Building Energy Model Calibration with Schedules Derived from Electricity Use Data

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Abstract

Building energy models can accurately predict energy performance of buildings, if properly calibrated. This study developed and demonstrated a novel method to calibrate building energy models based on the occupancy and plug-load schedules derived from metered electric use data. Importantly, this study also proposed an occupancy assessment method applicable to resource limited situation when a building sub-metering system is not available. Furthermore, the developed method can facilitate accurate predictions of building energy performance without a requirement to simultaneously monitor energy use and occupancy rates. The method development process used data from an office type building (OB1), and further verified the method accuracy with data from two campus buildings (CB1 and CB2). The developed method is novel because it considers interactions of the validated modeled occupancy patterns, processed electricity use patterns, and the calibrated building energy model results at the hourly level. This approach allows addressing limitations in the current studies that are not fully capable of modeling occupancy patterns, electricity use patterns, and calibrated building energy models with this level of granularity. The accuracy of the building energy modeling results increases with the derived occupancy schedules and plug-loads. Specifically, the Coefficient of Variation Root Mean Square Error (CVRMSE) of OB1 building energy modeling results improved from 21% to 12% compared to the modeling results obtained with default schedules. The results from case study buildings CB1 and CB2 show that the accuracy of modeling results increased as the hourly electricity CVRMSE decreased from 128% to 31% and from 156% to 16%, respectively. These improvements are significant, while the

developed method is applicable to other office or campus buildings from the category of medium-size commercial buildings. Finally, the identification of actual occupancy rates provides opportunities for inexpensive implementation of occupant-based controllers in buildings.

Introduction

Building energy models could provide opportunities to predict building energy consumption performance accurately [1,2]. However, evidences suggest that there are several reasons, including occupancy patterns and internal loads, could contribute to discrepancy between the predicted energy consumption and actual metered data [3-5]. Therefore, prediction and calibration of a building energy model strongly depend on accuracy of occupancy and plug-load rates. These parameters are among the most significant ones for improving accuracy of building energy model, particularly prediction of actual electricity consumption [6-10]. In addition, studies indicated that there is a stronger relation between the building occupancy and electric use than the occupancy and thermal loads [11]. Therefore, this study focuses on calibration of occupancy and plug-loads schedules that are critical parameters for the accuracy of total electric consumption in predictive building energy models of commercial buildings.

Occupancy and plug-load schedules are usually the first parameters to be adjusted in model calibration, typically by inverse modeling based on measured or metered occupancy and electricity data [12-14]. Plug-load schedules in particular are difficult to measure, given the required number and associated costs of sub-metering devices and strong temporal variation in their use. While current standards typically require energy models to be calibrated to monthly energy utility bills due to their ubiquitous availability, this approach does not provide sufficient resolution to understand the main drivers for the electric energy end-uses [15, 16]. There is a significant number of parameters that influence electric energy use, so the use of utility bills for calibration creates the identifiability problem,

1 where multiple combinations of parameters can produce the same outcome [17-19]. While many
2 studies present sensitivity analyses or optimization to determine most-likely model parameters,
3 occupancy and plug-load schedules are difficult to include in such algorithms because of the number of
4 possible schedule variations. If unconstrained, an algorithm can just match the plug-load schedule to
5 provide the best calibration statistics, regardless of whether this plug-load schedule is valid. This makes
6 monthly data calibration erroneous, especially without comparing the model results to the hourly
7 building load profiles. The specific consumers of the electric energy are important to determine because
8 the building energy modeling goal is to ultimately predict performance or choose energy conservation
9 measures. Appropriate attribution is needed to be able to choose between component replacement and
10 adjusted control scheme measures, especially when defining appropriate energy efficiency measures
11 [20-23]. Therefore, this study aims to provide a novel method to accurately represent occupancy rates in
12 building energy models, resulting in a reliable model calibration.

13 Several existing studies on occupancy and building energy use explain that depending on the
14 occupants' type and building usage patterns, the correlation between occupancy and energy use varies
15 [24]. Majority of recent studies focus on assessing the levels of electricity use in relation to human
16 occupancy, e.g. the WiFi usage [17]. The influence of occupants on the end-uses shows a stronger
17 correlation for lighting and plug-load end-uses than other end-uses [18, 25]. The lighting energy end-use
18 demonstrated a significant positive correlation with the occupancy rates in different types of buildings
19 [19, 26]. Among the reviewed studies, occupancy rates correlate best with electric energy use when
20 compared to the use of different fuels for heating and cooling. Consequently, this study uses electric
21 end-uses as an occupancy indicator for building energy models.

