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Modeling energy consumption in residential buildings: A bottom-up analysis based on occupant behavior pattern clustering and stochastic simulation

Longquan Diao [a], Yongjun Sun [b], Zejun Chen [c], Jiayu Chen [a,*]

[a] Department of Architecture and Civil Engineering, City University of Hong Kong, AC1, Y6621, Tat Chee Ave, Kowloon, Hong Kong, Hong Kong
[b] Division of Building Science and Technology, City University of Hong Kong, MMW-5424, Tat Chee Ave, Kowloon, Hong Kong, Hong Kong
[c] School of Business, Tung Wah College, 21/F,98 Shantung Street, Kowloon, Hong Kong

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ABSTRACT

In residential buildings, occupant behavior and occupancy status have a significant impact on energy consumption variation. Although the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) recommends a uniform occupancy schedule for building energy assessment, occupant behavior patterns and schedules could be different for each building due to occupants' lifestyles, preferences, occupations, and other differences. Existing occupant behavior models focus on analyzing occupants' sociodemographic characteristics to predict their energy consumption with statistical approaches. This paper proposes to identify and classify occupants' behavior with direct energy consumption outcomes and energy time use data through unsupervised clustering. Based on the American Time Use Survey (ATUS), the proposed approach integrates k-modes clustering and demographic-based probability neural networks and identifies 10 distinctive behavior patterns. With the results of the behavior classification and simulation, a bottom-up engineering model reveals that the proposed behavior model offers a more accurate and reliable prediction than the ASHRAE standard schedule. With qualified and sufficient time use data, the model is capable of automatically estimating energy consumption on even larger geographic scales.

1. Introduction

Among all energy-consuming sectors, building-related sectors use more energy than any other. In the United States, 74% of electricity, 56% of natural gas, and 41.2% of all primary energy is consumed by commercial and residential buildings [1]. The energy consumption of a building is usually affected by its physical properties, outdoor environment, and occupant behavior. Moreover, those aspects affect each other, especially the occupant behavior and a built environment in the operational stage. Over- and underestimation in energy consumption at the design stage strongly affects the performance of the building later [2]. If overestimated, not only will the construction and maintenance costs significantly increase, the service facilities will also occupy more space than needed. In addition, large centralized systems, such as air conditioning and cooling tower systems, cannot be switched on/off frequently due to the energy wasted during system boot-up [3]. In the case of underestimation, the systems may not be able to provide sufficient services to meet the comfort requirements of residents. The total energy demand of a building is a result of both its thermal environment and its occupant behavior. Compared to the building's envelope and its thermal environment, occupant behavior is more complicated to assess and quantify. Researchers have been working on this issue for many years, and it has been proven that through categorizing occupants' behavior patterns (occupancy status, number of occupants, location of occupants, activity of occupants), the occupants' energy demand can be estimated [4]. Based upon these findings, this paper aims to find a new approach to assess building energy demand and consumption based on identifying and classifying occupants' behavior in terms of time use data (TUD).

* Corresponding author.
E-mail address: jiaychen@cityu.edu.hk (J. Chen).

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2. Background

2.1. Identifying occupant behavior

Through field surveys and observations, researchers conclude that the behavior pattern of building occupants significantly affects their energy usage. Iwashita and Akasaka [5] utilized a questionnaire and gas tracer to measure the relationship between the dwelling ventilation rate and occupant behavior during summer. They reported that the occupants' habits caused 87% of the air change rate variation and significantly influenced the ventilation rate. Yu et al. [6] employed k-means clustering analysis to examine the effects of different behavior patterns on energy consumption. Their research shows some end-use loads, such as an HVAC load, present significant attributes of four identified behavior clusters. Emery and Kippenhan [7] surveyed the energy consumption data of four standard buildings in Seattle from 1987 to 2002. The historical data indicates that tenants with different lifestyles have distinctive energy-consuming outcomes. Ouyang and Hokao [8] compared electricity consumption between educated households (with energy saving training) and reference households (without energy saving training) and concluded that, on average, there is a 14.8% energy-saving potential in behavior change. Zhou et al. [9] also found that for large office buildings, lighting energy consumption is mainly determined by occupant schedule rather than outdoor luminance. Masoso and Grobler [3] reported that 56% of energy is wasted during nonworking or nonoccupied hours simply because the occupants do not turn off the equipment before they leave. Schipper et al. [10] compared the family types and time use schedules of residents and found that lifestyle changes, such as increasing leisure time at home, will cause energy consumption changes. Guerra Santin et al. [11] analyzed the public Kwalitatieve Woning Registratie (KWR) dataset of the Netherlands with regression models and concluded that occupants' characteristics and behavior significantly affect energy use (additional R square = 4.2%). Researchers also conducted a similar study on other robust public datasets, such as the American Time Use Survey (ATUS). Through a cluster analysis on ATUS data, Sekar et al. concluded that with variable rebates, utilities would offer higher incentives to high-use customers (e.g., heavy TV watchers) [12]. Dong et al. combined ATUS datasets and monitored occupant behavior and revealed that thermostat adjustment and appliance usage are two major behavior-driven energy consumptions [13]. All of these studies reveal that occupant behavior patterns have a significant effect on the energy consumption of building residents. On the basis of these facts, this paper proposes to estimate building energy consumption through differentiating behavior patterns and whole-building energy simulations.

