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Improvement of Building Energy Simulation Accuracy with Occupancy Schedules Derived from Hourly Building Electricity Consumption

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ABSTRACT

Commercial buildings account for nearly 18% of the national energy consumption in the United States, which produces approximately 12% of the annual global greenhouse gas emissions. To reduce greenhouse gas emissions and energy consumption from buildings, it is important to design and operate energy-efficient buildings. However, some buildings fail to perform as their designers intended, in part because users do not or cannot properly operate the buildings, and some occupants behave differently than designers expect. Therefore, the relationship between occupancy patterns and buildings' energy consumption is important. This study analyzes building occupancy rates and electricity consumption in a commercial building. The occupancy rates were measured by people counters, and electrical consumption was determined from the building's metering and submetering systems. The analysis used data from an office building in Philadelphia. This study found that occupancy rates have a higher correlation with plug-load consumption (87%) than with total electricity consumption (56%). This result indicates that the plug-load consumption can be the indicator of the occupancy rates in the building. This study presents a simplified method to derive the occupancy schedules and the plug-load consumption equation for building energy simulation. With a calculated occupancy rate and plug-load consumption equation, the coefficient of variation of the root mean squared error (CVRMSE) of building simulation results is reduced (CVRMSE = 48% → 4%).

INTRODUCTION

High oil prices, diminishing natural resources, and global warming are causing developed countries to investigate possible ways to reduce their energy consumption. Commercial buildings account for nearly 18% of the national energy consumption of the United States, which produces approximately 12% of the annual global greenhouse gas emissions (EIA 2011). Therefore, there is a pressing need to evaluate and understand the energy performances of commercial buildings during the design and operation phases in an effort to increase their energy efficiency and conservation (Azar and Menassa 2012).

With an increasing demand for more energy-efficient buildings, the industry is faced with the challenge to ensure that the energy performance predicted during the design stage is achieved once a building is in use (Meneze et al. 2012). There is extensive evidence to suggest that buildings usually do not perform as well as predicted (Bordass et al. 2004; Bordass et al. 2011). Some buildings fail to perform as their designers intended, in part because users do not or cannot properly operate the buildings or some occupants behave differently than designers expected (Andrews et al. 2011). The differences between real and predicted energy use depends on the differences between the predicted and actual final realization of the construction, technical installations, and the real use of the built systems operated by occupants. Recently, it has been shown that occupant behavior plays a fundamental role in the amount of energy used in buildings (Fabi et al. 2012).

Energy modeling software has been widely used by designers and engineers to simulate and predict buildings' energy performances during design and assist them in making better-informed decisions about the most appropriate systems for their buildings (Hoes et al. 2009). However, in reality, energy modeling tools oftentimes use simplistic and idealistic data inputs that are unrepresentative of the actual building systems and occupancy. As a result, large discrepancies are

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observed between the predicted and actual energy performance, typically averaging around 30%, but reaching as high as 100% in some cases (Azar and Menassa 2012; Meneze et al. 2012).

The influence of the occupants on a building can be broken down into several means of interactions, each of which can be represented by a stochastic model, as shown in Figure 1 (Page et al. 2008). Being present within the building is clearly a necessary condition for being able to interact with it. Occupant presence is an input parameter in all models, and the model for occupant presence will be central to the family of other models. As each human being emits heat and "pollutants" (such as water vapor, CO_2, and odors), their presence directly modifies the indoor environment in areas such as temperature changes, CO_2 concentration increases, and so on. Occupants also interact with a building to enhance their personal comfort. For example, they will heat, cool, or ventilate their environment to improve their thermal comfort, and they will adjust lighting systems or blinds to optimize their visual comfort. Finally, occupants' interactions also relate to the tasks that they are required to perform. In an office building, occupants may use various electrical equipment that contributes to the internal heat gain and the consumption of electricity. A pattern of presence of occupants in a building is therefore of paramount importance in simulating their behavior within a building and their effect on the buildings' demands for resources, such as energy in the form of heating, cooling, and electricity.

