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A Review of Data-driven Approaches for Occupant's Behaviour in Building Energy Conservation

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ABSTRACT

Occupants behaviour (OB) has significant impacts on building energy performance and promoting sustainability. Imprecision of evaluating the impacts of the occupant behaviour brings about excess energy waste. On the other hand, the increased quantity and quality of the various building energy data collected promotes the use of data-driven approaches, while recognising the potential for building energy prediction as innovative choices. It is significant to conduct research on the data-driven methods for occupants' behaviour in building energy management while considering the different impacts. In this regard, this paper aims to provide a literature review of the current research on data-driven methods for modelling, simulating and predicting the occupant's behaviour and its impacts on building energy, highlighting the opportunities for further research in this context.

Keywords: energy conservation in buildings, occupant's behaviour, data-driven models, machine learning algorithm, sustainable building design

NONMENCLATURE

Abbreviations	
ANN	Artificial neural networks
BPS	Building performance system
BMS	Building management system
HAVC	Heating, ventilation and air conditioning
ICT	Internet Communication Technologies
IoT	Internet of Things
OB	Occupants behaviour
SVM	Support vector machines

1. INTRODUCTION

The excess use of energy produced from fossil fuels leads to insufficient energy supply and different environmental pollution problems[1]. Globally, buildings accounts for more than 30% of the total energy consumption and occupant's behaviour has a considerable impact on buildings energy comsuption[2,3]. The more pressing problems facing today involve behaviour change on many levels, from the city to the individual[4]. Occupants' behaviour has greatly influenced the building energy consumption and performance. A deep understanding can assist with certain building-related application[5-7]. Energy-related occupant behaviour in buildings also is a critical concern for building energy simulation[8-9]. Hence, understanding and changing the behaviour of occupants in terms of energy consumption are effective ways to improve building energy efficiency and promote energy conservation[10–12].

On the other hand, innovation in the design and operation of buildings is important for addressing the threat of global warming and achieving ambitious energy performance targets[13]. Architecture, design and behavioural science need to get talking about sustainability together[14]. With the arrival of the era of scientific and technological revolution, the concept of sustainable technology, low-carbon buildings and smart city has drawn policy makers, environmentalist and researcher's attention[15-17]. The Internet of Things (IoT) which associated with big data analytics is one of the main components of smart sustainable cities' ICT networks as an innovative solution to urban development, owing to its tremendous potential for advancing environmental sustainability[18]. Methods of collecting data are evolving with the rapid development of sensors and Information and Internet Communication Technologies (ICT)[19]. Future buildings will also more and more rely on advanced Building Management Systems (BMS) connected to a plenty of different sensors to collect data, actuators and dedicated networks[20]. The increased quantity and quality of the various building energy data collected promotes the use of data-driven approaches, while recognising the potential for building energy prediction as a complementary, alternative, innovative choice to the more conventional approaches centred on physics. Having thorough understanding of occupants' behaviours through latest modelling and simulation techniques is critical to the design and operation of low energy buildings[21,22].

However, simplistic and incomprehensive approaches are always used in building energy simulation and prediction to evaluate the impacts of the occupant behaviour which mainly leads to the huge differences between simulated models and real building energy consumption, therefore bring about excess energy waste [23,24]. One of the future study directions in the area of big-scale energy data analytics include building retrofitting, sustainable operation, occupant behaviour and strategic energy management[22]. Data-driven approaches offers a novel way of observing and interpreting the behaviour of individuals engaged in energy consumption, thereby potentially enhancing energy efficiency and encouraging energy saving. In addition, the Multi-disciplinary approaches are needed to provide new insights into the inner dynamic nature of occupants' energy behavior[25-28]. The data-driven and algorithmic approach has advantages to synthetically research it among different disciplines.

2. DESGIN BHEVIOUR

Design behaviour provides untapped potential for saving energy and natural environment change. It affects different ways, whether the effect is on an architecture or a strategy, design activity transforms current circumstances into desired circumstances, on a large scale[29]. Occupants' behaviour has greatly influenced the building energy consumption and performance[5-7]. It is a worldwide, globally boundless phenomena[13]. Although design behaviour cannot be described simply by expanding the individual behaviour, it has greater significance and more subjectivists are covered.

Occupant behaviour belongs to the study of design behaviour. It is affected by outside factors such as culture, environment, and economic, as well as internal factors such as preferences for interpersonal comfort, physiology, and psychology. On the other hand, the interactions of the occupants in buildings have a strong impact on the different stage of buildings, such as the building operations, building energy use/cost and indoor comfort; this in turn influences occupant behaviour, thus forming a closed loop[21].

