Impact of Building Occupancy on Assessing the Effectiveness of Energy Conservation Measures

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ABSTRACT

Assessing the effectiveness of energy conservation measures (ECMs) prior to their actual implementation in buildings is critical. There is an increasing tendency to employ calibrated building energy models to quantify energy savings that could be achieved by ECMs to justify their implementation. However, there is empirical evidence that reveals noticeable discrepancies between simulated and measured performances of ECMs in buildings. One possible reason for such discrepancies is that actual building occupancy, which is a critical factor that determines the total and peak loads of building systems and related energy consumption, is not represented accurately in most energy models. This paper specifically examines the impact of actual building occupancy on the assessment of ECMs. Two energy models of an office building were built and calibrated with the same audit data following the same procedure, except that one used assumed occupancy and the other used actual occupancy. Both models were used to assess an ECM, which adjusts indoor air temperature set points based on the time of the day. Statistically significant differences were observed in the energy consumptions reported by the two models through paired t-tests. The results highlighted the importance of integrating actual occupancy in the assessment of ECMs.

Keywords –

Energy conservation measure; Building energy simulation; Energy model; Occupancy; Calibration

1. Background

Assessing the effectiveness of energy conservation measures (ECMs) prior to their actual implementation in buildings is critical for optimizing the ECM designs and providing a baseline that can be used later to gauge their actual performance. With the increased use of building energy simulation for evaluating the effectiveness of various ECMs, one of the most important factors for simulation is to substantiate how well the models represent the characteristics of real buildings [1]. However, there is empirical evidence that reveals discrepancies between simulated and measured performance of the ECMs. One possible reason for such discrepancies is that actual building occupancy, which is a critical factor that determines the total and dynamic loads of building systems and related energy consumption, is not represented in most energy models.

This paper examines the impact of building occupancy on the assessment of ECMs. Two energy models of an office building were built and calibrated with the same audit data following the same procedure, except that one used assumed occupancy and the other used actual occupancy. Both models were used to assess the same ECM, which switches the heating, ventilation and air conditioning (HVAC) system in the building between on and off modes based on the time of the day. Described below are our research motivation, research methodology and our findings, followed by our conclusions.

2. Research Motivation

There is an increasing tendency to employ calibrated building energy models, believed to accurately reflect the physical characteristics and internal dynamics of buildings, to quantify expected energy savings that could be achieved by different ECMs and justify their application [2]. ECMs are virtually implemented in modified models, and simulations are performed to examine the expected building energy performance given these new changes. Moreover, simulations in building energy models are essential in many cases to the design of ECMs. Buildings are complex and unique systems. In order to achieve maximum energy savings, ECMs need to be designed on a case-by-case basis and in the context of specific physical and functional characteristics of buildings, where building energy models can play a pivotal role. Repeated simulations can be performed to investigate potential opportunities for energy savings [3], identify optimal strategies for daily building operations [4], and select among competing energy retrofit plans [5].

The performance of ECMs in simulations usually lays the basis of their design and implementation. However, because of the discrepancies between actual buildings and their virtual representations, the optimality and expected energy savings of ECMs as reported in simulations are not met in practice. In fact, there is empirical evidence that reveals noticeable discrepancies between simulated and measured performance of the ECMs [6,7].

Occupancy could be one of the reasons why simulated performance of ECMs is not always accurate and realized in practice [8]. Occupancy is a critical factor that determines the total and peak loads of building systems and related energy consumption. Most building energy models built in prior research relied on assumed or simulated building occupancy, which inevitably deviates from actual occupancy. Such simplification might overlook the impact of the occupancy on building energy usages and, more importantly, cannot reflect the energy implications from interplays between occupancy patterns and the changes to building performance introduced by ECMs. For instance, occupancy (the time an occupant spends in a space) affects interior loads through activity and the use of other systems like lighting and equipment/appliance, which has an impact on the cooling or heating demands that is not accounted for in building energy simulations. Such implicit impacts of the occupancy on building energy usage is not observable when assumed occupancy is used, highlighting the need for using actual occupancy in assessing the effectiveness of ECMs. In fact, building occupancy detection itself is an area that has been actively researched in the past decade. Despite the large volume of research in occupancy, large-scale occupancy detection has remained a challenging task, and has rarely been deployed at a building scale for evaluating ECMs.

To address the above challenge, this paper introduces and tests the following hypothesis: Using actual occupancy data as opposed to assumed occupancy data improves the reliability of calibrated building energy models as a tool for predicting the performance of ECMs.