Much of the literature focuses on electricity consumption, with more recent studies assessing the levels of building use in relation to occupancy. One study investigated the influence of occupant numbers on energy consumption in a real building situation (Martani et al. 2012). The study assumes Wi-Fi usage as a representative value for the occupancy number that accounted for approximately 65% of the variation in electricity consumption for campus buildings. Another study statistically analyzed the rule of the quantitative influence of the hotel occupancy ratio on energy consumption during different

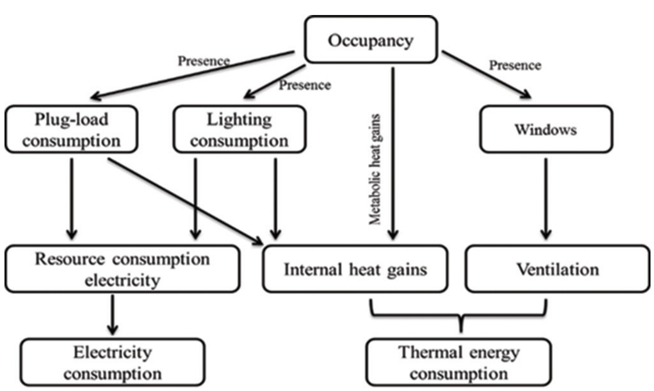

Figure 1 *The influence of occupants on the building energy consumption (Page et al. 2008).*

seasons (Gao and Zhang 2011). The mean daily total electricity consumption for a hotel room was linearly correlated with the occupancy ratio during each season. The correlation changes, depending on the season, ranged from 91% to 97%. The occupancy ratio reflects the hotel's utilization level, and different occupancy ratios naturally correspond to different numbers of guests using the rooms. Therefore, the hotel energy consumption level of the units' use could be reflected by the hotel's mean daily energy consumption. The electricity consumption demonstrates a significant positive correlation with the occupancy rates in the different types of buildings.

A wide variety of simulation programs are available to analyze building energy consumption, including ESP-r, TRNSYS, DOE-2, BLAST, EnergyPlus, IDA ICE, and Virtual Environment (Kim 2014). Their complexity levels range from steady-state calculations to very sophisticated programs, including computational fluid dynamics simulation (Tavares and Martins 2007). Assuming that the simulation is a theoretical representation of the status and operation of a building, it cannot perfectly replicate the actual dynamic environment that governs building energy consumption. For example, the actual climate can vary from the available meteorological data, and the systems may not work exactly as expected from the curves of the load operation. Performance may also vary with the actual number of worked hours and scheduled maintenance activities. Therefore, energy performance can also be affected by the actual behavior of the building occupants.

Building simulation tools are based on heat transfer and thermodynamic equations and typically model human activity as predefined, fixed schedules or predefined rules for the operation of lights, blinds, and windows. These tools often reproduce building dynamics using numerical approximations of equations, modeling only deterministic behaviors. In such a way, *occupant behavior simulation* could refer to a computer simulation generating *fixed occupant schedules*, representing the behavior of a building occupant over the course of a single day (Armel et al. 2013). Defining the occupants' behavioral parameters is an effort to better understand the typical 30% to 100% discrepancies that may be observed between the predicted and actual energy use in the buildings (Azar and Menassa 2012). Table 1 shows the occupancy-related parameters in the building energy simulation tools. The energy simulation tools have a plug-load parameter, a thermal sensible parameter, an indoor-air-quality-related parameter, and a temperature-set-related parameter. Information from ANSI/ASHRAE Standard 55 (2013) was used as a temperature setpoint in the building (Clevenger and Haymaker 2006).

RESEARCH METHODOLOGY

Prior studies show that occupants' behavior, occupancy rate, and occupants' presence/absence effect building energy consumption. Most of the previous studies were conducted with several case studies of specific buildings. These studies highlighted the importance of the occupants' behaviors and the importance of occupancy parameters in energy simula-

Table 1. Occupancy-Related Parameters in the Building Energy Simulation

Parameter	Description	Ranges
Power/plume	Heat gain from a work station, computer terminal, plus any task of lighting	watt/person
Activity level	Depending on the activity level	Related to thermal comfort
Occupied setpoint	ANSI/ASHRAE Standard 55 (2013)	Heating setpoint, 22.2°C (72°F) Cooling setpoint, 23.9°C (75°F)
Unoccupied setpoint	ANSI/ASHRAE Standard 55 (2013)	Heating setpoint, 16.7°C (62°F) Cooling setpoint, 29.4°C (85°F)
Outdoor air flow	Outdoor air per person $OA_{people} = Occ_{zone}(OA_{flow\_per\_person})$	0.00944 (m^3/s)/person = 20 cfm/person
CO_2 generation	CO_2 generation rate	0.0084 cfm/met/person 4×10^{-6} (m^3/s)/met/person
Heat gain	Convective heat transfer, latent sensible energy	

