Occupant behavior modeling for smart buildings: A critical review of data acquisition technologies and modeling methodologies

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OCCUPANT BEHAVIOR MODELING FOR SMART BUILDINGS: A CRITICAL REVIEW OF DATA ACQUISITION TECHNOLOGIES AND MODELING METHODOLOGIES

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ABSTRACT

At the outset, there is no question that building energy use is largely influenced by the presence and behavior of occupants. Among other, the key to realize energy use reduction while still maintaining occupant comfort is to seamlessly integrate occupant behavior in energy simulation tools with capabilities that would optimally manage building energy systems. This paper provides an in-depth survey of occupant behavior modeling state-of-the-art technologies employed to gather relevant data and modeling methodologies to reduce energy use. Several novel technologies that have been utilized for data collection are discussed in this paper. For the purposes of this review paper, occupant behavior modeling has been organized based on their underlying methodologies namely, statistical analysis; agent-based models; data mining approaches; and stochastic techniques. After providing a thorough review of state-of-the-art research work in the field of occupant behavior modeling for smart, energy efficient buildings, this paper discusses potential areas of improvement.

1 INTRODUCTION

Sustainability and energy conservation has become an important topic owing to increasing energy demands and diminishing energy resources. Buildings are one of the largest energy consumers in the United States, which account for approximately 40% of the total energy consumption (USEIA 2015). Although, a number of studies have been conducted to optimize building energy use, there are still potential avenues for more energy savings. These include simple additions to envelope or systems, for example, Cheung et al. (2005) added extruded polystyrene thermal insulation in walls, reflective coated window glazing, and overhangs and wing wall to windows for the goal of passive energy saving that saved more than 30%; Shuhui Li et al. (2014) investigated a learning-based demand response mechanism that is adaptive to weather, seasonal and house condition changes for real-time residential energy control. However, these research works only focused on building envelope or building system design themselves while ignoring the effect of building occupants. It is a fact that occupants are the main contributors to building energy usage and it is well known that they need to be inherently involved in the energy saving process in order to keep the same level of comfort and service. In other words, to compromise occupant comfort with more energy saving may not be considered as a wise and effective decision. In fact, the concept of smart building with intelligent building automation systems has been proposed a decade ago to facilitate both occupant comfort and energy efficiency at the same time.

Research has shown that occupant presence and behavior has a significant influence on building energy use. Nevertheless, current building energy simulation tools focus more on the effects of external climate and building equipment rather than occupant behavior and, in some cases, assume occupant status as a deterministic or static manner, or even use one or few hourly profiles to represent all the occupants rather than reflecting actual occupant behavior and its myriad complexity (Fabi et al. 2011). Such an approach, needless to say, causes discrepancy between simulated and actual energy usage. Moreover existing building systems, such as HVAC system often rely on a fixed schedule (Goldstein et al. 2010) based on certain code without referring to realistic occupancy status or occupant behavior, which result in energy waste. Therefore, the capability of understanding and integrating occupant behavior into building energy simulation and further implementation of real building systems is crucial to realize the target of "smart building". In this paper, occupant behavior refers to generalized activities of building users that adapt indoor environment, both passively and actively.

Recent research has engaged in tracking or modeling occupant behaviors within buildings using different approaches. This paper is based on the knowledge gathered by related research and aims to provide suggested improvements for potential researchers in the field of occupant behavior modeling for smart buildings. This paper is organized as follows: section 2 organizes state-of-the-art technologies and methodologies used for detecting and modeling occupant behaviors; section 3 elaborates the findings and discussion of recent research and proposes the future research directions; and section 4 concludes with potential future work.

2 OCCUPANT BEHAVIOR MODELING: TECHNOLOGIES AND METHODOLOGIES

In recent years, researchers dedicated their efforts to understand how building occupants react towards indoor environment and energy use and developed various approaches using state-of-the-art technologies that are now more advanced for reliable data acquisition easy deployment.

2.1 Data Acquisition Technologies

With the development of advanced technology as tools in field of electrical and computer engineering, researchers are able to identify occupancy status and occupant behavior amicably. Basically, the application of these tools usually surrounds the methods, objectives, and the parameters of the research and, therefore, certain technologies such as sensors or simulation software may be selected to assist the modeling process.

