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Data mining of space heating system performance in affordable housing

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ABSTRACT

The space heating in residential buildings accounts for a considerable amount of the primary energy use. Therefore, understanding the operation and performance of space heating systems becomes crucial in improving occupant comfort while reducing energy use. This study investigated the behavior of occupants adjusting their thermostat settings and heating system operations in a 62-unit affordable housing complex in Revere, Massachusetts, USA. The data mining methods, including clustering approach and decision trees, were used to ascertain occupant behavior patterns. Data tabulating ON/OFF space heating states was assessed, to provide a better understanding of the intermittent operation of space heating systems in terms of system cycling frequency and the duration of each operation. The decision tree was used to verify the link between room temperature settings, house and heating system characteristics and the heating energy use. The results suggest that the majority of apartments show fairly constant room temperature profiles with limited variations during a day or between weekday and weekend. Data clustering results revealed six typical patterns of room temperature profiles during the heating season. Space heating systems cycled more frequently than anticipated due to a tight range of room thermostat settings and potentially oversized heating capacities. The results from this study affirm data mining techniques are an effective method to analyze large datasets and extract hidden patterns to inform design and improve operations.

1. Introduction

Building energy consumption has steadily increased since 2008, representing 20%–40% of the total primary energy use in developed countries. In particular, energy consumption from the buildings sector has grown at a faster rate than the industrial and transportation sectors [1]. This upward trend in energy use becomes difficult to rebuke, due to the growth in population, increasing demands for building services and comfort levels, and the rise of occupied hours spent inside buildings. Parker et al. [2] studied energy use choices in experimental, low-income homes which were designed with high Seasonal Energy Efficiency Ratio (SEER) air conditioners, reflective roofing, solar water heaters and energy efficient lighting and appliances. They demonstrated that very different energy usage patterns were prevalent in the individual homes, especially with regard to cooling choices. In a follow up study conducted in 2012, Parker et al. [3] verified the Home Energy Saver (HES) suite for online simulation, by conducting a detailed year-long study to analyze the influence of occupant behavior on building energy use (Fig. 1). The homes studied exhibited a 3-fold variation in measured energy use, with variations at the end-use level conferred as even larger. For the space heating energy use, House 9 consumed a yearly cumulative of 1467 kWh, the most lavish user among the 10 houses, while House 9's total energy use was the least.

Occupant behavior has long been known to have a large impact on residential energy use [4]. Schipper et al. [5] indicated that approximately 50% of energy use in homes comes from the intrinsic building shell, equipment, lighting and electronics, while the remaining half comes from the occupant's interaction with the building components listed in Fig. 1. Two significant international collaborations under the International Energy Agency Energy in Buildings and Communities Program, focused on occupant behavior research, these programs include Annex 53 titled "Total Energy Use in Buildings" [6] and Annex 66 titled "Definition and Simulation of Occupant Behavior in Buildings" [7]. Wang et al. [8]

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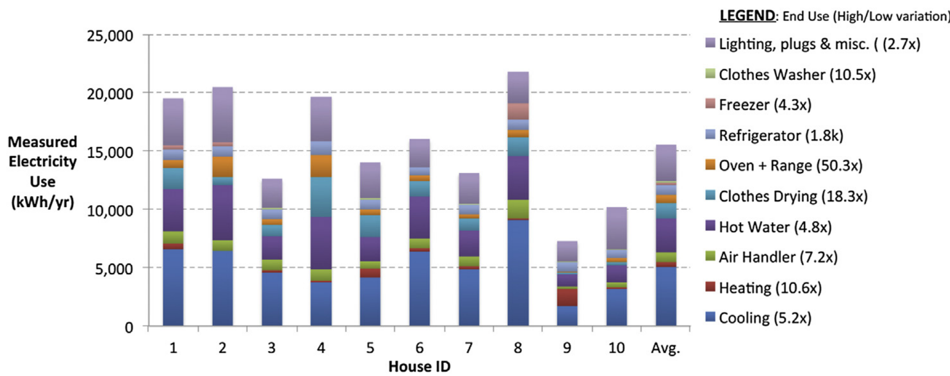

Fig. 1. Measured total and end-use annual energy for the Homestead Cohort [3].

developed a building occupancy model based on the Markov chain [9] to simulate occupant movement in a building. Peng et al. [10] developed a quantitative method to describe occupant behavior in residential buildings. Ren et al. [11] developed a conditional probability model to represent air-conditioning use in residential buildings based on Wang's [8] and Peng's [10] studies.

