A Data Collection and Analysis Framework to Improve the Performance of Energy-Intensive Commercial Buildings

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ABSTRACT

Commercial buildings show large discrepancies between estimated and actual energy consumption levels. Important challenges specifically lay in understanding the influence of human actions (by occupants and facility managers) on energy use and their contribution to commonly observed high energy consumption levels. This is particularly relevant in energy-intensive buildings such as laboratory facilities, which can typically consume up to five times more energy than other types of commercial buildings. This paper presents a framework to (1) collect relevant data about building energy performance and occupancy, (2) mine data, and (3) adapt and use energy analysis methods to understand the influence of occupants on energy performance, detect inefficiencies in the operation of building systems, and propose solutions. The framework is illustrated though a case study on a laboratory building in Madison, WI, identifying an excess of 40 percent in the energy consumption of the Heating, Ventilation and Air Conditioning System (HVAC).

INTRODUCTION

The commercial building sector accounts for about one-fifth of the energy consumed in the United States (US) and its energy demand is projected to grow by 22 percent by 2035 (US DOE 2012). Improving the efficiency of commercial buildings can therefore result in important economic, environmental, and social benefits, helping the US better face the global energy crisis. Several building solutions have been therefore developed and promoted both by the public and private sectors such as efficient building envelopes; office equipment; lighting systems; heating, ventilation and air conditioning systems (HVAC); to name a few (US EPA 2010).

Although the potential energy savings from the mentioned solutions is significant, important differences are typically observed between desired energy use levels, which are estimated during the design phase, and actual energy use levels, which are observed during the operation phase. This difference, referred to in literature as the “Energy Efficiency Gap”, is typically close to 30 percent and can go up to 100 percent for buildings with high process loads such as laboratory buildings (Yudelson 2010; Turner and Frankel 2008).

Therefore, facility managers and owners are increasingly gaining interest in collecting and analyzing data from their buildings to evaluate and improve their operation efficiency (Donnelly 2012). Commonly collected data types include energy consumption by end-use (e.g., lighting, equipment, HVAC), building characteristics (e.g., square footage, number of computers), and weather data (e.g., outside air temperature and humidity) (Granderson et al. 2011). Data visualization and analysis methods are then typically used to evaluate the energy performance of the building and detect faults that result in inefficient operations.

However, an important challenge remains unaddressed, which is the lack of understanding and control of human actions (by building occupants or facility managers) on commercial building energy performance (Duarte et al. 2013). Studies have in fact shown that human actions could hinder optimal operations of buildings, leading to excessive energy use and defeating the purpose of technology-focused improvements (Levine et al. 2007). For instance, Webber et al. (2006) observed that more than half of office building equipment are typically left running during non-occupied hours. Granderson et al. (2011) on the other hand showed that improperly maintained and controlled equipment are very common in commercial buildings and increase energy use between 10 and 30 percent. Moreover, it is very common to observe variations in occupancy patterns in commercial buildings, which further contribute to the discrepancies between estimated and actual energy consumption levels (Duarte et al. 2013).

Despite the highlighted influence of human actions on building energy performance, common energy analysis methods typically fail to determine the role of human actions in the observed inefficiencies (Granderson et al. 2011). These methods, which are detailed in the next section, typically focus on identifying building under-performance (e.g., increase in energy use) without necessarily uncovering the causing factors (e.g., variation in occupancy schedules, equipment running after-hours). Moreover, information such as occupancy presence/absence (i.e., schedule) is rarely included in the analysis. This is specifically important in high-load buildings where energy use can be highly driven by occupancy presence and actions (e.g., researcher entering and using laboratory equipment afterhours). Simultaneously, high-load buildings are typically characterized by shared-space areas (e.g., laboratories), where tracking the influence of individual occupants can become challenging (e.g., shared equipment, central HVAC and lighting) (Turner and Frankel 2008). As a result, it is currently challenging to evaluate the influence of occupancy actions on buildings energy performance, especially in high-load buildings where these actions can have a tremendous impact on energy consumption levels.

Therefore, this paper presents a framework to (1) collect relevant data about occupancy and building energy performance, (2) mine data obtained from different types of sensors, and (3) adapt and use energy analysis methods to better understand the influence of occupants on energy performance, detect inefficiencies in the operation of building systems, and propose solutions. The framework is then illustrated though a case study on a laboratory building in Madison, WI. The contributions of this paper are significant as facility managers can use the proposed framework to better analyze the performance of their buildings and guide their energy conservation efforts.