Wireless Sensor Networks (WSN) are the most common and popular tool for monitoring occupant-related variables such as temperature, humidity, carbon dioxide, sounds, and light, etc. WSN consist of sensor nodes that can be distributed throughout the buildings. By using wireless technology, operation and maintenance costs are reduced as no cabling is required, and wireless sensors could be deployed in a remote place where some of the wired devices may not be able to reach. By forming a network, sensor nodes will be able to communicate and exchange information with each other, and the data could be logged in a more organized way simultaneously. Yang et al. (2014) explored an improved method to estimate real-time occupancy conditions by utilizing several kinds of environmental sensors including humidity, temperature, carbon dioxide concentration, light, sound, and motion. A numerical model was developed by the researchers on the purpose of estimating occupancy without actually sensing that parameter. According to the researchers, their model could not only count the number of occupants at the room level without latency, but was also accurate with a lower cost than previous research. As a result, HVAC operations could be adjusted based on the demand of occupancy to reach the goal of saving energy while maintaining user comfort at the same time.

In another research work, more complex and advanced systems were used including cameras and RFID tags for occupancy study. For example, Agarwal et al. (2010) revised the HVAC operation schedule based on real-time accurate occupancy data collected by sensors as it was mostly run on fixed schedules and did not comply with occupancy conditions. The research study combined a magnetic reed switch with passive infrared (PIR) sensors which were commonly used for occupancy detection, and, then, developed an algorithm to estimate occupancy in a comparatively accurate and low-cost fashion. This research showed advantages over conventional approaches such as using cameras and vision algorithms, and the simulation results indicated that their system could indeed reflect the presence and absence of people in individual offices, therefore, improvising the HVAC control system based on occupancy data for greater energy use reduction.

In general, the application of different types of tools is based on the research methods and goals. Regular ambient sensors are typically used for environment monitoring associated with occupant behavior; electricity usage are sometimes measured directly to understand the patterns of occupants; self-developed sensors are often used for special purpose such as door/window opening status (Agarwal et al. 2010); PIR sensors and cameras are usually for occupancy; and other miscellaneous technology (RFID, Ultra-Wide Band) often needs the implementation of corresponding purposes and algorithms. Figure 1 depicts the most common application of state-of-the-art technology that assist for relevant data collection.

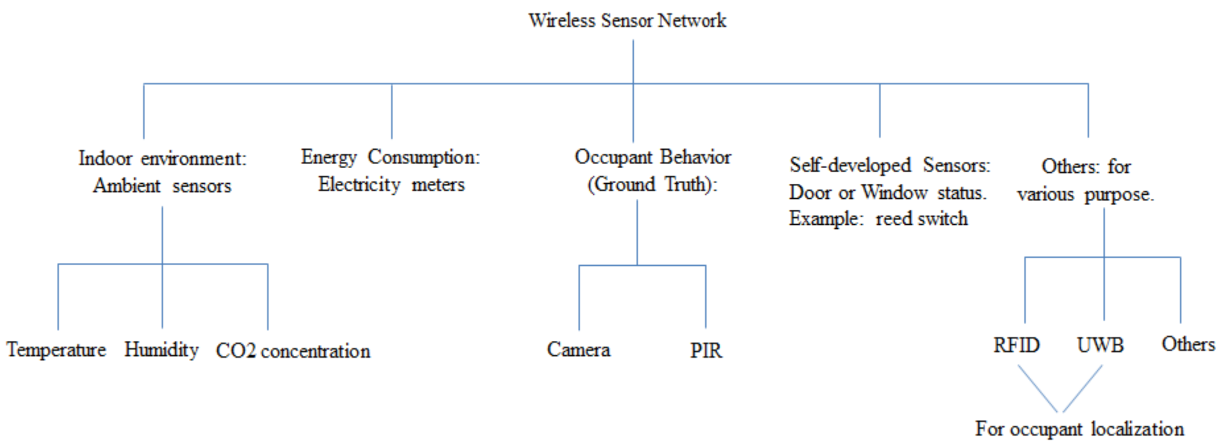

Figure 1: Classification of common WSN.