For the validation of this hypothesis, two calibrated models for a test bed building were built. Model #1 was built based on assumed occupancy schedules available in the simulation software. Model #2 was built based on actual occupancy schedules observed in the building. For collecting the actual occupancy data, an occupancy detection system proposed by the authors, was used [4]. High-resolution occupancy data of the test bed building was collected and used in the modeling process. Both models, after developed and calibrated with the same procedure and the same audit data (except for the occupancy data), were used to predict the energy consumption of the building after an ECM was introduced. Their respective prediction accuracy was compared to test the hypothesis. The tested ECM was designed for the HVAC system. Therefore, this paper focuses on HVAC energy consumption only.

3. Test Bed Building

The test bed building modeled in this paper is the Ralph & Goldy Lewis Hall (RGL), a typical office building on the University of Southern California (USC) campus near downtown Los Angeles, California. The RGL is a three-story building with a footprint of 3,735 m^2 with 89 mechanically ventilated rooms that have spaces of varying sizes and functions. Most of the rooms in the building are enclosed single occupancy offices; other rooms are classrooms, conference rooms, and auditoriums. The indoor environment of the building is monitored by 64 wired temperature sensors and 50 wireless sensor units. Each wireless sensor unit has a stand-alone single-board microcontroller with integrated support for wireless communications, and is comprised of the following sensors: a light sensor, a sound sensor, a motion sensor, a CO_2 sensor, a temperature sensor, a relative humidity sensor, a PIR sensor, and a door switch sensor. Data is automatically queried every one minute, time stamped, and stored in an SQL database. The energy consumption by various building systems such as HVAC, lighting, receptacle and mechanical is metered and recorded in a building energy management system (BEMS).

The test bed building is equipped with state-of-the-art BEMS and central HVAC system with air handling units (AHU) serving a total of 64 variable air volume (VAV) boxes and 3 fan-coil units (FCU). A VAV box is responsible for regulating the ventilation in the thermal zone with conditioned air, and reheating the air with hot water supplied by boilers if the zone needs heating instead of cooling. The conditioned air is supplied to VAVs by air handler units (AHUs) using fans and ductwork. There are two AHUs in the building, each servicing one side of the building with similar sizes of service areas. AHUs take in outside air, mix it with returned air from the building, and cool down the mixed air to 12.8 ^{o}C with chilled water supplied by chillers. The HVAC energy consumption in the building can be decomposed by fuel type to heating and cooling energy consumption, used by chillers and boilers to generate chilled and hot water, respectively, and ventilation energy consumption, used by AHUs and their embedded fans to distribute conditioned air in the building. The HVAC control implemented in the test bed building runs at an on-hour mode during the daytime (6:30 - 21:30 on workdays, and 7:00 - 21:30 on weekends). All thermal zones in the building are assumed to be always occupied under the on-hour mode, and a constant temperature set point (22.8 ^{o}C) is maintained on the demand side, which dynamically adjusts the airflow damper and reheating valve of each zone. The control has an off-our mode during the nighttime, where the HVAC system is shut off during the nighttime, and no cooling or heating services are provided. Only minimum airflow is maintained to satisfy the ASHRAE compliance.

4. Methodology

4.1 Occupancy Modeling

For real-time occupancy modeling, the fundamental principle the authors adapted is that occupancy regularly influences and interferes with the ambient environment. By mathematically or statistically bridging occupancy ground truth and ambient factor variation through supervised learning using historical data, future ambient data can be analyzed to output corresponding occupancy outcomes. A total of 11 ambient sensor variables were used in occupancy modeling. These variables could be categorized into three types of instant variables, count variables and average variables. Specifically, instant variables show the instant output of a sensor at the time the data is queried, including light level, binary motion, CO2 concentration, temperature, humidity, binary PIR, and door status (open/close). Count variables that sum number of times a sensor's output changes in the last minute, including motion count net, PIR count net, and door count net. Average variables that show average value of a sensor's output over a certain period of time, including sound average. Several machine-learning algorithms were tested. It was found that pruned decision tree had the best performance in solving the classification problem for occupancy modeling, demonstrating the relationship that each ambient factor was responsible for classifying part of the instances and occupancy classes were determined by the sequential consideration of ambient factors. The occupancy of a specific thermal zone was determined by integrating the occupancy of the associated rooms. Only if all the rooms within one zone are vacant, the zone was considered as vacant. By following the above methodology [4], occupancies of 28 rooms (16 zones) were calculated for a period of four months with three-minute granularity.