ENERGY ANALYSIS METHODS

Prior to proceeding with the methodology, this section reviews three of the most commonly used energy analysis methods and identifies their limitations, hence motivating the need for the proposed framework. First, *Benchmarking* is a method that consists of comparing the energy performance of a building to a baseline or "benchmark" (Granderson et al. 2011). The baseline can be obtained from a group of similar buildings (i.e., cross-sectional benchmarking), or from past performances of the building under study (i.e., longitudinal benchmarking). While this method can help identify under-performance in buildings, it fails to determine the causing factors. Second, *Regression Models* can help explain energy consumption levels through correlation with independent variables (Price 2010). However, studies typically use variables such as outside temperature to analyze energy consumption, overlooking occupancy information (i.e., presence/absence of occupants) (Granderson et al. 2011). As a result, it is challenging to determine if human actions are responsible for unexpected energy consumption levels. Finally, *Fault Detection and Diagnostics (FDD)* is another method that helps identify outliers in building energy performance (Katipamula and Brambley 2005). Similar to benchmarking, this method is limited to highlighting rather than explaining irregular energy consumption levels.

In summary, several methods exist to help facility managers analyze the energy performance of their commercial buildings. However, these methods fail to evaluate the influence of human actions on the performance of different building systems. As a result, it is currently challenging to understand the human drivers of under-performing buildings, limiting the development of corresponding energy conservation measures (e.g., energy conservation education for building occupants).

METHODOLOGY

The proposed methodology is summarized in Figure 1 and consists of three main phases: (1) data collection, (2) data fusion, and (3) data analysis. Each phase is further detailed in the following sub-sections.

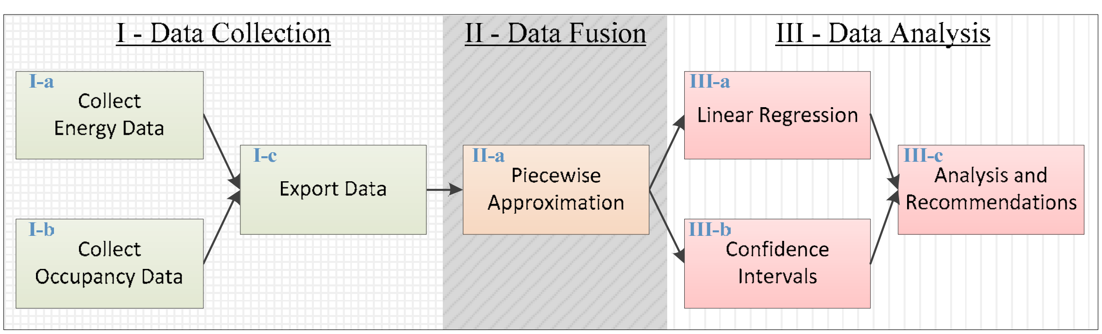

Figure 1. Methodology.

Data collection. Data can typically be obtained in commercial buildings using a building automation system (BAS). The term BAS is often used to describe a variety of data acquisition systems that monitor and control building operations (Granderson et al. 2011). In this study, the BAS refers to a network with which a building manager keeps track of all sensor information obtained from the facility under study.

As shown in Figure 1, data collection starts with step I-a where energy data is collected from the BAS for the building area under study (e.g., laboratory). The type of data typically needed includes total space energy use in addition to more granular end-use data such as lighting, equipment (i.e., plug-loads), and HVAC energy use.

Next, step I-b complements the collected energy data with occupancy information. One key occupancy metric is the presence/absence of occupants over time, typically monitored using occupancy sensors. In private spaces (e.g., single office), an occupancy sensor directly reflects the occupancy status of the space (i.e., occupant A either present or absent). In open-space areas, it is challenging to collect detailed information about individuals and occupancy sensors typically track groups of people. In this case, having several occupancy sensors in the space can help make better inference about the occupancy status. For instance, one active occupancy sensor would indicate a low level of occupancy while five active sensors indicate a higher level (i.e., more people in the space).

Step I-c then consists of exporting the energy and occupancy data from the BAS. Most commercial BAS software support data export to XLS, TXT, or PDF file formats (Granderson et al. 2011). Typically, the first column in the exported file is a "time stamp" indicating the time a measure was taken, and the second column is the value reported by the sensor (e.g., energy consumption level or occupancy status).

Data fusion. This phase consists of fusing the data obtained from different sensors to allow for data analysis in the next phase. An important distinction needs to be made between data obtained from energy and occupancy sensors. Typically, energy monitoring sensors use a "Pull-Based" data acquisition approach, where the user (e.g., facility manager) specifies the interval and frequency of the data reported by the sensor (Aggarwal 2013). A 15-minute interval is commonly used in commercial buildings. On the other hand, occupancy sensors employ a "Push-Based" data acquisition approach, where the sensor autonomously decides when to communicate values to the gateway. This typically occurs whenever the occupancy status of the room changes (e.g., a person enters or leaves the space) (Aggarwal 2013).

