regression was used by Jones et al. [56] to develop a stochastic model for window opening and closing. The probabilities were inferred based on environmental and contextual variables (e.g., season and time of day). The method used the resulting sign and magnitude from each multivariate linear logistic model to compare the effect of the explanatory variables.

The accuracy of window control models were evaluated by Fabi et al. [23] by means of comparison between building energy performance simulations using different models and monitoring results. Temperature, relative humidity and CO_2 concentration were used as output variables. Only the general tendencies for the first output variable were shown by implementing the window control models. A comparison between building performance simulations results using window control models and monitoring results was also conducted by Andersen et al. [39]. The monitoring results included indoor and outdoor environmental variables for five similar apartments. The values for simulations results and monitoring results were in the same range, which indicated that the window control model was able to provide similar tendencies.

The occupant behaviour model developed by Haldi et al. [48] included both window and blind control. A discrete-time Markov process was employed to infer on the probabilities of action, based on monitoring results. The window control modelling considered the probabilities of opening and closing the window with a dependency on the current status of the window. For the blind control, a sub-model was developed to account for fractions of aperture, therefore considering partially open status. The probabilities of blind control were estimated for three stages – arrival, departure and during occupancy. A mixed-effect approach was developed for modelling occupant behaviour, which differentiated the effects of environmental variables and occupancy from the random effects represented by individual's diversity. The probabilities of actions were estimated considering both effects.

Occupant behaviour regarding blind control is yet to be more explored in residential buildings. Most studies on blind control referred to monitoring results from office buildings. The lacking of studies for residential buildings reflects difficulties in monitoring this behaviour due to privacy issues, the influence of sensors on occupant's routine and the demand of a seasonal monitoring period. Moreover, modelling blind control for residential buildings comprises not only a dependency on routine (time-dependency) and environmental variables, but also regarding the surroundings of the building, since the demand for privacy, for example, may trigger an action of closing the blinds.

3.3. Heating and cooling system control

Occupant behaviour regarding heating and cooling systems control is associated with the indoor environment conditions. Furthermore, the main influencing variables of heating and cooling systems control are summarized in environmental variables, building characteristics, and occupants' characteristics. A review on these influencing variables was provided by Wei et al. [57]. Accordingly, the category of building and system variables included the size and age of the building, the type and insulation of the room, the type of heating system and temperature control. The variables related to the occupant comprehended socioeconomic characteristics, such as age, gender, family income, house ownership. In addition, variables related to occupants routine (e.g. time of day, occupancy) and the heating price were considered to influence heating system control.

Models for heating and cooling systems control were often developed in order to assess the impact of occupant's on energy consumption. Thus, a model based on patterns for heating system control, as developed by Guerra-Santin [50], represents a straightforward approach to explore the relation between heating system control and energy consumption. A clustering analysis was employed to identify such patterns in residential buildings in the Netherlands.

In a probabilistic model approach, the heating/cooling system control is associated with explanatory variables, adding a layer of complexity. As seen above, environmental variables have an influence on occupant behaviour related to heating/cooling system control, which was explored by Feng et al. [58] considering environmental conditions and events as triggers for switching on/off the system. A data mining approach was conducted by Zhou et al. [59] to identify air conditioning system control based on environmental variables. Monitoring results of indoor air temperature and relative humidity were used. The air conditioning system control was developed using two algorithms, the C4.5 decision tree algorithm and the curve description algorithm, which showed better suitable for relating environmental variables to the occupant behaviour.

A bottom-up model was developed by Wang et al. [60] to estimate the heating energy consumption in a large scale, considering the residential sector in a Chinese region. The model was based on monitoring results from Chinese Census and a questionnaire survey. The heating system control model used a distribution function for the variables heating set point and triggering temperature. The triggering temperature along with occupancy pattern were used to determine a heating schedule. The influence of triggering temperature and heating set point on the occupant behaviour relating to heating system control was shown through sensitivity analysis. In order to estimate cooling loads also in a residential district scale, An et al. [61] developed a stochastic modelling method that comprised cooling system control, lighting control and window control in an occupant behaviour model. Different probability models were created as part of the method to define several modes of control for each device in a building. Moreover, the method allowed to represent diversity regarding time and space, which was pointed out as an advantage, especially when focusing on results for multiple buildings.