2.2 Modeling Methodologies

With the support of latest technologies, a variety of important data can be collected to model occupancy and occupant behavior that can be further integrated in energy simulation software. For the purposes of this review paper, occupant behavior modeling has been organized based on their underlying methodologies namely, statistical analysis; agent-based models; data mining approaches; and stochastic techniques.

2.2.1 Statistical Analysis

This methodology is generally conducted by building numerical relationship between occupant behavior and indoor/outdoor environment conditions, electricity usage or time periods, whose results are expressed by occupancy state or the probability of studied behavior.

According to Mahdavi and Proglhof (2009), indoor environmental data, data related to user presence and absence intervals, and position of shading and windows in five office buildings of Austria were collected using weather station, occupancy sensors, and time-lapse digital photography respectively. They provided statistical relationship between these parameters and summarized that long-term general patterns of user control behavior on equipment could be expressed as a function of indoor and outdoor conditions.

Masoudifar et al. (2014) proposed a method of monitoring occupant behavior and energy consumption of IT equipment. They used UWB band to record location and presence of four researched occupants in an office for 7 days and logged their computer and monitor power usage by Zigbee wireless power meters. By showing the distribution and average durations of each occupant for each day in a week along with the energy usage for all the components, the authors were able to identify specific reasoning for energy waste, in this case, the occupants did not turn off the equipment while not in use. Besides, Masoudifar and team applied the occupancy patterns for this particular office for future energy savings.

Peng et al. (2012) presented a method to quantitatively describe occupant behaviors. They noted that equipment operational status and their energy use thereof may reflect occupant behavior. For their research experiment, they divided equipment energy usage modes into 3 types (time, environment, and random) to describe occupant behavior. They used probability and time steps, or environment and user feedback data to track the behaviors as a function of the above elements. Finally, they assumed three types of typical lifestyle of humans and simulated the energy consumption based on the division type.

There is also research for specific action tracking. Nan Li et al. (2015) collected ambient data of six factors for a building and used self-developed window open status recording device to collect window data. In this research, they used multi-factor variance analysis to find the statistical significance of the 6 factors to window opening activity to find outdoor temperature is the most important one. Then, a logistic regression was performed to obtain the relationship between probability of window opening and temperature. A second comparative method namely Monte Carlo simulation was also performed to get the probability distribution of window opening activity. And based on this, they could draw conclusion on the probability of window opening behavior in this region.

Fabi et al. (2014) integrated the methods of statistics and identifying driving factors to understand a very important energy-related occupant behavior: window opening. The authors measured indoor and outdoor environment parameters, window state, and door position in a temporal manner. A multivariate logistic regression was then conducted to obtain the probability of a switching on/off event through the input of other information. The results also indicated the magnitude of influencing factors on behavior change in different time periods and seasons.

Mahdavi and Tahmasebi (2015) compared two previously developed probabilistic models and a non-probabilistic model by fitting separate training data in view of their performances on occupancy prediction. The probabilistic models demonstrated the relationship between occupancy and time. The contribution of that research lay in the accuracy of training and validation datasets and an evaluation approach that these researchers mentioned.

2.2.2 Agent-based Modeling

Agent-based Modeling (ABM) is a computational model for simulation of objects interaction with each other and the external environment. The model is on the basis of regulated rules which enable assessing the effects on the whole system. Zimmermann (2007) is one of the earliest researchers who used ABM techniques for user activities modeling, and proposed the idea that individual agents are relatively simple entities by separating persons from roles and work places.

ABM on occupant behavior study has different emphasis. Most research focused on the interaction of human and building systems. For example, Klein et al. (2012) developed their own multi-agent comfort and energy system to model alternative management and control of building systems and occupants. They simulated four distinct control strategies, which are baseline, reactive, proactive, with Markov Decision Problems (MDP) for building operation as well as intelligent coordination of devices and occupant. They compared the results of energy and comfort and stated that proactive with MDP shows the best result.

