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AN ENERGYPLUS WHOLE BUILDING ENERGY MODEL CALIBRATION METHOD FOR OFFICE BUILDINGS USING OCCUPANT BEHAVIOR DATA MINING AND EMPIRICAL DATA

Khee Poh Lam[1], Jie Zhao[1], Erik B. Ydstie[2], Jason Wirick[3], Meiwei Qi[4], Jihyun Park[1]
[1]Center for Building Performance and Diagnostics, Carnegie Mellon University, Pittsburgh, PA
[2]Department of Chemical Engineering, Carnegie Mellon University, Pittsburgh, PA
[3]Phipps Conservatory and Botanical Gardens, Pittsburgh, PA
[4]School of Architecture, Tsinghua University, Beijing, China

ABSTRACT

This paper proposes a method comprising procedures to calibrate an EnergyPlus whole building energy model. An occupant behavior data mining procedure is developed and tested in an office building. Workday occupancy schedules are generated by mining the office appliance energy consumption data. Hourly and monthly power, energy, and temperature data are collected and used for lighting, equipment and HVAC systems energy performance calibration. The result shows a 1.27% mean bias error for the total annual energy use intensity. The proposed calibration method provides a scientific and systematic framework to conduct high accuracy EnergyPlus model calibration.

INTRODUCTION

Building energy modeling (BEM) is increasingly being used in the building industry. Currently, one main driver of BEM is to demonstrate code and standard compliances for green building certification purposes. However, the value of a BEM model can potentially extend beyond that. It can be used to optimize design solutions during the design stage as well as advanced model-based building controls and life-cycle performance analysis during the operation stage (Zhao et al. 2014).

There are many reasons why the value of the BEM model is under appreciated. A case study on LEED buildings showed significant disparities between modeling result and measured energy performance (Turner, Frankel, and Council 2008). BEM model calibration is the approach to modify and adapt the design case BEM model based on measured data to generate an updated BEM model that can accurately reflect the actual building operation performance. Model calibration is crucial to add value to the BEM model by extending its function to the building life cycle.

ASHRAE Guideline 14-2002 defines the evaluation criteria to calibrate BEM models. According to the Guideline, monthly and hourly data, as well as spot and short-term measurements can be used for calibration. Mean Bias Error (MBE) and Coefficient of Variation of the Root Mean Squared Error (CVRMSE) are used as evaluation indices. “The computer model shall have an MBE of 5% and a CVRMSE of 15% relative to monthly calibration data. If hourly calibration data are used, these requirements shall be 10% and 30%, respectively.” (ASHRAE 2002)

International Performance Measurement and Verification Protocol (IPMVP) Volume III stipulates the procedures of calibrating an “as-built” energy model. Model inputs such as weather input, occupant and equipment schedules, and system parameters such as equipment performance curves or system control, have to be calibrated based on the “best measured information available”. (EVO 2003)

Reddy noted that the empirical BEM model calibration method is a “manual, iterative, and pragmatic intervention” (Reddy 2006). Several studies have proposed and demonstrated systematic and structuralized empirical BEM model calibration methods. Raftery et al. developed a method to iteratively update an EnergyPlus (Crawley et al. 2001) model with empirical data. Human resources interviews, personnel counts, and multiple day/night occupancy survey were conducted to update the occupancy schedule in the design case BEM model (Raftery, Keane, and Costa 2011). Kandil and Love proposed and demonstrated a method to calibrate an EnergyPlus model for a school building. Empirical data were collected through interview, site visit, long-term measurement, and spot measurement (Kandil and Love 2013). Other studies also demonstrated the feasibility of various empirical BEM model calibration methods (Pedrini, Westphal, and Lamberts 2002, Raftery, Keane, and O’Donnell 2011, Pan, Huang, and Wu 2007).

Current empirical BEM model calibration methods often use a "walk through audit" approach to determine occupancy schedule. This approach is necessary but may not be scientifically accurate. It is well acknowledged that occupant presence and behavior have significant impact on building energy consumptions (Dong and Lam 2011, Haldi and Robinson 2011, Page et al. 2008, Zhao et al. 2013, Zhang et al. 2012). It is necessary to develop a scientific and practical method to generate occupancy schedules for BEM models.