OA = outdoor air volume flow rate based on occupancy, m^3/s (cfm)
Occ_{zone} = number of occupants in zone

tions. However, it is hard to normalize the occupants' parameters to use as an input parameter for an energy simulation. Also, most of studies were not done with actual building data. After addressing these issues, the simplest acceptable methodology to derive the occupancy rate can be a more practical option for the projects with limited resources.

The electricity consumption demonstrates a significant positive correlation (63% ~ 69%) with the occupancy rates in the different types of buildings. Also, occupancy rate and occupied area information effect the accuracy of the building thermal-energy simulations. Building electric-energy consumption patterns can be used to derive occupancy schedules and significantly improve the energy simulation results.

Before we derive the occupancy schedules with the electricity consumption in the building, it is required to understand the occupancy effect on building energy consumption. To quantify the occupant effect on the energy consumption in the office building, electricity and number of occupants data were used. Regression analysis was used to find the correlation between occupancy and electricity consumption. Also, a single office building was used to develop and validate a methodology to derive occupancy rates from submetered electricity consumption for inclusion in energy simulation tools. The methodology to estimate the occupancy rate with plug-load consumption was developed based on the submetered data and the actual number of occupants in the office building.

To derive the occupancy rate, a linear regression was used to find the equation. Our study used hourly data collected over a two-week time period to derive the occupancy rate and the equation for plug-load consumption. Another data set, also collected over a two-week time period, was used to validate the methodology. The occupancy rate and equation were validated with EnergyPlus (DoE 2012). To run an energy simulation model, an extensive set of inputs were required to define the building's geometry, internal loads, outdoor environment, equipment, and schedules. An occupancy model, which is derived with building electricity consumption, was used with other parameters instead of a simple number of occupants.

The simulation phase follows these several steps;

1. Build an energy simulation model with DesignBuilder (2014)
2. Modify the EnergyPlus input file to add an occupancy rate and plug-load consumption equation
3. Run EnergyPlus

The verification phase uses the EnergyPlus output data with the actual building consumption data to justify the accuracy of the model and the improvements. To calibrate simulations, the coefficient of variation of the root mean square error (CVRMSE) (ASHRAE 2002) of modeled energy use is determined by comparing simulation-predicted data ($\bar{y}$) to the actual consumption data (y) used for calibration; n is the number of observations (i = 1, … n) with p = 1.

$$\text{CVRMSE} = 100 \times \frac{\left(\frac{\Sigma(y_i - \dot{y}_i)^2}{n-p}\right)^{1/2}}{\bar{y}} \tag{1}$$

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VALIDATION IN EXISTING BUILDING

This study analyzed building occupancy rates and electricity consumption in a commercial building. The analysis used data from an office building in Philadelphia, shown in Figure 2. The total area of the building is 66,088 ft^2 (6138 m^2), and is composed of three stories and one ground floor. The building has 40% open offices, 60% common areas, and includes conference rooms.

The occupancy rates were measured by video-based detecting sensors. People counters were installed at every entrance of the building. The accuracy of the sensors is within a 5% error rate. Energy consumption data was collected from building metering and submetering systems. As a result of data availability, this study used aggregated data on energy consumption at the building level.

In the office building, the occupancy profiles were shown differently depending on whether it was a weekday or weekend. For the sample data, the hottest two weeks in August, 2013 were selected. As shown in Figure 3, the occupancy schedule in the office building did not change significantly, except when there was a special event in the building. Also, on weekends, compared to weekdays, the occupancy rate was greatly diminished. For the office building, the increase in the occupancy gradient is similar to the decrease gradient.