Alfakara and Croxford (2014) used agent-based modeling to explore the interaction between occupants in residential buildings and room systems of turning on/off of HVAC as well as opening/closing windows. They built the ABM by dividing the objects into 2 classes: person and room. Each of the class has their own attributes that were defined by the authors, which are generally based on probability. At the energy simulation stage, iterations are conducted combining the model and temperature input. Two cases were considered: a baseline and an improved-case, in which the improved case just changed the temperature threshold. The results showed that a reduction in using HVAC and increasing window opening rate. Also, cooling loads were reduced by 30%. Although some of the parameters used were simplified, the model set the foundation of future stages of research.

Langevin et al. (2014) presented a very detailed ABM using thermal comfort and behavior data from an office building. The rules of agent behavior conform to Perceptual Control Theory to maintain thermal sensation. Performance of prediction was compared to other modeling options for validation. Although the study may be only limited to office building, this approach provided a platform for more flexible simulation of interactions between occupants and surrounding built environments.

Other research studied the impact of different groups of people as main agents rather than buildings. Azar and Menassa (2011) analyzed the relationship and impact between occupants in their agent-based model to account for different occupant energy use characters and changes. The difference of their model from others is that they defined only energy-consumption behaviors and also include factors that cause behavioral change. Moreover, the model also simulated energy variation via energy use rates for each type of behavior.

Occupancy status such as number of people in a room could be simulated as well by means of ABM. Liao and Barooah (2010) presented an integrated approach to modeling and real-time estimation of occupancy in a large building. The model includes an ABM for occupant behavior, which they referred to as the mixed agent-based rule model and covariance graphical model to extract information for real-time estimation. They also used limited sensor data from rooms with sensor node to estimate number of people in every zone of the building. However, their work assumed a single room with single occupancy.

The work of Andrews et al. (2013) showed strong potential capability of ABM; their team have been trying to build a modeling framework for occupant behavior at building level by this method. These researchers created occupant perception and behavior model and integrated it with simulation software for energy simulation. Their whole modeling system is comparatively comprehensive as it includes not only building performance sub-model that modifies the state of indoor environment but also human agent sub-model that simulates decisions and reactions of occupants. As for the occupant module, a procedurally oriented framework called Belief-Desire-Intention (BDI) was introduced which was then enriched to a better version.

2.2.3 Data Mining through Electricity Monitoring

In most of the cases, electricity usage situation of certain equipment may reflect users' activity. Therefore, by mining energy usage data, corresponding occupant behavior pattern can be learnt, especially for a long-term mode. The following are some of the recent research work that deals with data mining approach for occupant behavior modeling.

D'Oca and Hong (2015) used a three-step data mining schedule learning method to deal with a data set of occupancy status of 16 offices to provide insights of patterns of occupancy. After transform raw data to pre-processed data, they applied C4.5 algorithm to get a decision tree model to predict the value of a label attribute (occupancy) based on several predictor attributes (season, day, time, window state). Second, they proposed 45 rules based on the tree model from the root node to a leaf node, which could understand repetitive occupancy patterns. Third, cluster analysis was performed to group these occupancy presence conditions into 4 types.

Alhamoud et al. (2015) utilized two sets of data to conduct three experiments for energy-related occupant behavior pattern detection in a residential building. The datasets comprised of power and environmental data while 9 activities were defined on the basis of regular motions. They record data by sensors and volunteer survey. In the first task, they used the Random Forest Classifier algorithm to build a model which established the relationship between user's current location and real-time power consumption. Second, they used Apriori Algorithm to extract the temporal relations between activities, trying to figure out the activity pattern for a certain occupant. Third, they compared the distributions of daily power usage for two different days and found high similarity between them which could conclude that people has a regularly routine power consumption behavior. All the information is mainly mined from electricity consumption of home appliances.

In a similar way, Zhao et al. (2013) developed a solution to predict occupant behavior and schedule based on office appliance energy use. By measuring electricity data of 4-6 appliances of 6 office workers and the ground truth data which represent the realistic occupant behavior, they trained and tested these data via 3 data mining algorithms and the results showed feasible performance of their model. However, they defined occupant behavior into 4 categories which did not cover all the possibilities and used their own technique to obtain the information.

Sometimes this data mining method may be combined with ABM to simulate occupant behavior. Baptista et al. (2014) developed an occupant behavior model in multi-agent systems. The approach is based on data mining techniques that model the behavior of occupants in a household as a set of coordinating agents that learn from historical real world data.

