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QUANTIFYING OCCUPANTS' ENERGY BEHAVIOUR: A NOVEL FUZZY APPROACH

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Abstract: Buildings contribute to nearly 40% of the global carbon footprint with a significant proportion of their carbon footprint is generated due to their energy consumption during the operational phase. To reduce the carbon footprint of buildings, efforts have been made to optimize energy consumption during the operational phase; and the fundamental requirement for all such efforts is the accurate prediction of a building's energy consumption. Existing energy prediction models for buildings often map a set of building characteristics to their energy consumption and disregard the occupants' energy behaviour (OEB). Consequently, significant discrepancies (up to 300%) have been resulted between the predictions of these models and the actual energy consumption values, which in turn reduce the applicability of these models in practice. This limitation can be addressed by incorporating OEB in buildings' energy prediction models; however, OEB is an ill-known phenomenon under the impact of several factors, namely, the intra-personal (e.g., education, culture) and inter-personal (i.e., social interactions) characteristics of occupants, as well as environmental factors (e.g., precipitation). This paper introduces a novel insight into the energy behaviour of the occupants of buildings and provides a comprehensive and quantitative measure for modelling OEB based on granular computing and fuzzy logic. Our proposed fuzzy approach can improve the accuracy of existing energy prediction models by incorporating OEB into these models and so help with the energy consumption optimisation of buildings.

Keywords: Occupancy Energy Behavior; Fuzzy logic

1 INTRODUCTION

Energy savings and improving energy efficiency in buildings have gained a lot of attention in recent years since the building sector is a major energy consumer in many countries around the globe. The energy consumption of the building is estimated to be approximately 40% of global energy consumption (IEA 2019). According to EnergyStar 2013, on average, 30% of the energy consumed in commercial buildings is wasted. To help improve the energy efficiency of buildings, it is essential to have accurate predictive models. These models should be able to forecast the energy consumption in a range of scenarios and enable parameter tuning to facilitate the optimisation of energy efficiency. To this end, several modelling techniques have been introduced in recent years to forecast buildings' energy consumption, the majority of which solely rely on a building characteristic for prediction purposes. However, several studies confirm that one of the key parameters that drive the energy consumption with a building is the occupants' energy behaviour (OEB), which is often ignored in these models (Kim et al. 2017; Jia, Srinivasan, and Raheem 2017). Occupants' energy behaviour can be defined as all the actions taken by the occupants of a building that affect the energy consumption of the building either (i) directly by causing generation or loss of energy (e.g., window opening); or (ii) indirectly by affecting the occupants' perception of the ideal indoor environment (e.g., clothing). Consequently, despite the advances made toward the development of novel and accurate algorithms for predicting the energy

consumption of a building, these models often fail to provide accurate predictions as they overlook the OEB. According to Chen et al. 2021, incorporating the OEB when predicting energy consumption is associated with several challenges due to the multi-faceted nature of human activities and interactions with the built environment. A few studies have tackled this problem by modelling the different aspects of OEB, including (i) window opening behaviour (Pan et al. 2018; Ren et al. 2021; Verbruggen et al. 2021; Xin Zhou et al. 2021; Liu et al. 2022); (ii) interacting with the air conditioning systems (Geronazzo, Brager, and Manu 2018; Ahn and Cho 2017; O'Neill and Niu 2017; Baldi et al. 2018; Esrafilian-Najafabadi and Haghighat 2022 and AlQadi, Zaghloul, and Taie 2021); and (iii) controlling the lighting systems (Park et al. 2019; Campano et al. 2022; Ding et al. 2020). However, there is no research addressing this gap by capturing the comprehensive picture of OEB and forecasting its impact on the energy consumption of buildings. This research gap is addressed in this paper by introducing a novel approach for quantifying OEB in the built environment using granular computing and fuzzy clustering techniques (Bargiela and Pedrycz 2016). The introduced fuzzy approach tends to capture the different aspects of the occupants' behaviour that may affect buildings' energy consumption (e.g., window opening, lightning and HVAC systems control) and defines and helps to categorise occupants based on their energy consumption.
The remainder of this paper is organized as follows: A review of the current body of literature is provided in Section 2, describing the fundamentals of fuzzy logic and explaining the existing state-of-the-art of predictive modelling for the energy consumption of buildings. Section 3 illustrates the proposed fuzzy approach for quantifying OEB; and then, this approach is implemented in a case study of small office buildings in Section 4. Finally, section 5 provides some concluding discussions to the paper and discusses the proposed areas of future research.