22 In the current practice of building modeling, the occupant presence and actions do not display
23 the necessary level of sophistication to reflect the complexity of occupants' passive and active impacts
24 on building energy use. Also, most of the previous studies base their findings on one or two case studies.

1 These previous studies provided valuable insights into the impact of occupants' behavior and the
2 importance of occupancy parameters in energy models. However, the model of occupants' behavior are
3 not easy to define and require both energy use data and measured occupancy rates. The difficulties in
4 measurements of occupancy rates create data uncertainties that could defeat the purpose of the
5 measurements. The most common way to consider occupant impact on building energy use within
6 models is by accounting for their presence with diversity profiles, which are templates of hourly building
7 occupancy rates defined for different building types [20, 27]. As a result of these findings, the present
8 study explores the use of metered electric use as an occupancy rate indicator. Furthermore, this study
9 suggests a method to derive the occupancy and plug-load schedules from metered electric use to
10 calibrate building energy models. The identification of the occupancy rate opens up opportunities to
11 implement occupant-based controllers in buildings for optimization of building energy consumption [28].
12 Also, this method is appropriate for projects with limited resources, unable to sub-meter electricity or
13 accurately measure occupancy rates.

15 **2. Data Collection and Analysis Methodology**

16 This study analyzes building occupancy rates and metered electricity use of three commercial
17 buildings, including one commercial office building located in Philadelphia, PA, and two campus
18 buildings located at the Pennsylvania State University campus, University Park, PA. The studied buildings
19 are labeled as the Office Building (OB1), the Campus Building 1 (CB1), and the Campus Building 2 (CB2).

20 These buildings are selected for a variety of reasons, including the availability of interval energy
21 data for all of energy commodities, building configuration for the installation of people counters, and
22 diversity of the building area usage. Primarily, these buildings provide different functions and
23 consequently are more likely to demonstrate distinguished energy use profiles. The data analyses use

electric energy consumption of the two campus buildings as well as the electricity use and sub-metered plug-loads at the integrated building level for the office building. The office building case study represents a typical medium-sized commercial building in the U.S. while the campus buildings are representative mixed-used campus building. The difference between the two campus buildings is their building principal activity. The majority of spaces in the case study CB1 are offices and common areas; for the case study CB2, the principal building activity is research laboratory. Steam provides space heating, and chilled water provides cooling in the campus buildings, so the electricity use can be attributed to Non-HVAC (Heating Ventilating and Air Conditioning) end-uses besides pumps and fans [29]. Availability and accuracy of the hourly utility end-uses are also another factor in the selection of these buildings. Overall, the criteria for the selection of these buildings include: (1) building layout and configuration of the doors, (2) availability and accuracy of the interval hourly utility data for each energy end-uses and energy commodities, and (3) differences between the building principal activities.

2.1 Description of Buildings and Data Collection

The studied buildings belong to the medium-size commercial building category that are less than 9,000 m² of the total floor area and less than four story high as shown in Table 1. Figure 1(a), Figure 1(b), and Figure 1(c) show case studies OB1, CB1, and CB2, respectively. While the OB1 has sub-metered plug-load and electricity data, the campus buildings have interval total electricity data. The electricity data for the case study OB1 entails lighting, plug loads, condensing units, supply fans, and pumps [30]. Existing studies provide details about the distribution of the end-uses for this case study [26, 31-33]. Both of the studied campus buildings earned the LEED (Leadership in Energy and Environmental Design) certification.

(a)

(b)

(c)

Figure 1. Three case study buildings: (a) OB1, (b) CB1, and (c) CB2

Table 1. Characteristics of the case study buildings

	OB1	CB1	CB2
Building Type	Office Building	Campus Building	Campus Building
Building Location	Philadelphia, PA	University Park, PA	University Park, PA
Building Size	6,140 m ²	6,940 m ²	8,965 m ²
Number of Floors	3 stories plus 1 ground floor	3 stories plus 1 ground floor	4 stories plus 1 ground floor

Existence of Sub-metered Plug-load or Total Electricity		Plug-load	Total Electricity	Total Electricity
Area Usage	Office (%)	40	42	19
	Classroom (%)	0	16	10
	Laboratory (%)	0	10	36
	Common Area (%)	60	32	35

For this study, occupancy rates were collected from the case study buildings for data analyses. As Figure 2(a) shows for the campus buildings, this study used Infrared (IR) thermal sensors (PC-THI60-N, Sensource) in front of each entrance door. For the OB1 building, this study used video-based detecting sensors (PC-VID2-N, Sensource). The accuracy of both thermal sensors and video sensors is within a 5% error based on a comparison of readings for both sensors at OB1. Originally, IR thermal sensors were selected to collect occupancy data from the campus buildings because the IR thermal sensor can detect occupants in dark conditions typically occurring during late night or early in the morning hours. However, building OB1 already had existing video-based detecting sensors. To verify the data consistency between the two different types of sensors, this study installed both IR thermal sensors and video-based detecting sensors at the same location in OB1. The difference in measured occupancy rates using IR thermal sensors and video-based detecting sensors is within 5%.