In the case of commercial buildings, plug loads are also referred to as *miscellaneous electricity consumption*. This miscellaneous consumption includes all electricity consumption except the consumption of the main building systems including heating, cooling, ventilation, lighting, and water heating. Figure 4 shows the electricity consumption and the occupancy schedule in the building. As shown in Figure 4, the electricity consumption and occupancy rates demonstrate pronounced daily recurring trends in the building during the weekdays.

Linear regression analysis was used to find the correlation between occupancy and electricity consumption. As explained in the previous section, occupancy rates during the weekends were small compared to weekdays. The only data used for this analysis was that of the weekdays. The results indicate that the occupancy rates have a correlation with the overall amount of electricity used ($R^2 = 56\%$). Linear regression analysis was used to find the equation (Equation 1) of the straight line:

$$y = \beta_0 + \beta_1 x \qquad (2)$$

where y is the predicted electricity consumption, x represents the occupancy number. β_0 is the baseline electricity consumption and β_1 is the corresponding regression coefficient. Table 2 shows the baseline electricity consumption and corresponding coefficient. When the occupancy number changes, the total electricity consumption changes with a corresponding coefficient.

Total building electricity consumption includes different kinds of electricity consumption such as equipment, heating, cooling, ventilation, lighting, and water heating. Some of the parameters are related to occupancy, but some of them are related to the building operating systems. Occupants have an effect on the plug-load schedule and lighting schedule by using computers and other electric equipment in the building. To verify the assumption, the building was used to break down the end electricity-energy use. Building plug-load data was collected and analyzed with the occupancy rate. Figure 5 shows that the plug-load consumption trend exactly follows the occupancy schedule compared to the total electricity consumption. When the building occupancy rate increased in the morning, the plug-load consumption increased, and when people leave the building during lunch time, the plug load decreased. After office hours, the occupancy rate decreased to zero and the plug-load consumption returned to the baseline. Compared to the plug-load consumption, the total electricity consumption trend does not exactly follow the occupancy rate. Total electricity consumption increased a few hours before the occupancy rate started to increase. Also, it decreased to baseline after all of the occupants left the building.

Figure 2 *Office building in Philadelphia.*

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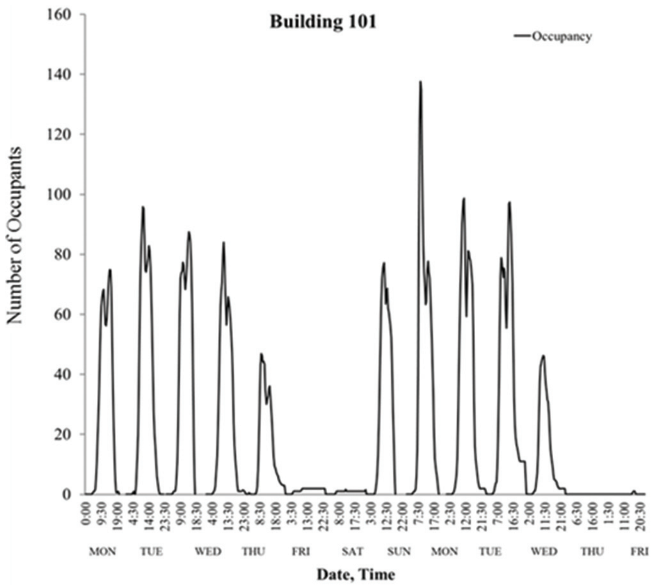

Figure 3 *Number of occupants in the office building.*

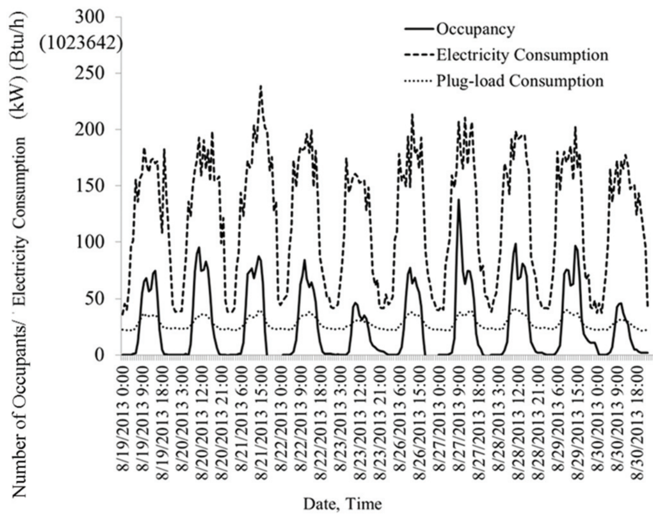

Figure 5 *Total electricity consumption, plug-load consumption, and number of occupants in the office building.*