2.1 The factors influencing OB in buildings

Energy consumption in buildings is closely affected by the characteristics of their operational and space use and the occupant's behaviour. The factors influencing occupants' behaviours in building are varied and numerous while the interaction cannot be ignored. A lot of researchers over the years have studied occupants' behaviour and how it influences energy consumption in buildings. The relationship between occupant behaviour and building energy consumption can be obtained, as shown in Fig1. Long-term factors such as comfort, culture, and the economic conditions on occupant behaviour is illustrated, as well as short-term impact of psychological, physiological, and economic issues. Hence, occupant behaviour and building are closely coupled, with numerous feedback loops, making consistency complicated[21]. Long-term impact factors could be understood as external factors which indirectly

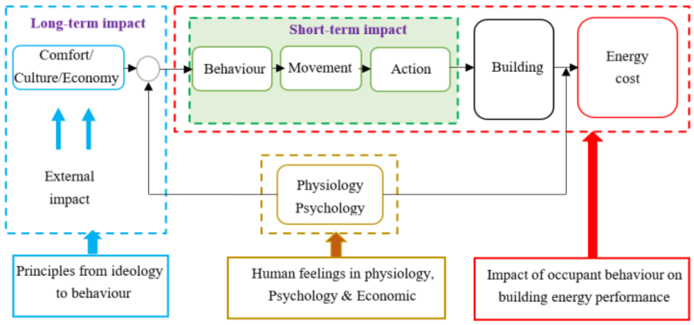

Fig 1. The relationship between occupants' behaviour and building

and long-term influenced occupants' decision making and lead to the objective impact on energy consumption. It is generated from the occupants' principles from ideology, including the thermal comfort, culture background, gender, age, consuming habit. Those external impact factors could be classified by common reason which influencing occupant's behaviour rather than individual reason. Different from the long-term impact, the short-term impact generally has individual difference due to the human feelings in physiology, psychology, personality, and directly influence occupant's movement and action. Because of the different factors which has impact on occupant's behaviour, the building energy cost and performance will be influenced in varying degrees. In addition, by disregarding the relation between occupant's behaviour and building energy performance, it is not conducive to the sustainable building design[18,21,30].

However, even though occupant behaviour in buildings play an important role in potential of building energy management, energy conservation and smart grids, the willingness of occupants to make changes still need to be promoted and paid attention. In the Netherlands a large-scale survey has been designed and conducted as an online survey[31]. The "Energy Cultures" conceptual framework was established with a culture-based approach to behaviour, while considering lifestyles and systems[12]. A framework based on the review work was set out for representing occupant's behaviour in builidng[24]. Occupants behaviour is still easy to be ignored universal concepts from the psychology and sociology perspective, and suffering from drawbacks linked to privacy constraints and other non-technical concerns. Boomsma, Jones et.al studied how psychological factors of resident's influence on building energy saving in low energy efficiency social building in UK[32].

2.2 *The classification of OB in building*

Owing to occupants' presence and activities in the building and their control actions aimed at improving indoor environmental conditions (thermal environment, indoor air quality, light)[33]. Occupants in buildings generally behave in two ways: adaptation to the indoor environment and occupants themselves. Environment-related behaviours include lighting switch on/off, windows opening/closing, or thermostat adjustment, whereas personal behaviours include changing the level of clothing, positions or gestures, lifestyle etc[34,35].

Wei et al used dynamic building model to simulate and predict energy-saving potential under different occupant behavioural conditions of common refurbishment measures[3]. de Almeida et al. studied the electricity consumption structure of household in European,followed by a lifestyle study to improve awareness of energy use in EU countires[9]. Ouyang Jinlong and Hokao Kazunori discussed relationship between electricity consumption and resident's[23]. Ding Yan et al proposed a prediction model that accurately describe the behaviour of the lighting and shading coupling different occupants' control behaviour[36]. Herkel, Knapp and Pfafferott create a model to simulate and predict window status in office building with different occupancy and outdoor temperature[37]. Fabri et al reviewed existing studies on the topic of window opening behaviour. Pan Song et al used logistic regression and Pearson correlation approaches to explore the impact on window-opening behaviour of both potential environmental and non-environmental factors[38].

A theoretical framework to deal with occupant's interactions with building controls to improve indoor thermal comfort is also established[39]. Kong Deyu, et al experimentally collected real data and analysed the effects of indoor air humidity on building occupant's thermal comfort in terms of climate adaption[40]. Gupta, Kapsali and Howard used six case study social houses located in UK to investigate the factors including building structure, services and occupant related factors such as mechanical ventilation heat on actual building energy consumption[41]. Masoso and Grobler studied the energy consumption during non-occupied hours in commercial buildings[6]. Yun et al investigated the occupancy and lighting using patterns on energy consumption of office building [33].