2 LITERATURE REVIEW

2.1 Buildings' Energy Consumption and Occupants' Energy Behaviour

The energy consumption of buildings is dependent on a variety of factors, including the physical characteristics of the buildings, the type of systems or appliances used, and the environmental factors of their surrounding area. Nevertheless, the behaviour of a building's occupants also plays a vital role in the energy performance of a building, as the occupants commonly regulate and determine the buildings energy conservation (Uddin et al. 2021). Therefore, the energy consumption of a building greatly depends on its occupancy level and the interactions of its occupants with the building (Chen et al. 2021). A plethora of studies has been conducted to reduce energy consumption of buildings and improve their energy efficiency. A common requirement of these efforts is their dependency on accurate predictive models to determine a building's energy consumption in different scenarios (Li et al. 2021). Thus, several studies have focused on predicting the building's energy consumption, which can be categorized as:

- Physical energy models (white-box models): The white-box models receive a building's envelope parameters and the characteristics of their surrounding environment and simulate the energy consumption using the fundamental laws of mass, energy, and momentum conservation. In this context, the white-box models are categorized as law-driven prognostic models (Coakley, Raftery, and Keane 2014), in which the predictive model functions based on scientific laws rather than empirical data collected from a known phenomenon. Due to the reliance of the white box models on fundamental laws of physics, these models are considered the most accurate predictive tools for forecasting energy consumption. However, these models do not capture any parameters of the occupants' energy behaviour, except for the occupancy schedule (i.e., time of presence).

- Data-driven models (black-box models): Black-box models predict energy consumption based on empirical data that represent the different parameters that affect energy consumption, including the buildings energy characteristics (e.g., number and total area of windows), historical weather data, and the appliances and tools used in the indoor environment. In this context, the black-box models use the historical data for training and testing purposes and are categorized as data-driven prognostic models (Coakley, Raftery, and Keane 2014). Although the black-box models provide more flexibility to the modellers for capturing the OEB, these models are also limited to capturing those parameters of the occupants' energy behaviour, for which historical data are available for training and testing purposes.

- Hybrid models (grey-box): Grey box models represent building behaviour based on the building's envelope characteristic and using a simpler set of physics equations than those used for white-box models. This simplification helps with the computational efficiency of the grey-box models, as compared to the white-box models, though it comes with the expense of prediction accuracy, which is in turn addressed by model calibration using empirical data (Tobias 2022). Accordingly, the grey-box models make a compromise as compared to the white-box models due to their dependency on empirical data for calibration (Tobias 2022). Given the fact that grey-box models are a combination of the white-box and black-box models, these models are still subject to the OEB modelling limitations of the white- and black-box models.

Generally, most of the existing predictive models only consider a selected set of a building's characteristics and often neglect the OEB or simplify this parameter by considering a few factors that affect OEB, such as the occupancy schedule or window-opening behaviour (Yan and Liu 2020; Z. Wang, Hong, and Piette 2020; Fang et al. 2021; Xinlei Zhou et al. 2022; Bassi et al. 2021; T. Cao et al. 2021; Truong, Ngo, and Pham 2021; Alduailij et al. 2021; Akbar et al. 2020; Khan et al. 2020; Hwang, Suh, and Otto 2020; J.Q. Wang, Du, and Wang 2020; Bourhnane et al. 2020; Alanbar, Alfarraj, and Alghieth 2020; Zeng, Ho, and Yu 2020).