The development of a probabilistic model of heating and electricity consumption in a residential building is described in [62]. The objective of the model was to account for the variation seen in the actual energy consumption, providing an upgrading of the inputs used in building energy simulation. The probabilistic approach was applied to a large dataset from which random samples were selected for the application of the Monte Carlo method. The probability of the energy consumption was calculated using the Gaussian Process Classification. A large variation between the minimum and maximum values for the actual energy consumption was observed. This variation indicates that typical values used in building simulation are limited and do not approximate the actual energy consumption for specific building types.

4. Applying occupant behaviour models

The application of occupant behaviour models often focused on predicting energy consumption, which has been led in different scales. A city-scale study was conducted by Shimoda et al. [63] using an occupant behaviour model to evaluate energy consumption results for different energy conservation policies. An occupant behaviour model was also applied in city scale study by Taniguchi et al. [53]. Simulations were conducted to estimate the influence of occupant behaviour in residential buildings to the electricity peak demand. In addition, energy saving strategies were evaluated, which remarked the influence of lighting system control. In another scale, the study focused on a single dwelling comparison between monitoring and simulation results [20].

The current approaches to implement occupant behaviour in building performance simulations include: (1) static schedules for occupancy and actions; (2) customized codes that can overwrite existing values (without re-compiling) or be added to an existing code (requires re-compiling); and (3) co-simulation, which allows the real-time exchange of information between occupant behaviour tools and the simulation tool [64].

Occupant behaviour models were employed in order to evaluate the influence of a specific interaction with building device on energy consumption. According to Yu et al. [9], results from these evaluations showed a potential for energy saving thought improving occupants awareness.

The influence of occupant behaviour combined with a specific building variable were also evaluated using models as input in building performance simulations. By improving the accuracy of the input variables with the occupant behaviour model, the simulation results were able to provide more realistic scenarios, in which the modification of a specific building variable can be assessed. In a study performed by De Meester et al. [65], different levels of insulation were analysed considering the impact of occupants lifestyle on the indoor environment conditions and heating energy consumption. Similarly, a parametric study by Kolaitis et al. [66] used patterns of occupant behaviour representing different energy awareness to explore the potential of internal and external thermal insulation systems as a retrofitting strategy for Greek residential buildings. Occupancy and interactions with devices in buildings influence indoor conditions, and consequently, building energy performance. The risk of indoor overheating was evaluated by Mavrogianni et al. [67] considering occupancy, window and blind control. The influence of occupant behaviour patterns combined with building variables (e.g. building geometry, orientation, insulation level) were analysed through overheating metrics.

Occupant behaviour models were applied in building performance simulations in order to assess the accuracy of two approaches: a probabilistic and a deterministic modelling. The comparison conducted by D'Oca et al. [68] showed that the use of probabilistic model improved the accuracy of the simulated results, by considering different scenarios of occupancy and interactions with window and thermostat. The representation of occupant behaviour in building performance simulation was also assessed in a study by Daniel et al. [69]. Simulations were conducted using occupant behaviour inputs according to the Australian regulatory house energy rating scheme. In this application, the representation of occupant behaviour proved to be inaccurate of the actual behaviour in low energy houses, overestimating the energy consumption.

The application of occupant behaviour profiles in building performance simulations was conducted by Barthelmes et al. [70] in order to assess the energy consumption for two cases: a nearly-zero energy building and a reference building. The results showed that for the high performance building the most influencing behavioral variable referred to equipment use. In contrast, for the reference building, the behaviour related to heating and cooling control influenced the most.

The application of occupant behaviour input in building performance simulation was conducted by Carpino et al. [71] to assess its influence in the energy consumption of a nearly zero energy building. The inclusion of a reference occupancy and a reference users' behaviour in the evaluation of such buildings was proposed as an assurance that the final balance of energy consumption reach the theoretical goal.

The demand for high efficiency buildings emphasizes the importance of understanding human-building interactions. A study by Pisello and Asdrubali [72] showed that buildings with high efficiency technologies still present a potential for energy saving referred to the occupant behaviour. A denominated human-based energy retrofit yield a reduction in energy consumption in a green village by employing simple actions towards a waste reduction behaviour. The application of occupant behaviour models as input in building performance simulations was conducted by Guerra-Santin et al. [73] in order to reduce output uncertainties and to assess design strategies towards zero energy renovation. High efficiency buildings are usually characterised by high insulation levels and sealed windows. These building design variables combine with occupant behaviour may yield a discomfort level of indoor humidity. Therefore, a study by Winkler et al. [74] evaluates the balance of sensible and latent cooling loads in high efficiency buildings for different climates. A stochastic model for internal gains representing the occupant behaviour was applied along with moisture-buffering and air-conditioner latent degradation models. The importance of considering occupant behaviour in the analysis referred to its impact on indoor conditions.