3. DATA DRIVEN OF APPROACHES IN BUILDING

Energy consumption prediction is essential for improving building energy management and conservation. Data-driven models provide a practical approach to energy consumption prediction and has gain a lot research attention in recent years[42].

Two main approaches have been taken for building energy consumption prediction: physical modelling approach and data-driven approach. Data-driven building energy consumption prediction model, in other words, does not require detailed data about the simulated building or actual building, and instead learns from historical/available data for prediction (advantages). Especially in building energy simulation, most of previous studies have focuses on the capability of machine learning algorithms to predict and simulate the energy consumption, uncertainty analysis, sensitivity analysis building stock, optimization, and building retrofit[28,44,45,46,57]. Data-driven building energy consumption prediction studies always based on the machine learning (generally supervised learning) algorithms, generally including artificial neural networks (ANN), support vector machines (SVM), statistical regression, decision tree and genetic algorithm[25]. Applying machine learning model to predict building related energy consumption based on different features such as outdoor weather conditions, indoor air conditions, building types, time, occupancy and occupants 'behaviour, and historical energy use data.

Amasyali Kadir and El-Gohary Nora M. classified statistics of previous research for different types of research objectives such as the different factors that related to the energy consumption, the type of building and the type of the data-driven methods[22]. In the past research, overall, 67% of the studies used real data to train and test, while 19% and 14% studies used simulated data and public data respectively. 47% and 25% of the studies used ANN and SVM, respectively[22]. Considering the application of data-driven methods in building, the insufficiency and sophistication of energy data also is still the obstacle. Future study goals in the area of energy big data analytics include building retrofitting, sustainable construction, occupant behaviour[22].

4. DATA-DRIVEN MODELLING OB IN BUILDINGS

In the latest review work, Carlucci Salvatore et al systematically constructed an extensive database of different research approaches, methods and key findings related to model occupants' presence and actions in buildings[47,48]. Gunay H. Burak, O'Brien William, Beausoleil-Morrison Ian reviewed the research on adaptive occupant behaviors[36]. Peng Yuzhen, et al used machine learning methods to predict occupancy of office building based on cooling control. Unsupervised and supervised learning methods were applied to learn occupancy information to infer real-time setpoint for controlling the room's cooling system[49]. Mo Hao et al adopted machine learning algorithm (XGBoost algorithm) toc develop window behaviour models for residential buildings[50]. Pan Song et al also experimentally verified that Gauss distribution model has more advantages over Logistic Regression Analysis to predict window behaviour in office building[51]. Park and Nagy used a data-driven methodology to examine all the study areas and their relationship to analyze the connection between thermal comfort and building control analysis[52]. Ferracuti et al compared three data-driven models for predicting short-term thermal behaviour in a real building[53]. Han et al reviewed a reinforcement learning method for occupants' thermal comfort control in buildings[54]. Ahmed Gassar et al used different machine learning algorithms to developed data-driven models for predicting electricity and gas consumption in London's residential buildings[26]. Despite the excellent work that those researchers have gained There are still not plenty examples in the study that use data-driven models or machine learning algorithm study the building energy on behaviour level of the occupants, let alone considering multi-disciplinary factors.

5. CONCLUSION

This paper reviews the current research of the application of data-driven methods for occupant's behaviour in building energy from two aspects. Firstly, the definition of occupants' behaviour in building is introduced as well as impacts that influenced occupants' behaviour in buildings, then the classification of occupants' behaviour and its relation to building energy consumption are provided. The next content is about the data-driven methods. The brief introduction of data-driven methods and its application in buildings are illustrated, then the current research of data-driven methods applied to the occupants' behaviour are summarized. Even though the excellent work that those researchers have gained, the research has not reached the stage that occupant behaviours could be effectively simulated, obstacles are mainly from a lack of adequate quantitative research describing energy-related occupant behaviour in buildings. However, despite there are not plenty examples in the study that using data-driven models or machine learning algorithms to analysis building energy considered detailed occupants' behaviour data, the data-driven methods still offer an innovative possible because of their advantages.

Furthermore, data-driven models describing the occupant behaviour develop by different researchers are lacking considering a more interdisciplinary perspective, both the long-term factors and short-term factors, for instance the culture, environment, and economic, as well as preferences for individual comfort, physiology, and psychology. Therefore, there is also an imperative need to investigate the application of data-driven approaches to energy optimisation of buildings at the level of occupant behaviour considering comprehensive factors as well as integrating model with building performance simulation building performance system (BPS) programs. Future research should consider a more interdisciplinary way requiring the integration of the knowledge of architecture, psychology and data analysis.

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