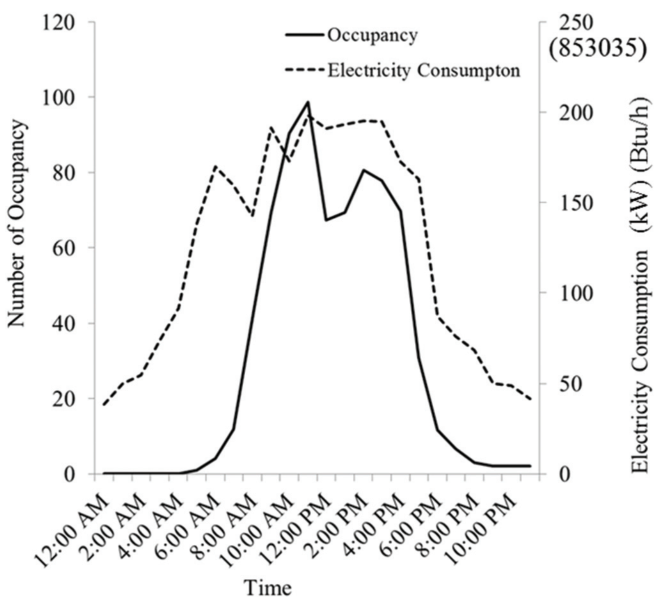

Figure 4 *Total electricity consumption with the number of occupants in the office building.*

Table 2. Correlation between Total Electricity Consumption and Occupancy Number

	Office Building
R^2 (%)	56
Baseline (kW)	88.69
Coefficient (kW/occupant)	1.32

Table 3. Comparison of the Correlation between Total Electricity Consumption and Plug-Load Use with Occupancy Number in the Building

	Total Electricity Consumption	Plug-Load Consumption
R^2 (%)	56	87
Baseline (kW)	88.69	23.93
Coefficient (kW/occupant)	1.32	0.16

According to the results, plug-load consumption was highly correlated to the occupancy rates in the building. Occupancy rates were able to account for 87% of the variation shown in the plug-load levels in the building. Compared with the correlation between total electricity consumption and the occupancy schedule (R^2 = 56%), plug-load consumption has a higher correlation (R^2 = 87%) (Table 3). Figure 6 shows the difference between total electricity consumption and the plug load's baseline and gradient. Total electricity use has higher baseline than energy consumption, and a higher value for the gradient.

In the case study from the office building, the plug-load consumption is directly related to the occupancy rate (87%) compared to the total electricity consumption in the building. Most of the plug-load consumption data comes from the first floor and second floor office areas. However, total electricity consumption includes interior lighting, exterior lighting, and the HVAC system. Some parts of electric consumption, such as exterior lighting and the HVAC system, are not as affected by the presence and behavior of occupants. This is one reason that total electricity consumption has a weaker correlation with occupancy rate compared to plug-load consumption.

According to the results from the case study at the office building, the occupancy rate is directly related to plug-load consumption (R^2 = 87%). The plug-load consumption can be used to drive occupancy schedules and to improve the accuracy of energy simulation results. Figure 7 presents the schematic of the method for occupancy schedules and plug-load equation of the case study. It consists of two different data sets for deriving the equation and validating the equation. First, two weeks of data were used to derive the occupancy schedules equation with plug-load consumption. Also, the plug-load consumption equation was derived by calculated occupancy rates. A single equation was used to derive the calculated occupancy rate and another equation to calculate the plug-load consumption. The plug-load consumption equation derived with the calculated occupancy rate was applied to EnergyPlus simulation. The calculated occupancy schedule and plug-load consumption equation were used in energy simulations to verify the accuracy of the energy simulation results.