2.2.4 Stochastic Model: Markov Chain

As occupants behave in a random way, stochastic model is applied to predict energy consumption under different situations. This method is often used for occupancy status modeling and estimation.

Virote and Neves-Silva (2012) improved the occupant behavioral model based on Hidden Markov Models for predicting building energy consumption using actual measured data with stochastic process knowledge. They stated that human behavior still plays an important role in the overall energy consumption though technologies on buildings are already efficient. The models they built provided valuable information for simulating the influences that occupants have on a building in terms of energy consumption as they showed that different occupancy patterns result in different patterns of energy usage.

Most recently, Christopher Lee et al. (2014) delivered a stochastic model capable of seizing randomness in building operation. The model also used agent-based modeling with respect to time related factors. Duration is based on assumption in the research. Also, Dong and Andrews (2009) related to occupant presence and behavior patterns recognition is based on semi-Markov models to optimize occupancy schedule for lighting and HVAC control.

Erickson et al. (2011) made their contributions on temporal dynamics of occupancy detection by developing two advanced Markov Chain Models from ground truth data collected from a sensor network. In addition, they proved that their previous two models namely, ABM and Multivariate Gaussian model both have limitations. Their study showed good accuracy in occupancy estimation and by implementing the real time occupancy data into HVAC operation schedule, 42% annual energy savings would be achieved.

2.2.5 Others that Track Occupant Behavior from Natural or Physical Aspect

Some research exists that focuses on nature relations of environment and occupant behavior. For example, Cali et al. (2015) established a math model based on physical relationship between occupants number and CO_2 concentration of a closed room. The algorithm is based on mass balance equation of the CO_2 in rooms and delivers occupants presence profiles. They monitored three office rooms and two residential rooms with sensors, and collected data of CO_2, temperature, fan power, ground truth profile, etc. At the model validation phase, they created three test scenarios with different uses of window/door status.

In another insight and perspective, Turner and Hong (2013) proposed a framework to describe occupant behavior for building energy simulation according to the foundation of human nature. The framework consists of four important components: drivers, needs, actions, and systems. The aim was to provide a standard method for future capture of occupant behaviors. Through understanding every certain situation with the four factors in detail, occupant behaviors and their impact on building energy consumption could be identified in a more organized and scientific way.

3 OBSERVATION

Based on the comprehensive review of the most recent research work on occupant behavior modeling, both technologies and modeling methodologies, and its relationship to building energy efficiency, a few notable observations are listed below. These are suggestions only; besides, it is not an exhaustive list.

- Assumptions vs. measured data: Several of the research that analyzed the impact of occupant behavior on building energy use is only based on assumptions and not actual measured data. For instance, in the energy simulation portion of Duan and Dong (2014), the optimization attempts of the two cases for comparison with baseline were change of operation of thermostats and temperature set point adjustment towards an energy efficient direction, which lacks practical support that occupants would actually act this way. Similarly, in Peng et al. (2012), the researchers assumed three typical types of lifestyle of occupants without a data source. Therefore, it is suggested that the future research may need to combine real-world occupant preference and behavioral tendency data that may be obtained through a survey or other more effective ways.
- Occupancy status vs. occupant behavior ("active" sense): Needless to say, researchers have already realized the importance of tracking occupant behaviors, yet some of them are still at the phase of occupancy status detection, i.e., status of space if it is occupied or unoccupied. Occupant behavior could have a broad conception. It could be considered as long-term occupant behavior pattern in the research of Lee et al. (2014) and Dong and Lam (2011). Their contributions lie in the prediction of occupancy state so that actual operation schedule of HVAC or lighting system could be optimized for a better performance. In fact, occupants could influence the energy performance of building systems in two senses (Andrews et al. 2013): "passive" sense, which as occupancy usage patterns change over time and "active" sense, which as they adjust building systems like operating window, blinds or equipment. Much research has been done at the concentration of passive sense, while a large potential of understanding and reducing energy use could be achieved at the more detailed active sense portion.
- Occupant behavior and "driving factors": Although results may be show that there is certain relationship between occupant behaviors and the factors that drive (initiate) the behavior, the information is insufficient to offer an accurate and complete evaluation. A more improved model may be needed that utilizes real-time data for better understanding of this relationship. Fabi et al. (2014) showed that driving factors such as indoor environment may result in a high probability of occupant behavior change, e.g., window opening or light switch; however, in real world, people may also behave and act based on several other conditions in different situations owing to individual psychology. Thus, monitoring real-time data may be a perfect solution for tracking occupant behaviors in integration with the research above.
- Generic nature of modeling solution: Some research has limitations, for example, the patterns acquired by data mining or stochastic model techniques may be only feasible in the buildings and situations studied, i.e., the method is specific to the given problem and not generic in nature. In general, researchers may select one or more experimental buildings as test beds, therefore different methodology may have to be selected to fit the actual scenarios when implementing the proposed approach. What is needed is the solution that is generic enough for a wide range of building types and occupant behaviors.
- Dynamic system: There is a causal loop of building performance and user behaviors. Their connections are established on a mutual basis. The whole building-user interaction system should be modeled as a dynamic system as they influence each other in a loop. Building energy use will directly lead to different comfort level of occupants, that may cause users to react and take corresponding actions, and the actions in turn will result in building energy usage variation under this circumstance, as could be depicted in Figure 2. According to Fabi et al. (2012), it is necessary to classify users' behavior typologies depending on the way their actions are performed.