These sensors have a limitation associated with the requirement that the mounting heights are from 2.7 m to 4.5 m. When the sensor is installed outside of this range, the measurement error increases significantly. Therefore, depending on the building entrance features, it was difficult to install the people counters in some of the studied buildings. For example, one of main entrances at the CB1

building has an entrance lamp that created an area without detection for thermal sensors. To address this problem as Figure 2(b), an additional sensor was installed at the edge of the “blind spot”. Furthermore, the CB2 building had two large entrances with a relatively high ceiling (13 m) located above the upper installation limit (4.5 m). Therefore, an additional pole provided support for a counter just above the entrance doors as shown in Figure 2(c). Importantly, during the study planning phase, there is a need to assess trade-offs between the number and type of the occupancy sensors since the installation cost for each building is significant. Overall, the results of this study suggest that based on the type of doors in office/campus buildings, there is a need to consider various people counter installation strategies to ensure high quality data collection.

(a)

(b)

(c)

Figure 2. Thermal imaging IP people counters: (a) IR thermal sensor, (b) additional sensor installed to cover the blind spot, (c) a support installed to cover doors with high ceiling

This study collected aggregated electricity data for the two campus case study buildings and sub-metered building energy data for the office building. Table 2 shows that the timeframe of this study covered a period of at least 14 weeks during 2013 and 2014. These time periods provided sufficient

amount of data to observe daily, weekly, and seasonal trends, as well as the seasonal variations in the electricity usage and occupancy rates in the studied buildings.

Table 2. Data collection time periods for the studied buildings (OB1, CB1, and CB2)

	OB1	CB1	CB2
Spring	05/01/2013- 06/21/2013	03/20/2014- 04/28/2014	03/20/2014- 03/28/2014
Summer	06/24/2013- 09/20/2013	08/14/2013- 09/22/2013	08/12/2013- 09/20/2013
Fall	09/24/2013- 12/19/2013	09/23/2013- 12/02/2013	09/21/2013- 10/02/2013
Winter	12/20/2014- 01/25/2014	02/12/2014- 03/19/2014	01/29/2013- 03/19/2014

2.2 Data Analysis Methodology

The measured data demonstrated that the occupancy rates had a significant correlation with the overall amount of used electricity ($R^2 = 50\%$ to 80% , $p < 0.001$)[18]. This correlation had a form of a linear equation as following:

$$y(t) = \alpha_0 + \alpha_1 x(t), \quad (1)$$

where y is the predicted electric energy use, x represents the occupant number, α_0 is the baseline electric energy use, α_1 is the corresponding regression coefficient, and t is time. Coefficient numbers for Equation (1) are α_0 and α_1 , Table 3 provides these coefficients for the three reviewed buildings.

Table 3. α_0 and α_1 coefficients for the three reviewed buildings

Buildings	OB1	CB1	CB2
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α_0 (kW)	57	45	160
α_1 (kW/person)	1.0	0.3	0.2

Our previous study also found a significant correlation between occupancy rates and plug-load driven electric energy consumption ($R^2 = 74\%$, $p < 0.001$) [18]. Therefore, the present study collected both plug-load and occupancy data for four weeks in August 2013 and used the first two weeks of data for development of a regression and the last two weeks of data for its validation. Based on the first two weeks of plug-load and occupancy data, the following linear regression emerged:

$$z(t) = \beta_0 + \beta_1 x(t), \quad (2)$$

where z is the plug-load, x represents the occupant number, β_0 is the baseline plug-load, β_1 is the corresponding regression coefficient, and t is time. Coefficient numbers for Equation (2), β_0 is 22.6 and β_1 is 0.2. Importantly, if properly calibrated, these two equations can characterize occupancy rates and equipment use patterns based on metered total electric energy consumption and/or metered plug-loads, allowing for data assimilation in building energy modeling. Specifically, this study used metered plug-load data to calculate hourly occupancy rates and associated electric equipment schedules as inputs for EnergyPlus models.