In some recent studies the number of occupants is also considered, in addition to their occupancy schedule. This is done using techniques such as the number of WiFi and internet connections (Pombeiro et al. 2017), interactions with the heating, ventilation, and air conditioning (HVAC) systems (Geronazzo, Brager, and Manu 2018), interactions with the hot water system (S. Cao et al. 2019) and window opening behaviour (Du and Pan 2021). Despite the recent advances made in capturing the OEB, recent studies confirm that predicting the impact of OEB on a building's energy consumption is not accurate if it is limited to the number of occupants in a building (Chen et al. 2021) or only captures a few aspects of the behaviour. This is due to the fact that OEB is a multi-faceted concept that might be significantly impacted by numerous interacting factors, including the culture of occupants, their level of education, and upbringing (Giskes 2017). This, in turn, can adversely affect the accuracy of predictions made regarding a building's energy consumption. As a result, the results of those prediction models that overlook or simplify OEB often differ from the actual values of buildings' energy consumption (Schakib-Ekbatan et al. 2015). Accordingly, there is still a research gap for providing a comprehensive picture of OEB and occupants' impact on buildings' energy consumption (Giskes 2017). To fill this research gap, the primary objective of this study is to propose a fuzzy-based approach for quantifying OEB in buildings.

2.2 Fuzzy Logic

Fuzzy set theory is an artificial intelligence (AI) technique introduced by Zadeh 1965 for capturing the ambiguity, imprecision, and subjectivity that exist in real-world systems. Fuzzy set theory is defined as an extension of the classical set theory that allows each element of the universe of discourse to belong to multiple sets simultaneously with different levels of belongingness. The belongingness of each element in a fuzzy set is specified by a real number $\mu \in [0,1]$, which is calculated by a membership function (f), where $f: \mathbb{R} \to [0,1]$. The partial belongingness to different sets differentiates fuzzy sets from the classical (or crisp) sets, in which an element is either a member or not a member of a given set.

There are several methodologies introduced in the literature to develop the fuzzy membership functions (FMB), either using expert knowledge (i.e., expert-driven techniques) or empirical data (i.e., data-driven techniques). The analytical hierarchy process (AHP) (Saaty 2003) is a commonly used expert-driven technique, and fuzzy clustering algorithms are common data-driven techniques. Clustering techniques are unsupervised machine learning algorithms that divide a set of data into groups or clusters based on their similarity (distance) from one another. In classical (crisp) clustering algorithms, such as *k*-means clustering, each point of a given dataset belongs to one and only one cluster. However, in fuzzy clustering algorithms, each point of a given dataset may belong to different clusters with different membership values (μ_i), where $\sum_{i=1}^{c}(\mu_i) = 1$ and c indicates the total number of clusters. There are different fuzzy clustering algorithms introduced in the literature; some of the most common ones are: fuzzy *c*-means (FCM) clustering, subtractive clustering, and Gustafson and Kessel clustering. While there are several shapes of FMB introduced in the literature, fuzzy clustering algorithms commonly develop Gaussian FMB due to their flexibility and simplicity of definition (Pedrycz and Gomide 2007). In this paper, the quantification of OEB is accomplished through the application of the FCM clustering algorithm (Bezdek, Ehrlich, and Full 1984), which is one of the most common fuzzy clustering algorithms in the engineering literature.

3 METHODOLOGY

In order to quantify the OEB, the discrepancy between the simulated energy consumption of a building (i.e., by a white-box model) and the actual energy consumption values must first be determined. For this purpose, the simulated energy consumption is collected from the reference buildings' data published by the US Department of Energy (DOE), and the actual values of energy consumption are acquired from the Genome Project (Miller et al. 2020). It can be assumed that if the data collected from these two repositories represent similar building types (e.g., small office), then, the discrepancy between the simulated and the actual values represent a comprehensive measure of the occupants' energy behaviour. To confirm this assumption, the data collected from these two repositories should represent one common type of building (small office in this study) located in a common geographical location. The context-dependency of data should be removed by determining the energy consumption per square meter of the building's area at given points of time. Equation 1 represents the mathematical representation of the relationships between OEB and the simulated and actual data.

$$OEB\left(\frac{kWh}{m^2}\right)_t \propto \left(\frac{AE_i}{Area_i}\right)_t - \left(\frac{SE_j}{Area_j}\right)_t \qquad (Equation\ 1)$$

where AE_i stands for the actual energy consumption of building *i*, and SE_i represents the simulated energy consumption of building *j*, which is of the same building type as building *i*. Additionally, it should be noted that the actual and predictions are both captured at the same time step of *t*, as shown in Equation 1.