This study proposes and demonstrates an empirical calibration method for the EnergyPlus model of a medium size office building in Pittsburgh Pennsylvania. Occupancy schedules are learned by using data mining algorithms from office appliance energy consumption data. 2013 Actual Meteorological Year (AMY) weather data (DOE 2013), monthly energy meter data and hourly Building Automation System (BAS) data are collected and used for the calibration. An inverse calibration procedure is developed for lighting and equipment schedule and power density calibration. HVAC system parameters and controls are calibrated with hourly zone temperature data and monthly energy data. The method comprising several procedures is introduced, and results are presented and discussed.

METHODS

Overview

Figure 1 illustrates the proposed EnergyPlus whole building energy model calibration method. The purpose of the calibration is to ensure the energy model can generate energy use result close to the measured values using actual inputs, including weather, occupancy schedule, lighting and equipment schedules and densities, and the HVAC system parameters and controls. The baseline model is created based on ASHRAE 90.1 Appendix G (ASHRAE 2007). The proposed design case model is created based on design drawings and specifications, with the same input assumptions as the baseline model for fair comparison purpose.

The first step of the calibration is to replace the TMY3 weather file (DOE 2013) with real weather information in accordance with the actual data collection period. The second step is to replace the design case occupancy schedules with the "real (or learned)" occupancy schedules generated from the data mining study. The third step is to calibrate the interior lighting, interior equipment, exterior lighting, and exterior equipment power densities and schedules with monthly and hourly energy consumption data with an "inversed calibration method". The fourth and final step is to calibrate HVAC system parameters and controls. It is important that the HVAC system should be calibrated after other input parameters and systems are calibrated, because most of these inputs will influence the HVAC system performance (such as internal loads and "disturbances"). The calibration acceptance criterion for each calibration step are MBE<5% and CVRMSE<15% for monthly data calibration, and MBE<10% and CVRMSE<30% for hourly data calibration, respectively. MBE and CVRMSE are defined by Equation (1 - 3).

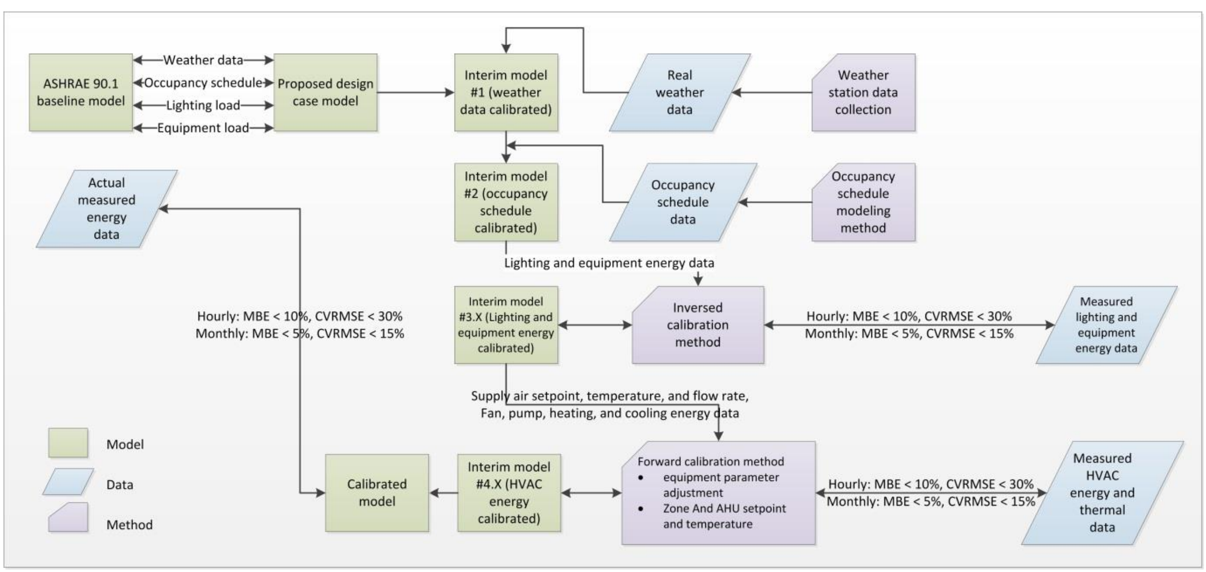

Figure 1 EnergyPlus whole building energy model calibration method

$$\text{MBE} = \frac{\sum_{i=1}^{N_s}(y_i - \hat{y}_i)}{\sum_{i=1}^{N_s} y_i} \quad (1)$$

$$\bar{Y}_S = \frac{\sum_{i=1}^{N_s} y_i}{N_s} \quad (2)$$

$$\text{CVRMSE}_{(S)} = \frac{\sqrt{\sum_{i=1}^{N_s}((y_i - \hat{y}_i)^2/N_s)}}{\bar{Y}_S} \quad (3)$$

where, y_i is the measured data; $\hat{y}_i$ is the simulated data; N_s is the sample size; and $\bar{Y}_S$ is the sample mean of measured data.