Table 4 provides four different scenarios for the consideration of occupancy schedules and electricity (or plug load when the aim is to analyze plug loads) consumption to demonstrate accuracy of the proposed data analysis. As a first step, this study uses electricity (sub-metered plug-load) consumption data in August 2013 for OB1 building. This is named as Scenario 1 in Table 4, and the inputs for this step are default schedules and default electricity (or plug load). Scenario 2 only assumes the average values for the occupancy schedules and electricity (or plug load) consumptions. Scenario 3

uses the proposed equations, Equation 1 and Equation 2, that provide the regression correlations for the electricity (or plug-load) and occupancy rate data for the first two weeks of August. When the analyses use electricity consumption, the data lend themselves to α_0 and α_1 . For the plug load consumption analyses, the regression coefficients are β_0 and β_1 . In Scenario 4, the electricity (or plug-load) data from the third and fourth week of August provided $y(t)$ (or $z(t)$) inputs into Equation 1 or Equation 2 to calculate the number of occupants $x(t)$. Consequently, this scenario considers both calculated occupancy schedules and electricity (or plug load) consumption from Equation 1 or 2. Calculated number of occupants was used with the equation for EnergyPlus inputs to verify their influence on the model accuracy. Finally, the energy modeling results were compared with the third week and fourth week of August building energy data. The model results compared to the metered total electric energy consumption provided a basis to quantify potential improvements in predictive model performance. Overall, this study evaluated the proposed methodology for assimilation of metered plug-load data for calibration of building energy models using EnergyPlus software.

Table 4. Four scenarios with different occupancy schedules and electricity (or plug-load) uses

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Occupancy Schedule	Default	Averaged Occupancy Schedule	Actual Occupancy Schedule	Calculated Occupancy Schedule
Total Electricity (or Plug Load) Use	Default	Averaged Electricity (or Plug Load)	Electricity (or Plug Load) Equation	Electricity (or Plug Load) Equation

2.3 Accuracy quantification for the building energy models

ASHRAE Guideline 14-2002 is a widely-accepted building energy model calibration standard [8]. The Coefficient of Variation of the Root Mean Square Error (CVRMSE), and the Normalized Mean Bias

Error (NMBE) are the reference calibration metrics. The CVMSE and NMBE are determined using Equation (3) and Equation (4):

$$NMBE = \frac{\sum_{i=1}^n (y_i - \tilde{y}_i)}{n \times \bar{y}} \times 100 \quad (3)$$

$$CVMSE = 100 \times \frac{\left[\frac{1}{n} \sum_{i=1}^n (y_i - \tilde{y}_i)^2 \right]^{1/2}}{\bar{y}} \quad (4)$$

where parameter n is the number of measured data points, $\tilde{y}$ is model predicted results of building energy use, y_i is the measured data of building energy use, and $\bar{y}$ is the average value of y_i . ASHRAE Guideline 14-2002 recommends that there are two time scales for the calibration criteria: (1) hourly and (2) monthly. For monthly data calibration, the NMBE acceptance requirement is 5%, and the CVMSE is 15%. For hourly data calibration, the requirement is 10% for NMBE, and 30% for CVMSE. This study uses hourly calibration as the more relevant and difficult one to accomplish when considering improvements in building energy efficiency.

3 Application of the methodology when the sub-metering system is available

The total building electricity consumption may include different kinds of electricity end-uses, such as plug-loads, heating, cooling, ventilation, lighting, and water heating. Some of the end-uses are directly related to occupancy, while the rest of them are related to the building operating system and outdoor weather conditions. Specifically, occupants affect the plug-load and lighting schedules by using computers and other electric equipment in the building. As previous studies indicated that the plug-loads are highly correlated with the total number of occupants in the building. Figure 3 shows that the plug-load curve follows the occupancy schedule. When the building occupancy rate increases in the morning, the plug-loads increase and when occupants leave the building at lunch time, the plug-loads

decrease. After office hours, the occupancy rate decreases to zero and the plug-loads return to the building baseline value. The observed trends in this specific example are persistent for all data collected in OB1 building.

Figure 3. Total electricity consumption, plug-loads, and occupancy in OB1 for a period of one day

From the regression analysis results, plug-loads were significantly correlated to the number of occupants in the building. The number of occupants was able to account for 68% to 79% of the variation shown in the plug-load levels for OB1 building. Compared with the correlation between the total electricity consumption and number of occupants ($R^2 = 50\%$ to 61% , $p < 0.001$), plug-loads have a higher degree of correlation. The total electricity consumption had a higher baseline value and a higher value for the gradient than the same values associated with the plug-loads, but the plug-loads had a higher correlation coefficient compared to the correlation coefficient for the total electricity consumption.