2.2. Occupant behavior recognition and classification

Traditional behavior pattern classification observes and groups people's behavior based upon their personal information or characteristics, such as gender, age, number of children in the household, marital status, employment status, and income. Table 1 summarizes some of recently published work and the authors' grouping criteria.

However, behavior classification based purely on personal information and individual characteristics has significant drawbacks. First, there might be no apparent and explicit pattern within a population group. Under most conditions, even if occupants have the same or similar characteristics, that does not guarantee they will have similar behavior patterns [14]. If applied to energy simulation, such a bias will result in inaccurate and unrealistic results. Second, most personal-characteristics-based behavior classifications yield to confined information because of uncertainty regarding which data to collect [15]. Although this can be improved by including as many characteristics as possible, it also potentially comes with high data collection costs and the problem of overfitting. Also, more complicated human characteristics, such as personality, opinion, emotional status, and so on, are impossible to completely identify from simple surveys [16]. Since events recorded in TUDs are frequently associated with occupant energy-consuming behaviors, TUSs were adopted as a supplementary criterion for pattern clustering and classification. Individual characteristics are associated with TUD and mapped into behavior clusters later. Clustering is one of the most widely used pattern recognition methods, and aims at partitioning the dataset into a set of unsupervised groups (clusters) that keep objects in the same group when they are more similar to each other than to those in different groups. Since there is no predefined patterns are given, this study adopt unsupervised clustering so that the algorithm will automatically identify the proper number of clusters with Akaike Information Criterion. In previous studies, several clustering methods were used to recognize occupancy patterns. D'Oca and Hong [17] successfully found four typical working occupancy patterns in office buildings by k-means clustering. Vazquez and Kastner [18] tested the capabilities of different clustering methods to identify occupancy patterns and suggested that fuzzy c-means and self-organizing maps have better performance. In the residential sector, the hierarchical clustering method can be applied to TUD to recognize occupancy patterns [14]. In this study, the clustering method should be able to process categorical data due to the nature of the behavior schedule; hence, the k-modes clustering method is selected to address this issue.

2.3. Occupants' behavior simulation

Many academic studies have implemented various behavior emulations from different perspectives. These emulation outcomes are commonly categorized as number of occupants, occupancy schedules, and behavior pattern groups. (1) Number of occupants could help to roughly estimate the energy demand of the thermal and ventilation services of a building; for example, Richardson et al. [19] applied an inhomogeneous Markov chain to simulate the number of active occupants in a building based on UK Time Use Data (UKTUD). (2) Occupancy schedules are closely connected to the operation periods of artificial lighting [20], HVAC [21], and other appliances [22] in buildings. This information could help engineers determine the facility system sizes in the design phase and optimize system operation after project delivery. López-Rodríguez

Table 1
Grouping criteria of some recently published works.

Authors	No. of groups	Grouping criteria
Richardson et al. [19]	12	Number of household members, working days
McKenna et al. [15]	12	Number of household members, working days
Chiou et al. [59]	5	Age, gender, employment status, marital status, number of children, adults
Yoo and Kim [60]	5	Marital status, number of children and employment status
Muratori et al. [34]	5	Gender, employment status and adults
Johnson et al. [61]	5	Gender, employment status and adults
Farzan et al. [58]	8	Working days, employment status and gender