4.2 Building Model Calibration

The aforementioned two models were generated and calibrated following the procedure described below. First, the geometry of the test bed building was created in SketchUp [9] and 64 thermal zones representing the physical building structure. The geometry was then imported to OpenStudio [10], in which most model parameters were set. The model was then saved as an IDF format, and imported to EnergyPlus [11] for setting advanced parameters and simulating the energy performance of the building in a given period. Energy consumption ground truth data were collected from Jan 1 to Feb 10, 2013 (a total of 41 days) for calibrating the energy model, and the data from Feb 11 to Feb 21 and from Apr 1 to Apr 31, 2013 (a total of 41 days) were used for evaluation.

The guideline used for setting the types and values of model parameters is summarized as follows. Parameters related to construction layers and materials were defined based on as-built architectural, structural and mechanical drawings, and site surveys. Parameters related to thermal loads associated with lighting and electrical equipment were defined based on recommendations in OpenStudio. In addition, there were 560 parameters, whose values could not be determined based on available audit data. The values of these parameters were set based on the modeler’s best guesses and tuned later in the calibration process. The outside weather profile was linked to typical meteorological year (TMY) data [12] for Los Angeles. Assumed occupancy schedules based on the default occupancy schedules in EnergyPlus were used in model #1, and actual occupancy schedules based on the occupancy modeling approach explained in section 4.1 were used in model #2.

When a complete model was developed, it was calibrated following a typical calibration process [13]. First, a sensitivity analysis was carried out to identify the top influential parameters among the aforementioned 560 parameters on thermal loads of the building. For performing the sensitivity analysis, each parameter was assigned a value domain, based on its definition in EnergyPlus input/output reference guide [14], and a probability distribution of its value, based on the following guidelines: (1) A normal distribution was assigned to parameters that have preferred values but no specific value domains in the reference guide, such as "central cooling design supply air humidity ratio"; (2) A uniform distribution was assigned to the parameters that have specific value domains but no preferred values in the reference guide, such as "cooling minimum air flow"; (3) A triangle distribution was assigned to parameters that have both preferred values and specific domains in the reference guide, such as "fan efficiency"; and (4) A discrete distribution was assigned to non-numerical parameters, such as "boiler flow mode". A total of 8000 models were then generated, by randomly sampling the above parameters within their respective domains using the commonly adopted Latin Hypercube Sample (LHS) technique.

All models were then simulated in EnergyPlus using parallel computing. Since the parameters were sampled independently without considering the relationships between them, the integrity of some models was violated, causing errors in simulation. For around 50% of the models simulations were completed and valid HVAC energy consumption data were gathered. The parameter values of the models, and their corresponding HVAC energy consumption data were then analyzed by using the analysis of variance (ANOVA) method, which provided an assessment of the impact of each parameter on HVAC energy consumption.

Based on the ANOVA analysis results, the top influential parameters were identified and assigned with random values within their value domains. Additional simulations were then run and the results were compared with the actual energy consumption. A genetic algorithm based method was applied to update the parameter values with better fitness for matching actual energy consumption through crossover and mutation. Two tolerances were used to evaluate the deviations between simulated energy consumption and actual energy consumption data. One was the mean bias error (MBE) and the other one was the root mean squared error (CV (RMSE)). Table 1 summarizes the tolerances used in the literature. However, since the energy consumptions of different ECMs have significant variations on a daily basis and are not sensitive on a monthly basis, the energy consumption estimation and prediction were done on a daily basis in this paper, for which a tolerance does not exist in literature. Hence a daily tolerance was introduced in this paper, based on existing monthly and hourly tolerances, as 8% for MBE and 20% for CV (RMSE).

Table 1. Existing tolerances for building energy model calibration

	Monthly (%)		Hourly (%)	
	MBE	CV (RMSE)	MBE	CV (RMSE)
ASHRAE	5	15	10	30
IPMVP	20	-	5	20
FEMP	5	15	10	30

5. Findings

After calibration, the estimated actual occupancy based on ambient sensor data were compared with assumed occupancy in order to evaluate the discrepancies between the two. It was found that the average discrepancy between assumed and actual occupancy profiles was 17% considering the weekends and the winter break, or 20 % without considering the weekends and winter break, indicating that assumed occupancy was deviated from reality. The comparison, including the weekends and winter break, is shown in Figure 1

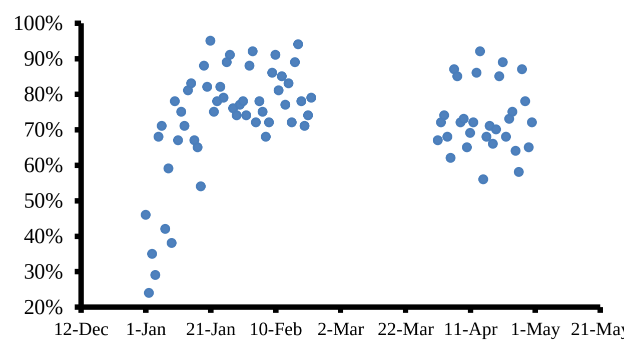

Figure 1. The similarity between assumed and actual daily occupancy profiles

A daily simulation was conducted for both model #1 and #2, and tolerances were used for evaluating the simulation performance. Daily MBE and CV (RMSE) were calculated for each week during the test period. The results are shown in Table 2 and Table 3.