- Enabling behavioral change: Encouraging behavioral change could be another solution for building energy efficiency. Occupant behavioral change has higher energy saving potential and more benefits compared with technological innovation. It costs less, needs no high-technology knowledge, applicable to either new or existing buildings, easy and fast to be implemented, etc. (Masoso and Grobler 2010). Research on how to most effectively influence building occupant behavior is currently being conducted from perspective of human nature (Elmualim 2012). Some other research emphasized the importance of peer network impact on individual energy saving behaviors. Chen et al. (2012) built an agent-based model and studied how an individual's energy use is influenced by peers and how peer networks affect individual energy-saving behaviors. The networks are generated according to the ER model and a GBM process was employed for incremental reduction of each agent's energy use. To understand which factor influence the most, they built three other models by adding vertices, edges, weight, to compare with the original model. This work suggested a possible area of how to reduce energy usage from the aspect of changing user behavior itself.

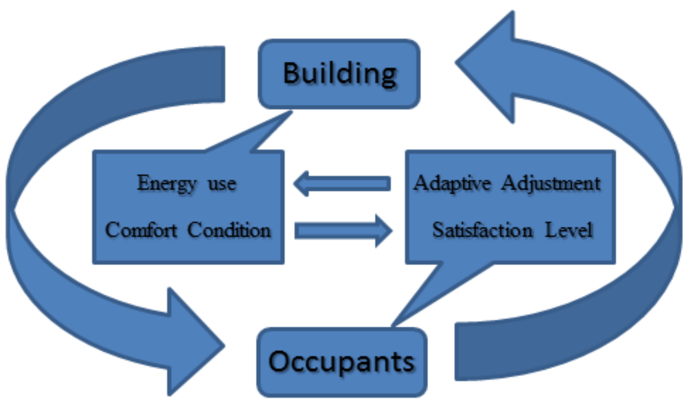

Figure 2: Interaction between occupants and building (Adapted from Andrews et al. 2013).

4 CONCLUSIONS

Energy use reduction is a fundamental component of smart buildings. Building occupants play a critical role in energy efficiency compared to other conventional energy savings modes such as tightening the envelope system, fine-tuning HVAC systems, etc. Hence, the understanding of occupant behavior influences on building energy consumption and the interaction between occupants and buildings is necessary to achieve higher order of sustainability. This paper provided an in-depth survey on the topic of occupant behavior or activity and building energy usage. The state-of-the-art technology and methodology that are used by most of the researchers were summarily discussed and compared. The paper also addresses the significance of quantifying influences of occupant behavior as input on energy saving potential. Limitation of previous studies and possible improving and research directions were proposed to suggest appropriate modeling methods of building occupant behavior for further exploration. Among others, one of the important findings of this work is that not only should the occupant behavior modeling approaches be improved, but also the energy-saving occupant behaviors be encouraged and educated for greater adoption of energy savings strategies.

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