Therefore, data fusion becomes essential to convert energy and occupancy data to a common format (e.g., 15-minute interval data), which is required for data analysis (Duarte et al. 2013). This can be achieved using "Piecewise Constant Approximation (PCA)", a commonly used data stream approximation technique that approximates a data segment with a constant value (Aggarwal 2013). In this case, since occupancy sensors can report several data points within a 15 minute interval, PCA is used to approximate these points with one value, allowing for a comparative analysis with energy data. Figure 2 illustrates the data fusion process starting with screenshot examples of typical occupancy and energy data exported from a BAS. Occupancy data is then converted to 15-minute interval data using a Java code developed by the authors and highlighted in the dotted box. Occupancy and energy data are then gathered in one excel spreadsheet to be used in the data analysis phase.

Data analysis. Following data fusion, two of the methods discussed in the "energy analysis methods" section are adapted to analyze energy consumption and occupancy patterns. The first method is linear regression, which allows testing the correlation between energy consumption and occupancy status (i.e., presence and absence). This is particularly helpful in open-space areas with multiple occupancy sensors, where the number of occupancy sensors activated can be used as the independent variable. A high correlation value indicates that (1) energy is mostly consumed when occupants are present in the space, and (2) minimal energy is used when the space is unoccupied. In contrast, a low value can be an indication of (1) sensor failure, (2) control failure (e.g., lighting system improperly connected to occupancy sensors), or (3) occupant-related actions (e.g., leaving equipment running after-hours). It is important to mention that the influence of occupancy actions on building energy performance can vary between buildings and for different types of building areas. For instance, it is common to give occupants of single offices a high level of control over different energy systems (e.g., manually controlled lighting and HVAC), while occupants of shared space being given less control (e.g., central lighting and HVAC).

The second method proposed in this paper is the use of confidence intervals to compare energy consumption during occupied and unoccupied hours. In this case, a large difference between the two scenarios is desired, particularly with low values for unoccupied hours. This method is specifically helpful for shared spaces (e.g., laboratory) and energy systems that cover multiple areas such as HVAC. For instance, it is common in laboratory areas to have a ventilation "air-flushing" system that is activated whenever an occupant enters the area. As a result, HVAC energy consumption is not necessarily correlated to the number of occupants in the area but to the overall occupancy status (i.e., either occupied or unoccupied). Therefore, confidence intervals can be very helpful to evaluate the overall performance of such a system. An example is shown in the upcoming section.

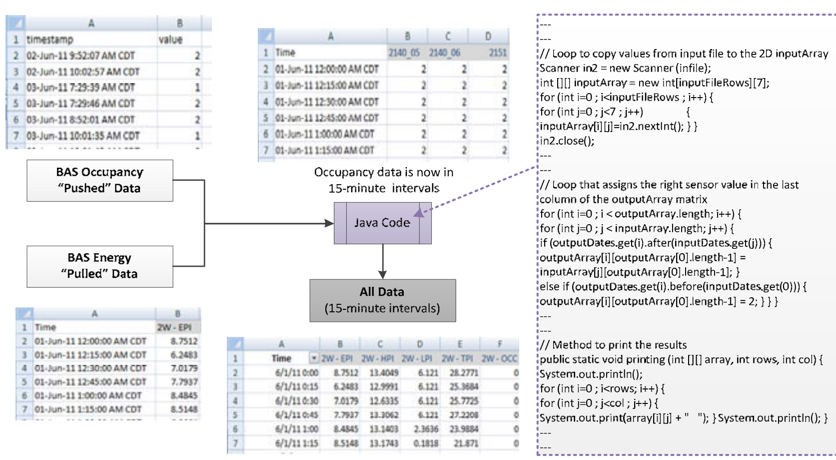

Figure 2. Data Fusion Process.

CASE STUDY

The proposed framework is illustrated in a case study performed on a laboratory facility located in Madison, WI. Over 25 thousand sensors have been installed in the building to track various performance metrics through a BAS. The building contains several laboratory areas or "pods", one of which is considered for this case study.

Following the methodology steps of Figure 1, data was collected from the BAS for a period of one year (from June 1, 2011 to June 1, 2012). Energy information was "pulled" at a 15-minute frequency and included total energy, lighting energy, equipment energy, and HVAC energy. Occupancy information was obtained from 14 occupancy sensors spread in the different laboratory areas. It is important to note that data from 2 defective sensors was ignored in the analysis. Data was then mined using the process illustrated in Figure 2 to transform occupancy information to a 15-minute interval format. All data were then combined in one large excel spreadsheet with 35,000 rows of data, each row representing one time step (i.e., 15-min intervals over a one-year period). An example of the collected data is shown in Figure 2 (lower central box), with the last column showing the number of occupancy sensors activated over time.