Test-bed building model and data collection

A 2-story 2,262m^2 office building – Phipps Center for Sustainable Landscapes (CSL) in Pittsburgh, Pennsylvania is selected as a test-bed (Phipps 2012) to demonstrate the calibration method. The building baseline and proposed design case energy models are created with DesignBuilder and EnergyPlus programs, as seen in Figure 2 (Zhao et al. 2012). The EnergyPlus model is then linked with Matlab/Simulink to simulate the actual control settings (Zhao, Lam, and Ydstie 2013). The CSL building construction was completed in December 2011 and was officially occupied in spring 2012. For this study, hourly system operation, indoor environmental, and energy data have been collected from the BAS since August 2013. Monthly energy data from utility bills are available since January 2013.

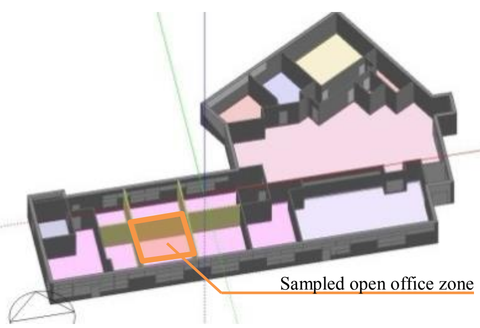

Figure 2 Model view of the CSL building

Weather information

2013 AMY weather data of Pittsburgh International Airport is used to replace the TMY weather file used in the design case energy model.

Occupancy schedule data mining

The occupancy schedules are derived by mining the electricity data of the office appliances. A field experiment was conducted in the CSL building from September to December 2013. Figure 3 shows the data collection system architecture. Occupancy status "ground truth" data is collected with Fitbit® Flex™ (Fitbit 2014) pedometer with its Bluetooth Dongle, which receives signal every 9 seconds when it is within a 6-meter range, and with a computer idle-time logging program installed in the participants' computers, which records the time that neither keyboard nor mouse is used within 5 minutes.

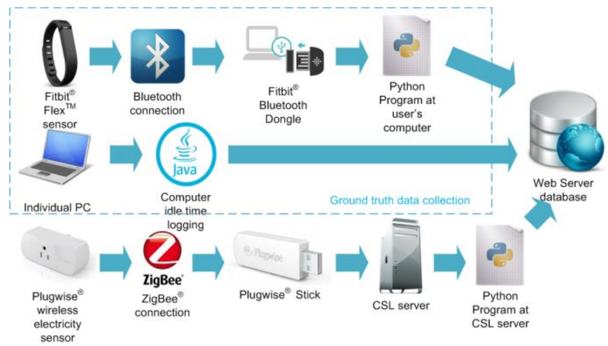

Figure 3 Occupancy ground truth and training data collection system architecture

Plugwise® wireless smart meters (Plugwise 2013) are used to collect individual office appliance electricity data for each occupant in 5-minute time interval, including laptop computers, task lights, computer monitors, personal fans, chargers, and printers. This data is used as training data to predict occupancy status. Both "ground truth" and electricity data are collected with Python (Python 2012) programs and stored in an online database.

Support Vector Regression (SVR), Linear Regression (LR), and Locally Weighted Learning (LWL) are tested as candidate algorithms to build occupancy schedule models (Zhao and Lam 2012, Zhao et al. 2013).

Lighting and equipment system calibration

An inverse calibration procedure is developed for lighting and equipment power density and schedule calibration. A Python program is written to automate part of the process (solid lines) in Figure 4.

