On the Complexity of Smart Buildings Occupant Behavior: Risks and Opportunities

Invited Talk Paper

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ABSTRACT

Smart buildings are run by Cyber-Physical Systems (CPS), termed as Building Management Systems (BMS). Typical goals for the operation of BMS are increasing occupant comfort and decreasing buildings energy consumption. The central and critical figure, however, for achieving both goals are buildings' occupants. In some BMS, occupants have a high level of interaction with the system, whereas in others this is limited to a large extent, barring occupants from even opening windows. Every interaction, however, is a form of feedback, which in some cases poses a risk, whereas in others, it is an opportunity to discover issues in the system. In this paper we aim to emphasize the complexity of buildings' occupants' behaviour and interactions with BMS. We further aim to identify the risks and opportunities that these interactions pose with respect to the circumstances that lead to them and their impact towards achieving BMS' goals. We, furthermore, provide classification of occupant interactions based on their circumstances and relate this to their meanings with respect to BMS goals.

CCS CONCEPTS

• **Computer systems organization** → **Embedded and cyber-physical systems**; • **Human-centered computing** → Human computer interaction (HCI)

KEYWORDS

Smart buildings, occupant behavior, risks, opportunities, classification

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1 INTRODUCTION

Smart buildings are buildings that are equipped with the latest technologies, aimed at increasing the likelihood of reaching their goals, which are typically increased occupant comfort and reduced energy consumption. While smart buildings are emerging and slowly becoming a standard, at least for commercial facilities, they are surely facing a number of challenges. The reduced energy consumption is a significant goal for Building Management Systems (BMS) in general as buildings are attributed to ca. 40% of the overall energy consumption [1]. Therefore, by making buildings' operations more energy efficient, it can have a substantial impact on the global struggle for environmentally friendly solutions. Occupants, however, are the main reason that buildings exist; thus, energy savings should not come at a cost for occupant comfort [2]. Furthermore, there are numerous studies that show the positive effect that energy-conscious occupant behavior can have on buildings' energy consumption [2, 3]. For this reason, occupant comfort has to be raised at the same level of importance as the energy savings.

Another potential for saving on buildings' energy related cost is through timely and accurate fault detection and diagnostics (FDD), estimated at ca. 15-30% of building's energy consumption [4]. One of the main challenges for FDD, however, is obtaining meaningful data [5]. Since occupants are the ones that interact with the system on regular basis and on a large scale, crowdsourcing occupants is an obvious way of obtaining useful data for FDD, as it has been shown in [6, 7]. This data collection is, however, intrusive, and that is not always welcome and easy to perform as occupants need a clear incentive to participate in such initiatives. Therefore any non-intrusive collection of data would be very beneficial and supportive for the FDD processes. However, this non-intrusive data collection is already happening at a subtle level, although with the increased level of automation it will be happening less and less. Namely, occupants often interact with the system to match their comfort needs (i.e. increasing lighting level, reducing heating level, or opening a window), which is a significant feedback (and data) that needs to be utilized for optimizing BMS.

Occupant behavior, while being very complex and, at times, hard to predict, it can also be very revealing to problems and shortages in BMS [8]. Therefore, in this paper we aim to do a preliminary study to emphasize the complexity of occupant behavior, along with its risks and opportunities. The level of automation of a building is certainly one factor that limits the interaction of occupants with the building management system; thus, this will also be considered as part of our study.

The level of automation in BMS can range throughout different levels. There are buildings that do not allow occupants to even open a window, but also buildings that permit occupants to interfere with a wide range of components of the building management systems. Furthermore, there are zones in buildings with different levels of automation, dependent on their purpose and use. What is an optimal level of automation in a smart building? This is not a trivial question, and the answer is even less straightforward. It certainly depends on the goals of the concrete building management system, as well as on the occupants themselves, in terms of what kind of background they have, what are their tasks, or what kind of interaction can be expected from them. Apparently, the deciding parameters will differ from case to case.

To illustrate the complexity of occupant behavior, we use the example of an “open window”. This is a scenario that can have a number of interpretations, some of them being the following:

a) A window is open due to high temperature
b) A window is open due to bad air quality
c) A window is forgotten and left open during night

Both cases (a) and (b) illustrate scenarios that communicate potential problems with the equipment, it could be that either of the temperature or CO_2 sensors are faulty, or a problem with the ventilation actuator, or some other unknown issues. Both events (a) and (b) have negative impact on the energy performance of the corresponding building. At the same time, both events are also significant feedback. If occupants were not allowed to open windows, this communication would have been omitted. Further factors in this scenario are whether there are sensors on the windows and whether an open window can be easily detected. Another beneficial factor is that occupant behavior should be quite straightforward to model due to the straightforwardness of reproducing it. The scenario (c), on the other hand, is not a feedback; however, it does need attendance, and it needs to be discovered as it could also pose a security threat. Furthermore, scenario (c) can also have a negative impact on the energy performance of a building as e.g. if it is in winter, due to the temperature drop the heating might be unnecessarily activated. Therefore, scenario (c) apparently carries a different message, compared to (a) and (b).