Next, the different energy analysis methods discussed in the "methodology" section are applied to the fused data to evaluate the influence of occupancy presence on energy consumption. Regression analyses are first performed between the different energy use categories and occupancy status. Results are presented in Table 1 showing a very low correlation between total energy use and occupancy status, which can be a sign of poor building energy performance. Correlations by end-use are discussed next to isolate any sub-performing system.

First, lighting energy use shows a correlation value of 0.578, indicating a relatively good performance of the lighting system. This system has a 30 minute timer that turns lights off when the laboratory becomes unoccupied, a control strategy that seems to be minimizing after-hours energy use. On the other hand, no correlation exists between equipment energy use and occupancy. A visual representation of the correlation is then generated using the R software package and shown in Figure 3. The results indicate a high variance in the observed energy use levels, even when the pod is unoccupied (i.e., zero occupancy sensors activated). Since equipment are mainly controlled by occupants, the results confirm the inefficient operation of equipment by the occupants, which entails additional investigations by the facility manager (e.g., interviews, surveys, training). Finally, the HVAC system also shows no correlation with the number of occupancy sensors activated. However, as discussed earlier, HVAC energy use in laboratory areas is oftentimes not correlated with the number of occupants present. A more adequate analysis of this system can be performed using confidence intervals as shown next.

Table 1. Linear Regression Results.

Energy Category	Total	Lighting	Equipment	HVAC
Adjusted R^2	0.067	0.578	0.035	0.001

Confidence intervals are therefore computed to compare the energy use of the different building systems during occupied and unoccupied periods. A summary of the obtained 95 percent confidence intervals is shown in Table 2. Results indicate that large amounts of energy are being consumed when the pod is unoccupied, with the confidence intervals of the two occupancy states being relatively close in values. Table 2 results confirm that the lighting system is relatively efficient with minimal after-hours energy consumption. Equipment energy use on the other hand is highly inefficient, with almost the same energy levels for the two occupancy states. Finally, results point out a major problem with the HVAC system that is showing high energy use levels when the pod is unoccupied. This observation has been reported to the facility manager who requested an extensive evaluation of the HVAC control system. Major flaws in this system were then diagnosed, which was failing to efficiently control the “air-flushing” of the space. These errors were estimated to cause more than 40 percent of excessive and unnecessary energy use levels.

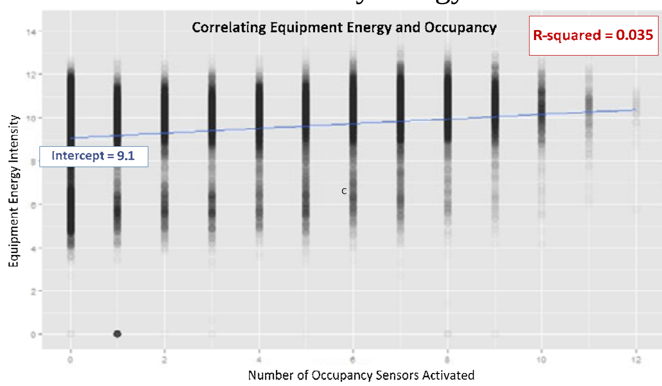

Figure 3. Equipment Energy Use and Occupancy Correlation.

Table 2. Confidence Intervals.

Energy Category	Total	Lighting	Equipment	HVAC
Occupied periods	[21.6 ; 21.8]	[2.4 ; 2.5]	[9.5 ; 9.6]	[9.6 ; 9.8]
Unoccupied periods	[18.1 ; 18.5]	[0.2 ; 0.3]	[9.2 ; 9.3]	[8.6 ; 8.9]

CONCLUSION

This paper presents a methodology to evaluate the influence of human actions on the performance of energy-intensive commercial buildings. While building performance metrics might change based on building type and availability of information, the framework is general and can be applied on any commercial building. The framework is however limited by the availability of granular energy and occupancy data, which is not necessarily common especially in old commercial buildings. However, the promising results of the case study can serve as a motivation for building decision-makers to invest in BAS and monitoring systems. Such systems, in conjunction with the proposed methodology, can help closely monitor building systems and ensure a proper operation by occupants and facility managers. Finally, this paper confirms that human actions can have a significant impact on building energy performance. While studies oftentimes pejoratively refer to the human role as a negative source of unnecessary energy use, it can also be perceived as an opportunity to save energy in existing buildings. Interesting insights reside in evaluating how efficient human operation can complement technological advancements in building systems design and renewable energy generation, helping achieve a more sustainable built environment.

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