The optimisation of building design and systems is one of the most important applications of occupant behaviour models. Through the implementation of a suitable occupant behaviour model in building performance simulation, it is possible to predict the impact of the presence and actions of the occupants combined with passive and active strategies.

5. Conclusions

This review paper presented an overview of the methods employed to collect information on occupant behaviour and its application in building performance simulation through the development of occupant behaviour models.

Occupant behaviour in residential buildings was reviewed highlighting the potential of energy saving through a better understanding of human-building interactions. Residential buildings account for a more diverse occupant behaviour related to hours of occupancy and the range of activities, in comparison with office buildings. This higher diversity represents challenges in monitoring occupant behaviour, especially when combined with higher concern for privacy. The challenges faced when monitoring occupant behaviour in residential buildings reflected in the scale and the period of the monitoring campaigns.

Physical monitoring requires equipment, which can be financially prohibitive for large-scale studies. The most frequent equipment used in monitoring occupant behaviour referred to sensors, as image-base equipment is too intrusive for residential buildings. For instance, reed sensors were successfully used in monitoring window control. Motion sensors employed to monitor occupancy were able to preserve the identity of occupants. The increase of technology available in occupants' smartphones and automated systems in residential buildings has brought the opportunity to monitoring occupant behaviour using radio-based and human-in-the-loop methods. Radio-based monitoring uses GPS and Bluetooth technology to track occupancy, while human-in-the-loop method monitors the input of automated systems, learning occupants' preferences and routine. Both methods require additional attention to privacy and must be able to secure sensitive information. Questionnaire application was a recurrent method employed to monitor occupant behaviour in residential buildings. This monitoring method relies on self-reported behaviour, for that matter, the elaboration of direct questions was pointed as a way to overcome misinterpretations. All monitoring methods present uncertainties, which can be reduced by employing a mixed-mode approach. Monitoring occupant behaviour with a combination of equipment and questionnaire application allows the triangulation of monitoring results. In addition, monitoring results would be able to provide explanatory variables for occupancy and interaction with devices in building.

Monitoring occupant behaviour was frequently conducted with the purpose of developing mathematical models. In the selection of monitoring and modelling methods, the objective of the study needs to be considered as the main priority, in order to avoid adding unnecessary complexity.

Modelling occupant behaviour was conducted through deterministic and probabilistic methods. The models resulting from both methods present a dependency on the dataset used in their development. However, deterministic models are only able to reproduce the monitored occupant behaviour. Probabilistic models can create new patterns of occupant behaviour in agreement with the information on the dataset. The results from deterministic models are associated with characteristics of building, occupants and location, from the monitoring results. In contrast, probabilistic models explored the dependency of occupant behaviour with time and environmental variables. A time-inhomogeneous Markov chains was frequently used to develop stochastic models with time-dependency. The importance of time-dependency in occupant behaviour models referred to the representation of a routine.

Most occupant behaviour models were developed using a binary state. For window and blind control, a binary state differentiates between open and closed. For these interactions, further study might identify if a partially open state is necessary to provide a closer agreement with the actual occupant behaviour in residential buildings.

With regard to the main limitations, occupant behaviour models cannot be extrapolated due to the direct relation with monitoring data. Hidden information and unexplored parameters prevent the use of these models in different contexts. The cultural and socioeconomic characteristics of the occupants are imprinted in the model [25]. Furthermore, the model represents the behaviour in a specific building typology and climate.

Occupant behaviour models have been applied in building performance simulations to evaluate the energy consumption. In that manner, studies have focused either on a specific action of occupant behaviour or on the combination of occupant behaviour and a building characteristic. The results from the application of occupant behaviour models revealed the influence it has on building energy consumption.

An important contribution of occupant behaviour models is the possibility to evaluate accurate scenarios for human-building interaction, based on which design decisions can be made, enhancing the building energy performance and providing visual and thermal comfort. Occupant behaviour models are an important input for building performance evaluation. Human-building interaction can significantly change the indoor conditions. Therefore, a thorough evaluation is conducted with accurate occupant behaviour inputs. In addition, the optimisation of systems and building design represents a great opportunity for the application of occupant behaviour models to be further explored in future studies.

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