As one of the critical occupant behaviors in residential buildings, space heating and thermostat use in buildings have gained much attention due to their significant impact on energy consumption. Several space heating models have been developed for energy consumption and control scheme [12–14]. Peffer et al. [15] reviewed studies on how people use thermostats in homes, finding that nearly half do not use the programming features of the thermostats and suggesting that further research is needed to design thermostats which can provide more comfortable and economical indoor environments.

Recently, more sensor data on occupant behavior and building systems operations has become available. However, it is still challenging for designers and operational managers to effectively analyze the data to extract valuable information to support their decision making. Data mining can be a powerful tool to address such challenges. Data mining is the analysis step of the Knowledge Discovery in Databases (KDD) process [16]. In the 1990s, the modern data mining techniques improved, but were mainly used in areas such as economics, sociology, computer science and a few engineering subjects. In his book, Hand [17] demonstrated that the analysis of large observation datasets, using data mining methods, could reveal hidden data relationships, enabling the data to be summarized in novel ways which provided insight for decision making.

In recent years, data mining has gained popularity in the building science area, including occupant behavior, fault detection [18], building automation systems [19] and building energy performance [20–22]. Data mining is an effective technique to gain new knowledge from big data, finding the new relevance from a nonobvious context. For example in occupant behavior studies, the literature suggests that both psychology and physiology influences are important and hard to describe quantitatively. Data mining can be used to overcome this challenge, resulting in knowledge gained. Therefore, the data mining approach shall be generally used in new research areas to discovery new knowledge, from established areas. Especially with the rapid development of information technology, massive amounts of data will be available in the building sector. This presents an excellent opportunity for data mining applications to discover new science.

In occupant behavior research area, Yu [23] developed a new methodology for examining the influences of occupant behavior on building energy consumption using a clustering analysis approach. Another study from Yu et al. [24] used a methodology for discovering knowledge though a data mining approach to makes inferences from building operational data. Luhr et al. [25] and Dong et al. [26] used data mining to reveal occupant behavior trends, with a specific focus on smart homes and intelligent buildings, respectively. Wu and Clements-Croome [27] conducted a case study to understand the indoor environment through the mining of the sensory data. Motta-Cabrera and Zareipour [28] used data association mining to identify the lighting energy waste patterns in

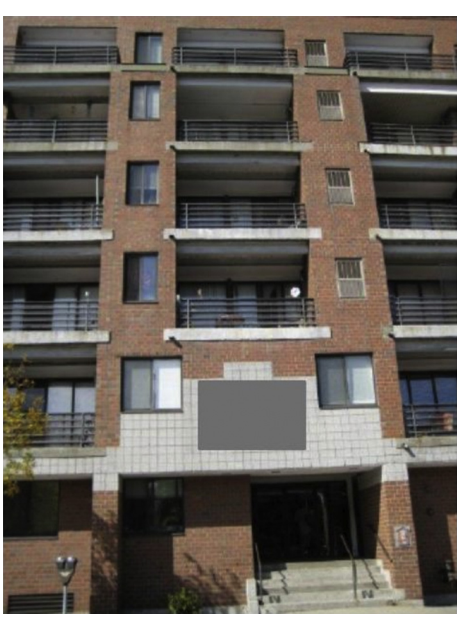

Fig. 2. Front view of the studied affordable housing complex.

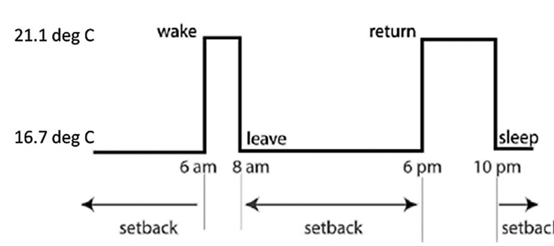

Fig. 3. Default settings of the thermostat.