The method follows 4 steps. (1) Assumed power density and hourly schedule are fed into the EnergyPlus model. (2) EnergyPlus hourly output power consumptions are compared with the actual measured data to meet the MBE and CVRMSE criterion. (3) If the criteria are not met, an hourly inverse calibration factor, as calculated by taking the hourly measured power (PD), divided by the simulated power density (PD-hat), will be multiplied by the hourly schedule and generate an 8760-hours schedule including weekdays, weekends, and national holidays to be directly used in the next iteration of EnergyPlus simulation. If the criteria are met, the program will check the monthly MBE and CVRMSE criteria; (4) The monthly energy simulation data will be compared with monthly metered data to calibrate the total lighting and equipment power. The calibrated total power densities are calculated by multiplying the calibration factor E/E-hat by the assumed simulation lighting and equipment power densities. Some manual effort is involved in the process, represented by the dash lines in Figure 4. Daylight responsive control is implemented in the CSL building, so during times when daylight provided sufficient illuminance, the lighting electricity is reduced. Therefore, the electrical lighting electricity use and the EnergyPlus lighting schedule input (illuminance demand) are no longer correlated during those periods. Two steps are performed to solve this issue. (1) The daylight harvesting system is disabled in the model to get the total power consumption value without daylight contribution; (2) the difference between the actual and the daylight-disabled power consumption is derived and used to adjust the actual schedule.

Exterior lighting is also controlled by daylight sensor, so the monthly schedule is also adjusted according to astronomical clock (number of daylight hours are taken into account).

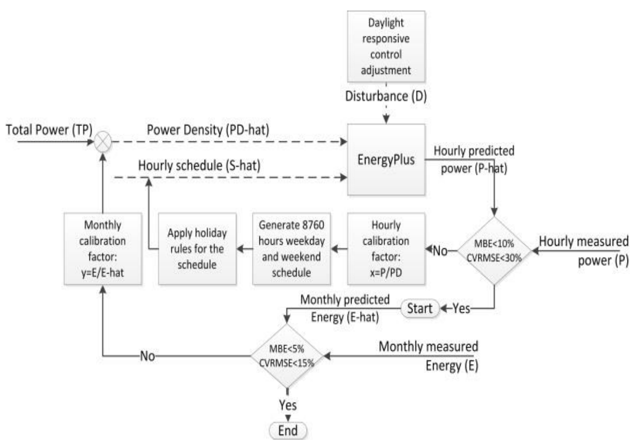

Figure 4 The inverse calibration procedure

HVAC system calibration

A central air handling unit (AHU) with a geothermal heat pump system is used to heat, cool, and ventilate the CSL building. The parameters of key HVAC equipment are first calibrated based on installed manufacturer datasheet and testing data. Table 1 illustrates the calibrated EnergyPlus model HVAC input parameters.

Zone control setpoints are then calibrated based on measured hourly data for both heating and cooling modes. Simulated monthly HVAC energy consumption by end use is then compared with metered data.

Table 1 HVAC equipment parameter calibration

	EnergyPlus model input
AHU supply fan	Maximum Flow Rate: (5.85 m^3/s)
	Pressure Rise (Total): 1740.595 (Pa) Equation (4-7)
	Motor Efficiency: 0.813
Geothermal heat pump	Rated Cooling Capacity: 123320.8 (W)
	Rated Heating Capacity: 104450.5 (W)
Geothermal Heat Exchanger	Bore Hole Radius: 0.073 (m)
	Bore Hole Length: 155.45 (m)
	Ground Thermal Heat Capacity: 2250000 (J/m3-K)
	Ground Thermal Conductivity: 2.86 (W/m-K)

RESULTS AND DISCUSSION

Occupancy schedule modeling result

The occupancy schedule modeling procedure is tested in the CSL building. 11141 valid data instances of 10 valid participants are collected over 49 workdays out of 84 total days of the measurement, as shown in Figure 5.

With 95% confidence interval, the margin of error of the mean value for the 49 workday schedules is less than 10%. However, when comparing the mean value of different days of a week, variations are bigger. Figure 6 shows the different weekday ground truth mean value of the occupancy schedule. In general, Tuesdays and Wednesdays have relatively higher occupancy rate. Fridays have the lowest occupancy rate. The proposed design case occupancy assumption is also shown in Figure 6. The average weekday occupancy difference between the assumed and the actual weekday schedules is 43.18%.

The baseline data mining training dataset includes 14111 instances of 5-minute power consumption data of all the 28 appliances for the 10 occupants.