To further aggravate the issue, buildings’ low automation levels coupled with inadequate occupant behavior can also pose a risk for the proper functioning of BMS equipment, as not all occupants interact with the equipment in its prescribed manner. Moreover, the increased penetration of advanced technologies makes interaction between smart buildings and occupants quite challenging for ordinary occupants; thus, increasing the likelihood of inadequate interaction, and, consequently, faults. Therefore, the automation/interaction levels need to be carefully studied and observed, as their optimization is far from trivial, and we expect that to even be a function of both space and time.

2 RESEARCH ON SMART BUILDINGS’ OCCUPANT BEHAVIOR

Smart buildings’ occupants have been studied from various perspectives and for various purposes. In the following we summarize the most significant efforts in this area. To begin with, we list some of the more significant purposes that have inspired studies of smart buildings’ occupant behavior, as follows:

- to predict energy consumption [9, 10]
- to develop strategies for energy-aware behavior [10, 11]
- to develop more accurate models of buildings [11, 12]

With respect to the prediction of the energy consumption, there are many studies that focus on developing models of occupant behavior for the purpose of predicting the energy consumption of a building and better matching the demand and response in an energy network. This is especially important for decentralized energy systems where buildings are seen as potential energy producers, besides being one of the largest consumers.

Furthermore, there have been numerous studies pointing out the impact that energy-conscious occupant behavior can have on the overall building energy consumption [11, 13]. This has motivated research on how to induce more energy-conscious behavior in building occupants. In one of the more significant approaches, the authors report a 12% reduction in energy consumption and a 5% improvement in occupant comfort using multi-agent systems to coordinate both building system devices and building occupants through direct changes to occupant meeting schedules using multi-objective Markov Decision Problems [14]. In a recent effort [15], Khashe et al. use social messages to inspire more energy conscious behavior among occupants with positive results. Furthermore, D’Oca et al. introduce a framework for occupant behavior motivation with the goal of inspiring behavioral change [16]. Therefore, occupant behavior in buildings has been studied from various perspectives, and in particular, window opening, has been thoroughly studied along with the development of a theoretical framework accounting occupants' interactions [17]. However, we have not discovered a study that attempts to study and categorize different interactions and observe their potential for collecting subtle feedback.

The challenge that we aim to address through our work is the finding of balance between automation and occupant interaction in a building, and this might differ from building to building and from occupant to occupant, as well as from one point in time to another.

3 CATEGORIZATION OF OCCUPANT BEHAVIOR

Based on all of the above written, we provide a classification of occupant behavior and relate it to the associated opportunities and risks. Feedback is typically considered an opportunity (to collect data and learn about the system). Risk is typically a situation where there is no feedback, but only loss. In Figure 1 we illustrate the classification of the occupant interaction with BMS. The final nodes also denote the interactions as opportunities and risks.

We begin by defining interactions with the system as events. Next, we need to distinguish between events and "lacking events". Examples of an event are "opening a window" or "turning on lights", and examples of *lacking events* would be "forgot to close window" or "forgot to turn off lights".

The next classification is based on the fact whether an interaction is intentional or unintentional. If it is intentional, then it can be considered a feedback, i.e. an opportunity, e.g. opening a window due to poor air quality or high temperature is a feedback from occupants that the system does not behave as expected, and it might as well signal that a component is faulty. Therefore, timely recognition of such events and directing attention to its diagnosis is an opportunity to improve the system's performance. Unintentional interaction is turning on a switch by mistake. E.g. when leaving an office, by mistake we might turn the light on.

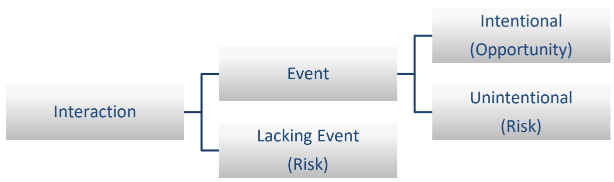

Figure 1: Occupant Interaction Classification

Typically, lacking-events cannot be intentional. However, there could always be exceptions to this, but we have no way of discovering this and it is out of the scope of our interest for this paper.