Figure 8 presents the correlation between the number of occupants and the plug-load consumption. The calculated occupancy schedule was used in EnergyPlus to simulate the workday. In the case that a building has meeting events, the occupancy rates increased without significant impact on the plug-load consumption. The use of the linear regression equations based on the actual occupancy rates for the plug-load consumption can result in inaccurate predictions of peak building loads, as shown in Figure 9, Case 3. This problem was avoided when the occupancy rates were calculated from the measured plug-load consumption. Therefore, the calculated occupancy schedule can have a better correlation with the plug-load consumption equation.

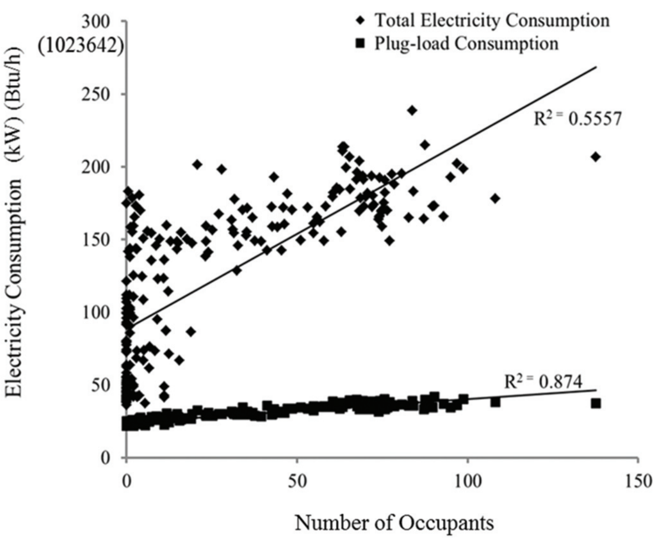

Figure 6 *Comparison graph (total electricity consumption versus number of occupants, and plug-load consumption versus number of occupants).*

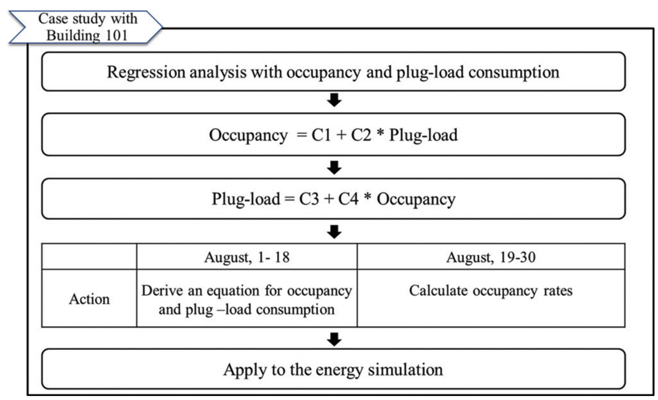

Figure 7 *Schematic of the method for occupancy schedules and plug-load equation.*