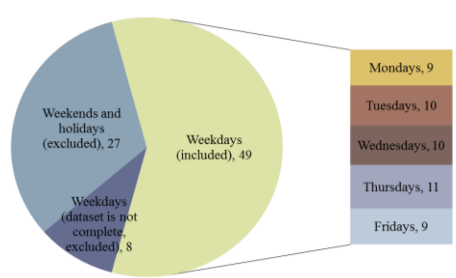

Figure 5 Total days of the study

Table 2 shows the correlation coefficient, relative absolute error, and computation time of the 3 algorithms. With p=0.05 two-tailed paired T-test, LR and SVR have no significant differences in correlation coefficient and relative absolute error. But LR is chosen for the learning algorithm due to its shorter computation time.

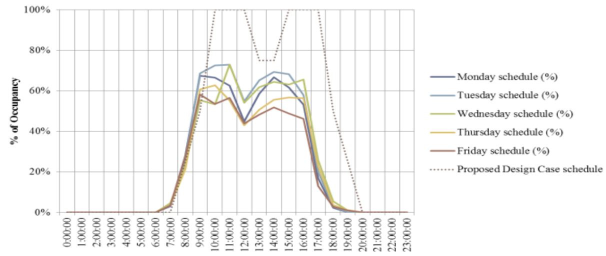

Figure 6 Comparison of the weekday ground truth mean value and the proposed design case assumption

Table 2 Occupancy schedule data mining comparison results with different algorithms

	SVR	LR	LWL
Correlation coefficient	0.95	0.95	0.87*
Relative absolute error	20.13%	21.76%	37.19%*
Computation time (s)	1706.85	0.19	0.01

*LWL has significantly lower performance than LR and SVR.

The first baseline mining study has 28 attributes (number of appliances) in the dataset. For practical application, it would be useful to identify key attributes and do feature selection to reduce the number of attributes. The attributes can be classified into 3 categories: computers, task lights, and others (personal fans, computer screens, chargers, and printers). The total weights of the 3 categories are 38.34%, 24.30%, and 37.37%, respectively. As all the occupants have computers, this attribute is selected as a key attribute to do the second data mining study using LR algorithm with 11 attributes (computer power consumptions).

In the test-bed building, each occupant has a power strip. All the appliances are plugged into the power strip, so another practical way to reduce the number of attributes is to study the energy consumptions by power strip (by person) instead of by individual appliance. The third data mining study is conducted using LR algorithm with 10 attributes (total power consumptions per person).

Table 3 shows the number of attributes, correlation coefficient and relative absolute error with different attributes. With p=0.05 two-tailed paired T-test, no statistical significant difference is found among the 3 mining methods. The methods can all be used for learning occupancy schedule depending on the data availability.

Figure 7 shows the occupancy schedule comparison among the ground truth value and the predicted value using the 3 different attributes on a typical weekday. It is noted that "by computer" predictions tend to have larger variations, "by person" predictions tend to underestimate, and "by appliances" predictions are generally in between the other 2 prediction values.

Table 3 Occupancy schedule data mining comparison results with different attributes

	By appliances	By computer	By person
# of Attributes	28	11	10
Correlation coefficient	0.95	0.94	0.92
Relative absolute error	21.76%	22.01%	31.07%

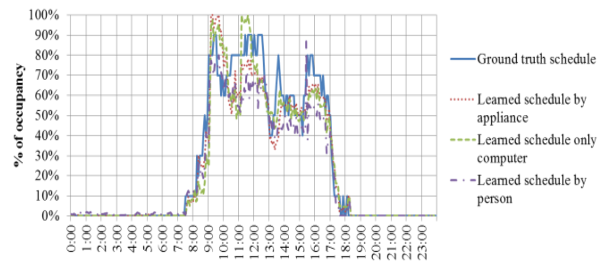

Figure 7 Occupancy schedule prediction comparison

Lighting and equipment calibration result

Two sample weeks of hourly data in both August and December, 2013 are calibrated. The inverse calibration method is used.

Figure 8 shows the interior equipment hourly power consumption calibration results in one weekday and one weekend.