The simulated energy consumption data are collected from the reference buildings provided by DOE, which involve the EnergyPlus models of 3,344 buildings from sixteen different categories of commercial buildings in nineteen climate locations (sixteen in the U.S. and three international locations) (EERE 2019). By offering these reference models, DOE aimed to develop the standard energy models for common commercial building types; these models can also serve as a starting point for research into buildings' energy efficiency (Field, Deru, and Studer 2010). Additionally, the actual energy consumption data are supplied from the open dataset by the Genome project (Miller et al. 2020), which contains 3,053 energy meters from 1,636 non-residential buildings covering two years of energy consumption data (2016 and 2017 collected from nineteen sites across North America and Europe). The Genome dataset contains one or more types of meter data per building measuring electrical, heating & cooling water, steam, and solar energy as well as water and irrigation data (Miller et al. 2020).

In EnergyPlus models of the reference buildings provided by DOE, the energy behaviour of occupants is considered by the average number of people in each zone of the building and the predicted occupancy schedule (not the actual occupancy). On the other hand, the Genome datasets contain actual energy consumption data for different types of buildings; thus, the comprehensive impact of the OEB on the buildings' energy consumption is already included in the readings of meters' data. Although these datasets do not include any data specifically related to the building occupants, comparing these data to the simulated energy consumption of similar building types from the DOE reference models can provide useful insight into the OEB. Table 1 shows how the building types in DOE match the building types in the Genome datasets. Since the size of the buildings may be different, the value of energy consumption per square meter is calculated to provide a more accurate comparison between the simulated and actual data.

The discrepancies between the simulated and actual data may change over time, depending on the occupancy level and behaviour. Accordingly, the application of fuzzy clustering techniques allows us to identify the different categories of OEB from the data, such as high-energy consumers, moderate-energy consumers, and low-energy consumers.

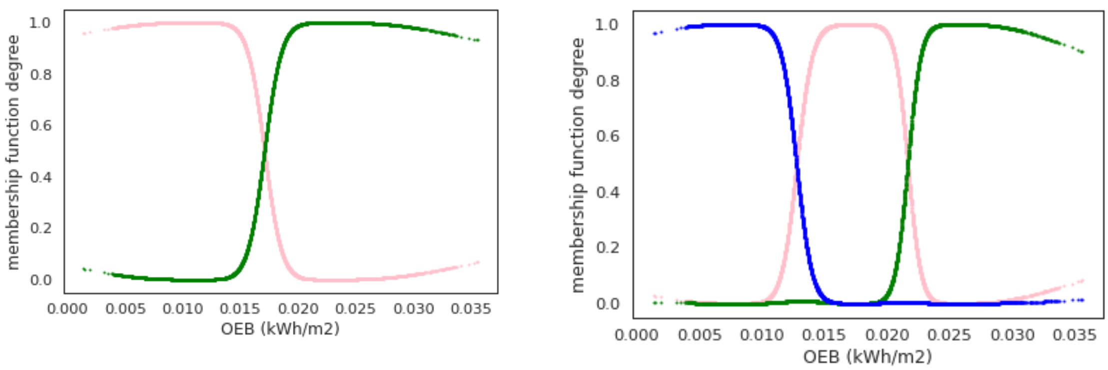
Table 1: Different building types

DOE Building Type	Genome Dataset
Small Office; Medium Office; Large Office	Office
Stand-alone Retail; Strip Mall; Quick Service Restaurant; Full-Service Restaurant	Entertainment/public assembly
Primary School; Secondary School	Education
Outpatient Healthcare; Hospital	Healthcare
Small Hotel; Large Hotel	Hospitality
Warehouse (non-refrigerated)	Other