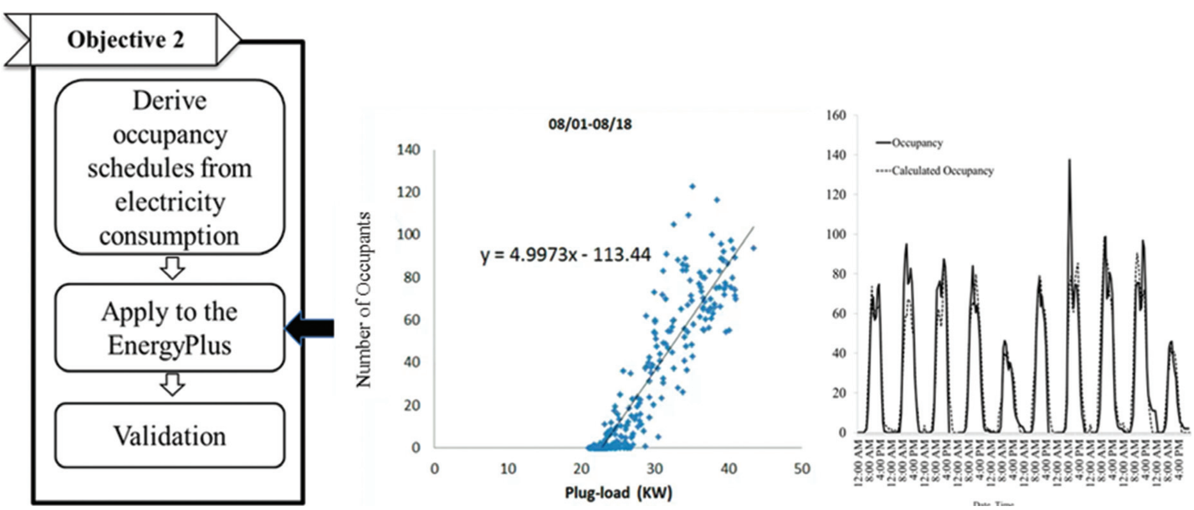

Figure 8 *Equation for occupancy schedules.*

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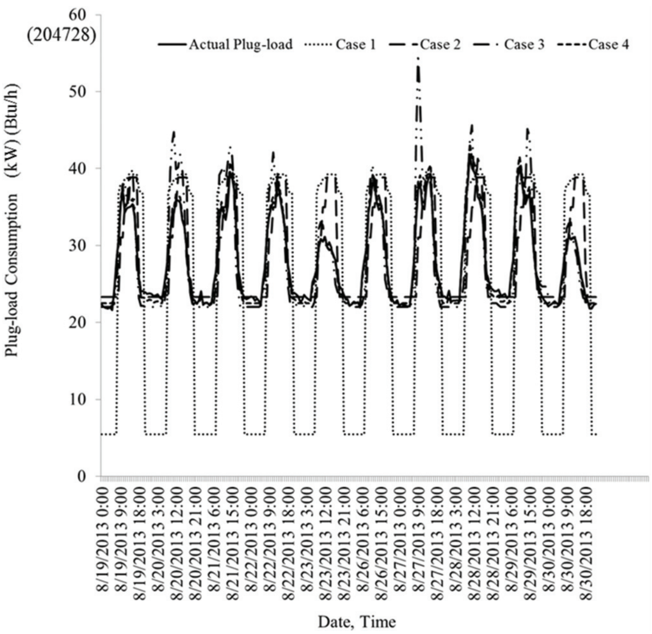

Figure 9 *Comparison between simulated results and actual building plug-load consumption.*

Table 4 presents four cases derived from combinations of the two different input parameters. To validate a derived occupancy schedule and plug-load consumption equation, the required input parameters are as below. The default schedule and plug-load consumption schedule in the energy simulation were used in Case 1. Case 1 shows the inaccuracy of the default schedules in a real building situation. In Case 2, an averaged actual occupancy schedule and averaged plug-load consumption schedule were used. Case 2 indicates that the averaged actual information brings better results compared to default schedules. However, it shows the inaccuracy of the results. In Case 3, an actual occupancy schedule and the plug-load consumption equations were used. This case shows that an actual occupancy rate with a plug-load consumption equation can cause an inaccuracy when the occupancy rate changes heavily without effecting the plug-load consumption. In Case 4, calculated occupancy schedule and plug-load consumption equation were used.

Figure 9 and Table 5 presents the results from four case studies. For Case 1, two default schedules for occupancy and plug-load consumption were used and 48% of the CVRMSE. As long as the input parameter changes, the results show different CVRMSEs. By using calculated occupancy schedules and the plug-load consumption equation, the CVRMSE of building energy simulation results decreased (CVRMSE = 48% $\rightarrow$ 4%).

CONCLUSIONS

This study presented a simplified method to derive the occupancy schedules and plug-load consumption equation for building energy simulations. To derive the occupancy schedules and plug-load consumption equation, the occupancy effect on the building's electricity consumption needed to be quantified. Total building electricity consumption included different kinds of electricity consumption such as equipment, heating, cooling, ventilation, lighting, and water heating. Some of the parameters are related to occupancy, but some of them are related to the building's operating systems. Occupants have an effect on the plug-load and lighting schedule by using computers and other electric equipment in the building. This is the reason why occupancy rates have a higher correlation with plug-load consumption (87%) than with total electricity consumption (56%). This result shows that the plug-load consumption can be an indicator of the occupancy rates in the building.