Figure 4(a) presents a correlation between the number of occupants and plug-loads, while Figure 4(b) shows the difference between the actual measured occupancy rates and the occupancy rates

calculated with the derived correlation, represented by Equation 2. β_0 is the baseline plug-load, β_1 is the corresponding regression coefficient, and t is time. Coefficient numbers for Equation (2), β_0 is 22.6 and β_1 is 0.2. The agreement between the calculated and actual occupancy is very good with the exception of a specific day/time (8/27/13, 12:00) showing a highest peak for actual occupancy. At that specific day/time, the building had a conference meeting, so most of the occupants were the visitors who did not directly contribute to the building plug-loads. This is similar to the findings from the sub-metered copiers, printers, computers, and personal equipment that shows for example copiers and printers can consume significantly for a specific time during a working week [26]. For this special day/time, the calculated occupancy schedule did not have a good correlation with plug-loads. Overall, the calculated occupancy rates are used as occupancy schedules in EnergyPlus model inputs to predict the building energy consumption.

Figure 4. (a) Empirical equation for occupancy schedules (b) difference between calculated number of occupants and actual number of occupants

1
2 This study uses four scenarios to evaluate the improvement of energy model accuracy with
3 changes in occupancy and plug-load schedules. Scenario 1 uses a default occupancy schedule with a
4 default plug-load schedule to estimate the electricity consumption. Scenario 2 uses the averaged actual
5 occupancy schedule with the averaged plug-loads as input parameters. Scenario 3 uses the actual
6 measured occupancy schedule (3rd and 4th week of August data) with the plug-load equation (Equation 2)
7 derived from the first 2 weeks of August data. Scenario 4 uses a calculated occupancy schedule based on
8 the measure plug-loads (3rd and 4th week of August data) and plug-load equation derived from the first 2
9 weeks of August data. Figure 5 and Table 5 present results of the measured and predicted plug-loads as
10 well as their statistical performance with CVRMSE and NMBE values.

11 The results from Scenario 1 were compared with actual plug-load data and the hourly CVRMSE is
12 34%. As long as actual schedules, the plug-load equation, and calculated occupancy schedules were
13 added, the plug-load estimation results improved the model accuracy. In Scenario 2, averaged
14 occupancy schedule and averaged total electricity schedule were used. Compared to Scenario 2,
15 Scenario 3 produced more accurate results with the actual occupancy schedule with plug-loads equation.
16 The differences between Scenario 2 and Scenario 3 showed that plug-loads equation could improve the
17 accuracy of the results. Scenario 4 provided more accurate results with the calculated occupancy
18 schedule based on the plug-loads than Scenario 3 (Equation 2). Our previous study showed that plug-
19 loads were directly correlated to the number of occupants [18]. Therefore, an accurate estimate of
20 occupancy rate is a key component of building energy model calibration. However, calculated occupancy
21 schedule based on the plug-load equation had better results when compared to the results based on the
22 actual measured occupancy schedule. The reason is that plug-loads were directly associated with the
23 occupants who are actually using power with devices, such as desktop computers, copy machines and
24 personal electronic devices. Therefore, if the actual occupancy schedule was used with the plug-load

equation, some of the occupants who were not actually using electricity are counted toward the estimate of plug-loads in the EnergyPlus model.

Table 5. CVMSE and NMBE values for four scenarios with different occupancy and plug-load schedules

OB1	Scenario 1	Scenario 2	Scenario 3	Scenario 4
CVRMSE Plug-load Hourly	34%	22%	10%	5%
NMBE Plug-load Hourly	21%	21%	7%	3%

Figure 5. Comparison between predicted and actual building plug-loads for the four Scenarios

From the building energy model results, when calculated occupancy schedules and the plug-load equation results were used as input parameters, the accuracy of building energy model for total electricity use results is improved. Table 6 shows the total electricity use in OB1 building. The table features the estimated total electricity use compared to the actual building metered data. The default schedules in Scenario 1 follow the inputs in the DesignBuilder software, which assumes the operation occupancy for an office building is from 8 AM to 5PM for working days. The energy model results demonstrated reduction of the hourly electricity use CVRMSE from 67% to 21%. Therefore, it is possible to improve the building energy model accuracy for total electricity with calculated occupancy schedules and plug- loads based on previously calibrated Equation 2.