4 Case Study

The proposed method is implemented for electricity consumption in a small office building in Arizona state, the United States, for which a DOE reference model exists, and two similar buildings from the Genome dataset were also available for analysis. Assuming that the OEB does not significantly change during a given day (a simplifying assumption), the average daily data is used to compare the simulation and actual energy consumption. The FCM clustering algorithm is then implemented, as the methodology explained in Section 3, and the results are presented in Figure 1.

For the implementation of FCM clustering algorithm, the number of clusters need to be subjectively selected by the modeller. Once fuzzy membership functions are developed by this algorithm, some fuzzy measures of the membership functions, such as energy and entropy, can be used to test the appropriateness of the membership functions developed. In this paper, the FCM clustering algorithm is implemented considering two ($c = 2$) and three clusters ($c = 3$). Figure 1 shows the scatter plot of the FMBs developed in these two clustering efforts that shows the different modes of OEB in office buildings (e.g., high-energy consumers vs low-energy consumers). In Figure 1(a), the spectrum of different energy behaviours of the occupants is divided into low- and high-energy consumers. In Figure 1(b), three clusters are developed representing low-, moderate-, and high-energy consumers. Considering the two clusters scenario (Figure 1(a)), the conjunction of the FMBs of the clusters occurs at the OEB value of 0.0175 kWh/m^2. This means the energy consumers that consume above 0.0175 kWh/ m^2; are considered high-energy consumers, and those with less energy consumption are considered low-energy consumers. On the other hand, considering the three clusters scenario (Figure 1(b)) representing three levels of energy consumption (low, medium and high), the OEB value of 0.0175 kWh/ m^2 has 100% belongingness level to the medium-energy consumer's cluster. Therefore, by taking three clusters into consideration, interpreted as three levels of consumers, the concept of OEB can be better represented by linguistic terms.



(a) (b)

Figure 1: OEB/membership function distribution for (a) two clusters, (b) three clusters

5 CONCLUSIONS AND FUTURE WORKS

A review of the literature on energy performance prediction in buildings shows that the existing studies dealing with energy predictions mostly failed to comprehensively capture the energy behaviour of buildings' occupants in their proposed predictive models. As a result, the accuracy of such predive models is adversely affected due to the significant impacts of the OEB on a building's energy consumption. Additionally, OEB is an ill-known and multi-faceted concept that might be affected by numerous factors, which further hinders capturing its impact on buildings' energy consumption. This study proposes a quantitative measure to capture the impact of OEB on buildings' energy consumption based on fuzzy logic. The proposed measure of OEB captures a comprehensive picture of OEB. As such, for each building type, the discrepancy between actual energy consumption and the corresponding simulated data from DOE reference buildings is considered a representative value for OEB. The results of the case study of a small office building in the state of Arizona, US, confirm the effectiveness of the proposed approach for identifying the different modes of occupancy in buildings' energy consumption low- vs high-energy consumers. Our research shows that considering three clusters for categorizing OEB in office buildings delivers more logical results than two clusters. The proposed approach presented in this paper delivers a comprehensive picture of the impacts of OEB on buildings' energy consumption and will facilitate the research and practice of developing more sustainable buildings. Additionally, these fuzzy values of OEB can then be fed into previously developed predictive models to calibrate their prediction values for more realistic results. Therefore, predicting future energy will not be a crisp number but rather a range of values based on the value of membership for each cluster.

Future work will evaluate different fuzzy clustering methods, including fuzzy c-means (FCM) clustering, subtractive clustering, and Gustafson and Kessel clustering, in order to identify the optimal clustering algorithm. Additionally, different fuzzy measures and testing approaches will be investigated to determine the optimum settings of the proposed approach in terms of the number of clusters for each building type and an aggregated measure of OEB considering electrical, heat, and other forms of energy consumption in buildings.

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