Finally, occupant behavior needs to be studied more in detail, as well as develop models and interpretations for all types of different occupant interactions (in terms of opportunities and risks), as they can provide a significant key to enhancing smart buildings' performance.

4 IMPLICATIONS

Occupant behavior in buildings and interactions with BMS create strong impact on the energy consumption for cooling, heating, ventilation, and lighting. It has been shown that careless behavior can add an extra of one-third of energy consumption to the building while careful behavior can save a third [18]. Automation with ambient intelligence can significantly improve energy efficiency in buildings [19, 20]. However, as we discussed in the previous sections there are some risks and opportunities involved in achieving the important BMS' role of enhancing energy efficiency and maintaining, or even improving, occupants comfort. These risks and opportunities can occur based on the level of automation used in the BMS and the level of interaction allowed between the BMS and the building's occupants. Limited levels of automation in BMS can generally increase the risks and reduce the opportunities of achieving a BMS' goals while higher levels of automation can generally reduce the risks and increase the opportunities of achieving the required goals for careful behavior. At the same time, allowing low occupant-BMS interaction levels is good for careless occupants as they will not have a strong role in negatively impacting the BMS' goals, thus reducing the possible risks in achieving the goal of energy efficiency. On the other hand, allowing high occupant-BMS interaction levels is good for careful occupants as this will provide opportunities that can be utilized to achieve the goals of BMS in enhancing energy efficiency and occupant comfort levels in buildings.

Generally, the goals of BMS can be achieved perfectly if the risks associated with the careless occupants are minimized while increasing opportunities in obtaining feedback from careful occupants to enhance the automation in BMS. Table 1 provides a summary and abstraction of the different possible combinations of BMS automation, allowable interaction levels, and occupant types, and their result levels in terms of risks and opportunities. As we can see from the table, a high level of BMS automation is generally good to use. However, the best allowable level of occupants-BMS interaction levels is based on the occupant's types. Based on these observations, a high-level of BMS automation associated with adaptive allowable levels of occupant-BMS interactions will provide the best solution in achieving BMS' goals. This adaptive level is determined based on the carefulness of occupants. Using an adaptive level of occupant-BMS interaction will reduce the risks associated with careless occupants and will increase the opportunities associated with careful occupants in finding and using obtained feedback and observations to enhance BMS' outcomes. This proposed adaptive approach could also be used within the same large buildings that have different parts with different purposes and functions where each part will have a different allowable level of occupant-BMS interaction to have best energy efficiency and comfort levels for the whole building. Furthermore, we could also imagine the level of automation as a function of time, optimized to allow higher level of interaction during calibration phases, followed by a lower one once the system has collected sufficient amount of feedback.

Table 1. Different possible combinations of BMS automation, allowable interaction levels, occupant types, and their result levels in terms of risks and opportunities.

	Low BMS Automation Level	High BMS Automation Level
Low Occupant-BMS Interaction Level	• Careless Occupants (high risks, low opportunities) • Careful Occupants (low risks, low opportunities)	• Careless Occupants (low risks, low opportunities) • Careful Occupants (low risks, low opportunities)
High Occupant-BMS Interaction Level	• Careless Occupants (high risks, low opportunities) • Careful Occupants (low risks, low opportunities)	• Careless Occupants (high risks, low opportunities) • Careful Occupants (low risks, high opportunities)

High BMS automation and adaptive allowable occupant-BMS interaction levels require using more sensor devices to collect more information about occupants behavior; more data storage space, advanced data mining algorithms to identify and classify occupant behavior; advanced intelligent decision making algorithms to best configure the BMS to enhance energy efficiency and occupants comfort in the buildings; advanced machine learning algorithms to learn about new occupants behavior and to help in enhancing the operations of BMS on a regular basis, and powerful processing powers. The outcomes of most of the required algorithms for smart buildings can be enhanced as more data is collected about the buildings and their occupants' behaviors [21]. In this regard, a collaborative cloud-based solution can be used to collect more information time from multiple buildings and to help in analyzing this collected data to enhance the operation of all BMS in the participating buildings in shorter time and in more cost-effective manner [22].

5 CONCLUSIONS

The goal of the paper is to observe and emphasize the complexity of occupant behavior in smart buildings in order to point out the importance of determining the right balance of automation and interaction with the system, as well as spot the opportunities that this interaction provides in terms of useful data. We also aim to further explore this and utilize the findings for developing more tailored approaches towards occupants for each building, utilizing every form in which they can be communicated, even the very subtle ones, to fine-tune BMS.

The presented work is a preliminary one, which we aim to further extend towards comprehensive categorization of occupant-building interactions.

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