Table 6. CVRMSE and NMBE results for total electricity consumption in OB1 building

OB1	Scenario 1	Scenario 2	Scenario 3	Scenario 4
CVRMSE Total Electricity Hourly	67%	30%	38%	21%
NMBE Total Electricity Hourly	30%	11%	9%	5%

4 Application of the methodology when the sub-metering system is not available

Most campus buildings do not have sub-metering systems to collect disaggregated building energy use data. Therefore, a calibration methodology without plug-load data is needed. If buildings provide the exact operating schedule of HVAC systems or facilities, it is possible to disaggregate the

plug-load data from total electricity consumption. However, it is difficult to obtain the exact operating schedule of HVAC system or facilities. Therefore, current study suggests using the differences of weekdays and weekends energy use to distinguish the background energy consumption from the total metered energy use data. As it is shown in Figure 6 (a) and (b), compared to weekday occupancy rates, the weekend occupancy rates were relatively low, representing the baseline unoccupied building condition. Therefore, this study assumed the weekend schedule as an unoccupied building condition. The baseline electricity use reflected the fact that the HVAC energy usages were not directly associated with the number of occupants in the building, but it is rather related to outdoor weather conditions and building operation set-points. Therefore, the baseline electricity use has certain peaks that are not impacted by the number of occupants in the building. These trends also appeared in the electricity use for the weekdays during the night time.

Figure 6. Electricity consumption and occupancy schedules in (a) CB1 and (b) CB2 building

To reduce the level of noise from values that did not follow the occupancy trends, this study processed raw 15-minute electricity use data. Specifically, an hourly data averaged from 4 days (marked with arrow on Figure 6) of weekend data were used as the baseline electric energy use. Furthermore,

1 this averaged baseline value was subtracted from the total electricity use at the building level to obtain
2 an electricity consumption component associated with occupancy rates. Figure 7 (a) and (b) show the
3 comparison between total electricity use and processed electricity use data (total electricity use –
4 baseline electricity use) in two studied campus buildings. After subtracting the averaged weekend
5 electricity use data from the total weekday electricity use, ideally, the electricity use peaks not
6 associated with occupants were erased from the trend. These processed total electricity use data could
7 be used to calibrate Equation 1 for these campus buildings that do not have a sub-metering system.

8 To verify this approach, a regression analysis was used with the processed electricity data and
9 the measured number of occupants. The results in Table 7 for CB1 indicate that the correlation
10 coefficient increased from 70% to 72%, and for CB2, the correlation coefficient increased from 57% to
11 66%. In comparison, CB2 building has a higher percentage of its floor area dedicated to laboratories than
12 CB1 building (CB1: 9.7%, and CB2: 36%). Usually, the energy use for laboratories was not directly related
13 to occupancy and was not easy to predict [24]. The laboratory spaces typically have fume hoods, clean
14 rooms, biosafety labs, ultralow freezers, and servers [34]; consequently the energy use of these facilities
15 are a function of these equipment as typically the usage of the equipment might be 7/24 [35]. Therefore,
16 their background energy consumption from laboratory facilities are large, even the area is not occupied.
17 This is the main reason why after removed the background energy consumption (averaged weekend
18 energy consumption), the correlation coefficient for CB2 improved significantly (9%) than the correlation
19 coefficient improvement from CB1 (2%).

Figure 7. Comparison between the total and processed electricity use to reflect occupancy rates in (a) CB1 and (b) CB2 building

Table 7. Correlation between the measured number of occupants and electricity use in campus buildings

	CB1		CB2	
	Total Electricity Use	Processed Electricity Use	Total Electricity Use	Processed Electricity Use
R^2 (%)	70	72	57	66

When a building does not have a sub-metering system, total or processed building electricity use can be used to derive occupancy schedules as inputs for building energy models. The proposed

methodology used the cleaned building electricity data instead of sub-metered plug-load data. For this application, one week from each seasons, including spring, summer, fall and winter with a total of 4 weeks, were used to derive the equations for occupancy schedules with processed electricity data. The rest of metered data were used to calculate the occupancy schedules for a validation of this methodology application in EnergyPlus. As shown in Table 8, similar to case study OB1, case studies CB1 and CB2 benefits from the four scenarios deploying the cleaned electricity use equation and a calculated occupancy schedules; consequently, the building energy models used the default values of the occupancy schedules and electricity use. The default occupancy schedules follow the pre-populated schedule for an office building at indicates occupancy of 8 AM to 5 PM for working days. For Scenario 2, the building energy models used the average occupancy schedules in the building with the averaged processed electricity use. In scenario 3, the building energy models used the actual occupancy schedules with processed electricity use equation for weekdays. In scenario 4, the building energy models used the calculated occupancy rates derived from the processed electricity use and processed electricity use equation.