With a calculated occupancy rate and plug-load consumption equation, the CVRMSE of building simulation results were reduced (CVRMSE = 48% $\rightarrow$ 4%) in this office building. In the case that the building has meeting events when the occupancy rates are increased without significant impact on the plug loads, the use of the linear regression questions based on the actual occupancy rates for the plug-load consumption can result in inaccurate predictions of peak building loads, as shown in Figure 9, Case 3. This problem can be avoided when the occupancy rates are derived from the measured plug loads. Therefore, the use of the occupancy rates based on the plug-load electricity consumption is a reliable way to track occupancy for building energy simulations.

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REFERENCES

Andrews, C.J., D. Yi, U. Krogmann, J.A. Senick, J.A. and R.E Wener. 2011. Designing buildings for real occupants: An agent-based approach. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans* 41(6):1077–90.

Armel, K.C., A. Gupta, G. Shrimali, and A. Albert. 2013. Is disaggregation the holy grail of energy efficiency? The case of electricity. *Energy Policy* 52:213–34.

ASHRAE. 2002. ASHRAE Guideline 14. *Measurement of Energy and Demand Savings*. Atlanta: ASHRAE.

ASHRAE. 2013. ANSI/ASHRAE Standard 55. *Thermal Environmental Conditions for Human Occupancy.* Atlanta: ASHRAE.

Azar, E. and C.C. Menassa. 2012. A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings. *Energy and Buildings* 55:841–63.

Bordass, B., R. Cohen, and J. Field. 2004. Energy performance of non-domestic buildings—Closing the credibility gap. *International Conference on Improving Energy Efficiency in Commercial Buildings,* Frankfurt, Germany.

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Table 4. Four Different Cases to Validate a Derived Occupancy Schedules and the Plug-Load Consumption Equation

Input Parameters	Case 1	Case 2	Case 3	Case 4
Occupancy schedule	Default	Averaged occupancy schedule	Actual occupancy schedule	Calculated occupancy schedule
Plug-load consumption	Default	Averaged schedule	Plug-load consumption equation	Plug-load consumption equation

Table 5. CVRMSE Results for Four Cases

Input Parameters	Case 1	Case 2	Case 3	Case 4
CVRMSE	48 %	14%	10%	4%

Bordass, B., R. Cohen, M. Standeven, and A. Leaman. 2011. Assessing building performance in use 3: Energy performance of probe buildings. *Building Research and Information* 29:114–28.

Clevenger, C.M. and J. Haymaker. 2006. *The impact of the building occupant on energy modeling simulations.* Montreal, QC: International Society for Computing in Civil and Building Engineering.

DesignBuilder. 2014. DesignBuilder version 4. DesignBuilder Software, Ltd. www.designbuilder.co.uk.

DoE. 2012. EnergyPlus engineering reference. U.S. Department of Energy. www.energyplus.gov.

EIA. 2011. Figure 1.0 Energy Flow. Washington, DC: Energy Information Administration. www.eia.gov/totalenergy/data/annual/pdf/sec1_3.pdf.

Fabi, V., R.V. Andersen, S. Corgnati, B.W. Olesen, and R.E. Wener. 2012. Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models. *Building and Environment* 58:188–98.

Gao, X., and D. Zhang. 2011. Analysis of the rule of influence of hotel occupancy ratio on energy consumption. *2011 International Conference on Electric Technology and Civil Engineering*. 1009–14.

Hoes, P., J.L.M. Hensen, M.G.L.C. Loomans, B. Vries, and D. Bourgeois. 2009. User behavior in whole building simulation. *Energy and Buildings* 41:295–302.

Kim, Y.S. 2014. Calibration of building energy simulations with occupancy and plug-load schedules derived from metered building electricity consumption. Doctoral dissertation, Pennsylvania State University, University Park, PA.

Martani, C., D. Lee, R. Robinson, R. Britter, and C. Ratti. 2012. ENERNET: Studying the dynamic relationship between building occupancy and energy consumption. *Energy and Buildings* 47:584–91.

Meneze, A.C., A. Cripps, D. Bouchlaghem, and R. Buswell. 2012. Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap. *Applied Energy* 97:355–64.

Page, J., D. Robinson, N. Morel, and J.-L.Scartezzini. 2008. A generalized stochastic model for the simulation of occupant presence. *Energy and Buildings* 40:83–98.

Tavares, P.F., and A.M. Martins. 2007. Energy efficient building design using sensitivity analysis—A case study. *Energy and Buildings* 39:23–31.