Table 2. Daily MBE and CV (RMSE) of model #1 and model #2

Model #1 (MBE %)				
Feb 11-17	Apr 1-7	Apr 8-14	Apr 15-21	Apr 22-28
4.0	7.9	8.1	7.7	7.9
Model #2 (MBE %)				
Feb 11-17	Apr 1-7	Apr 8-14	Apr 15-21	Apr 22-28
-4.5	-5.1	-4.9	-5.4	-5.0

Model #1 (CV(RMSE) %)				
Feb 11-17	Apr 1-7	Apr 8-14	Apr 15-21	Apr 22-28
12.3	15.8	16.3	16.9	17.7
Model #2 (CV(RMSE) %)				
Feb 11-17	Apr 1-7	Apr 8-14	Apr 15-21	Apr 22-28
12.5	11.8	13.1	12.0	12.4

Table 3. Comparisons of daily MBE and CV(RMSE) between model #1 and #2

	MBE (%)		CV(RMSE) (%)	
	Average	SD	Average	SD
Model #1	7.1	1.6	15.8	1.9
Model #2	-5.0	0.3	12.5	0.5
Significance Level	0.034		0.025	
Confidence Level	0.05		0.05	

The results show that model #2 was likely to underestimate the energy consumption, while model #1 had the trend to overestimate it. One of the reasons could be the fact that using actual occupancy information might lead to less internal loads and therefore less conditioning demands in a cooling-dominant climate zone (e.g., Los Angeles). The energy consumption prediction of model #2 was generally more accurate, with a lower MBE (absolute value), and consistent, with a lower CV (RMSE) value. The average and standard deviation of MBE for model #1 were 7.1% and 1.6%, while those for model #2 were -5.0% and 0.3%. There were absolute 29.6% difference in MBE average and 81.3% difference in MBE standard deviation of model #2 compared to model #1. Similarly, the average and standard deviation of CV(RMSE) were 15.8% and 1.9% for model #1, and 12.5% and 0.5% for model #2. Paired t-tests were performed to compare the means of MBE and CV (RMSE) of two models. The results (two-tailed Sig.0.034<0.05 (predefined confidence level) for MBE and two-tailed sig.0.025<0.05 for CV(RMSE)) show that the five MBE values and CV (RMSE) values from model #1 are statistically different than those from model #2, and because the average and standard deviation of MBE and CV(RMSE) of model #1 are larger than those of model #2, it could be demonstrated that model #1 is less accurate. The findings support the hypothesis presented in section 2.

Moreover, it needs to be pointed out that the list of top influential parameters, identified in the sensitivity analysis during model calibration, largely differed between the two models. The top influential parameters for model #1 were mostly related to the zone level HVAC configurations and load distributions, while some of the top influential parameters for model #2 were related to thermal related material properties. Such difference adds to the evidence that the use of actual occupancy in the modeling process led to essential changes to attributes of the calibrated model.

In addition, the predictions in February were less accurate and consistent than those in April, especially for model #1. One cause of such discrepancy could the occupancy pattern in the test bed building, which differed between January and April, which was the beginning and middle of the spring semester. Since occupancy is closely related to internal thermal loads caused by the use of lighting and appliances, building energy models should be calibrated using actual occupancy, so that the model is adaptive to changes in occupancy and would yield better predictions of energy consumption and therefore better assessments of ECMs.

6. Conclusions

This paper examines the impact of building occupancy on the assessment of ECMs. Two energy models of an office building were built and calibrated with the same audit data following the same procedure, except that one used assumed occupancy and the other used actual occupancy. Both models were used to assess an ECM, which adjusted indoor air temperature set points based on the time of the day. The results showed that the use of actual occupancy data in the modeling process led to essential changes to attributes of the model, especially its top influential parameters on HVAC energy consumption. Moreover, noticeable variation in model performance, in terms of both accuracy and consistency in predicting HVAC energy consumption, was observed when the model was calibrated using actual occupancy. These findings suggest that the traditional way of assessing ECMs is inherently biased, and could be possibly improved by integrating actual occupancy in the model calibration process.

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