Table 8. Four scenarios for CB1 and CB2 with different occupancy schedules and processed electricity uses

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Occupancy Schedule	Default	Averaged Occupancy Schedule	Actual Occupancy Schedule	Calculated Occupancy Schedule
Total Electricity Use	Default	Averaged Processed Electricity Use	Processed Electricity Equation	Processed Electricity Equation

When the electricity use was cleaned by the weekend-averaged data, the baseline of the building energy use decreased from 45 kW to 10 kW. This cleaned number could have a negative value

1 when the building is in an unoccupied condition or building energy use was smaller than the averaged-
2 weekend data. In this case, the cleaned data cannot be used in the building energy model. For the
3 adjustment of the cleaned electricity use, the building system needs to be studied to justify the amounts
4 of energy use in other parts: the HVAC system, and lighting. However, these case study buildings cannot
5 provide the exact amount of energy use from the other parts. Therefore, the difference between
6 unoccupied condition building energy use and averaged-weekend data was added to processed
7 electricity data to erase the negative values (CB1: 5kW, CB2: 40kW). When these building system energy
8 usages are justified, other amounts of energy can be used as a baseline plug-load use with the cleaned
9 electricity use.

10 From Equation (1) and Table 3, for both CB1 and CB2 buildings, the occupancy schedules were
11 derived with processed-adjusted electricity use. Figures 8 (a) and (b) show the average occupancy
12 schedules, actual occupancy schedules and derived occupancy schedules for the two campus buildings.
13 A comparison between the actual, averaged, and derived occupancy show that, the averaged occupancy
14 schedules under-predict and over-predict the occupancy rates compared to the actual and derived
15 occupancy. The derived occupancy patterns follow the actual occupancy for the week of 08/26 to 08/30.
16 However, the occupancy for the week of 08/19 to 8/23 shows differences between the actual and
17 derived occupancy since the buildings do not have the typical occupancy patterns. In the campus, the
18 week of 8/19 to 8/23 was the week before fall semester starts, therefore, the actual occupancy was
19 lower than typical time period but total electricity did not exactly flows the actual occupancy pattern.
20 The week of 08/26 to 08/30 is the first week of the classes and the derived occupancy could predict the
21 actual occupancy since the building has a typical occupancy pattern. As shown in Figure 4 and Figure 5,
22 the importance of this comparison is estimate the occupancy rates which is directly associated to the
23 electricity consumption and which can improve the simulation accuracy as an input.

Figure 8. Three different occupancy schedules for (a) CB1 and (b) CB2 energy model calibration

The proposed methodology was verified for campus buildings, which did not have a sub-metering system. The results were shown in Table 9 and Table 10. The accuracy of the building energy model increased with the derived occupancy schedules and electricity use equations. Compared to the default schedules in the building energy models, detailed occupancy and electricity inputs provided a decrease in the CVMSE and NMBE statistical parameters. For CB1 and CB2 buildings, hourly CVMSE decreased from 128% to 31%, and from 156% to 16%, respectively. Furthermore, hourly NMBE decreased from 84% to 6% for CB1, and decreased from 47% to 8% for CB2. The daily CVMSE for CB1 and CB2 decreased from 85% to 12% and from 61% to 13%, respectively. The daily NMBE decreased from 81% to 0.2% for CB1, and decreased from 47% to 4% for CB2. Figure 9 illustrates that the calibration results for all three buildings, OB1, CB1 and CB2, meet the ASHRAE Guideline 14 criteria when calculated occupancy schedule and associated electricity equations were used as input parameters. Therefore, for buildings without a sub-metering system, occupancy schedules based on the processed electricity resulted in calibrated building energy models.

Table 9. Four scenarios of CVRMSE in CB1 building

CB1	Scenario 1	Scenario 2	Scenario 3	Scenario 4
CVRMSE Total Electricity Hourly	128%	48%	40%	31%
NMBE Hourly	84%	31%	18%	6%

Table 10. Four scenarios of CVRMSE in CB2 building

CB2	Scenario 1	Scenario 2	Scenario 3	Scenario 4
CVRMSE Total Electricity Hourly	156%	46%	32%	16%
NMBE Hourly	47%	21%	21%	8%

Figure 9. CVRMSE and NMBE between estimated electricity use and actual building energy use for four studied scenarios

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2 **5. Discussions**

3 This study shows that the occupancy schedules derived from the building hourly electricity use
4 can improve the accuracy of the building energy modeling. However, not all of the occupants in the
5 building consume the same amount of electricity. Therefore, depending on the occupants' type and area
6 usage type, occupant's impact on the electricity use is different. In buildings with a high percentage of
7 office space, most of the occupants consume the electricity by using their own work stations, and
8 consequently increasing the electricity use in the building. However, in common areas and classrooms,
9 not all of the occupants contribute to the plug-loads. Most of these occupants are attending classes or
10 other events without directly consuming electricity. Therefore, the occupancy rates, which are directly
11 associated with building electricity use, should be considered to improve the accuracy of building energy
12 models.

13 With this hypothesis, to improve the accuracy of the energy modeling results, the measured
14 number of occupants and electricity use are required. However, there are several obstacles to measure
15 the accurate number of occupants in the building. Therefore, this study suggested to use the estimated
16 number of occupants. The estimated number of occupants can be calculated from the total electricity
17 use and building area information. From a previous study, kW/person calculation equation was derived
18 with 3 case study buildings and verified with 1 case study building [18]. Prior study found that depending
19 on the area usage type, overall electricity use per occupants is different. By using the equation previous
20 study suggested and total electricity consumption data, occupancy patterns which actually impact on
21 the building electricity consumption can be derived without occupancy data collection. Therefore, the
22 methodology suggested from current study can be helpful when the measured occupancy rates are not
23 available.

As Table 1 shows, OB1 building that has mostly office spaces has a higher kW/person electricity use (1.0 kW/person) compared to the electricity use of campus buildings (CB1: 0.3 kW/person, CB2: 0.2 kW/person). The electricity use per occupant can be linked with the baseline electricity use to derive the occupancy schedules from the total electricity use in a building. Also, future studies could consider different building percentage for the spaces, e.g. variation of the office spaces and laboratory spaces, and provide associated coefficients for the kW/person. This approach would provide opportunities to establish a database of correlations, empowering to widespread deployment the developed methodology in this study. In addition, this study provides opportunities for the on-site measurement of the occupancy patterns to adjust the occupancy patterns and establish a derived occupancy pattern than relying on the sensor measurements. The developed methodology in this study for the data processing and correlation of the plug-load as well as the electricity to the occupancy offers several benefits for the building energy model calibrations. Overall, the coefficients and implementation of them in the building energy models offer several benefits to calibrate mid-sized commercial and campus buildings.

6. Conclusions

This study proposed a methodology to calibrate building energy simulations using hourly interval electricity use data and associated occupancy schedules. The method was established for an office building case study (OB1) and further validated for two campus buildings (CB1 and CB2). The accuracy of the building energy simulations increased with the derived occupancy schedules.

This study provided equations for the correlations between the electricity (or plug load) correlation with the number of occupants. For the campus buildings, which did not have sub-metering systems to collect the plug-load data, the total or processed building electricity use can be deployed in building energy model calibration. The correlation between total electricity use and the occupant number varies in the three buildings (56% to 70%, $p < 0.001$). CB2 and OB1 buildings include more

laboratory and common areas with percentages in the total building area than the CB1 building. The combined laboratory and common area for these cases studies are CB1 42%, CB2 72%, and OB1 60%. Overall, laboratories and common areas had more unpredictable energy usage compared to classrooms and office areas.

The calculated occupancy rates and electricity (or plug load) consumption provided higher accuracy to the building energy models than the default, averaged, or actual values. For OB1, the hourly electricity Coefficient of Variation Root Mean Square Error (CVRMSE), an indicator of accuracy, improved from 21% to 12% compared to the results from the building energy models that use the default schedules. Campus buildings did not have a sub-metering system to collect the plug-load data. Therefore, this study demonstrated how to use processed electricity use data instead of plug-load data to calculate the occupancy rates. For case study buildings, CB1 and CB2, the accuracy of modeling results increased as the hourly electricity CVRMSE decreased from 128% to 31% and from 156% to 16%, respectively. The results of correlation between the plug load and electricity and occupancy offer an indicator, kW/person. Depending on the building spaces, kW/person varies from 1.0 kW/person for an office building to 0.2 kW/person for a campus building when the percentage of the laboratory space increases. Overall, the results of this study have implications for similar office or campus buildings when the sub-metered plug load data do not exist.

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