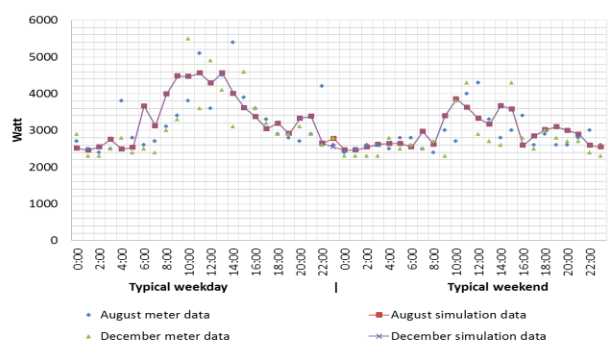

Figure 8 Interior equipment hourly power output

Unlike interior equipment, interior and exterior lighting power consumptions between August and December are different mainly due to the daylight-responsive control systems. Additional steps are used to solve this problem, as discussed in the "METHODS" section. Exterior equipment power consumptions have relatively regular schedules. It has similar operation schedules for both weekdays and weekends in December and August.

Table 4 shows the hourly and monthly MBEs and CVRMSEs for interior equipment, interior lighting, exterior equipment, and exterior lighting. The results are all within the ASHRAE Guideline 14-2002 thresholds.

Table 4 Lighting and equipment energy calibration statistical results

	Interior equipment	Interior lighting	Exterior lighting	Exterior equipment
MBE (hourly - weekdays)	-0.55%	1.94%	-2.62%	0.51%
MBE (hourly – weekends/holidays)	-0.55%	-0.23%	-2.62%	0.51%
MBE (monthly)	4.84%	-0.03%	0.01%	1.06%
CVRMSE (hourly - weekdays)	21.49%	29.32%	11.53%	22.08%
CVRMSE (hourly – weekends/holidays)	14.68%	29.53%	11.53%	22.08%
CVRMSE (monthly)	14.97%	10.29%	3.13%	2.99%

HVAC system calibration result

HVAC zone air temperature setpoints are calibrated based on the available measured air temperature hourly data from September to December 2013. Compared to the proposed design case assumptions, the actual implemented setpoint band is much narrower, which typically indicates higher energy consumption. Figure 9 is an example of the setpoint comparison between the proposed design case and the calibrated models in the heating mode. Figure 10 shows the hourly air temperature data of measured and calibrated model corresponding to outdoor temperature for one month in the 1st floor open office of the CSL building, as shown in the highlighted area of Figure 2. The scattered plot suggests a generally consistent match between the measured data and the calibrated model. Some inconsistency occurred when the outdoor temperature is above 16 °C, where the measured data has relatively lower value (21°C) but the model has higher value (23 – 24°C). A possible reason for the discrepancy is the passive mode setting difference between the real HVAC system and the EnergyPlus model. Further investigation is needed. Table *5* shows the zone temperature calibration results for the 4 months.

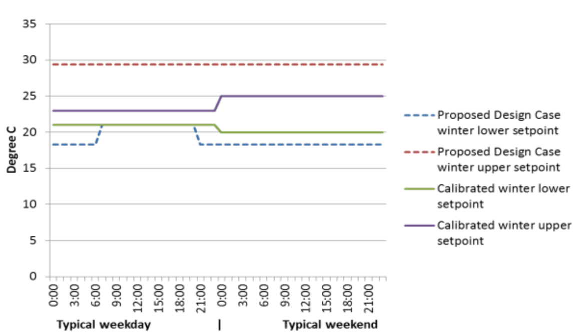

Figure 9 Heating mode zone air temperature setpoints

Monthly HVAC energy consumption calibration results are shown in Figure 11. The total energy consumption of the AHU is metered for the first 3 months of the study period, and then a separated meter is installed to measure AHU supply fan energy consumption. As shown in Table *5*, the MBE of the monthly HVAC energy between the calibrated model and the actual meter data is 0.10%, and the CVRMSE is 15.00%.

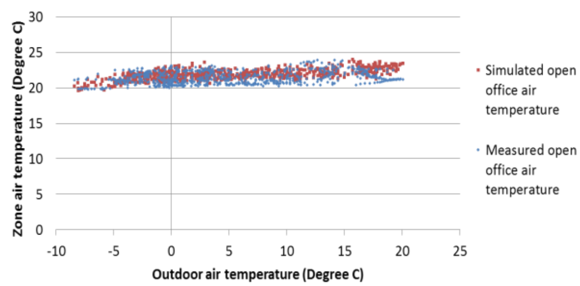

Figure 10 Heating mode zone air temperature

Table 5 HVAC system calibration result

	MBE	CVRMSE
September (hourly temperature)	-1.12%	6.29%
October (hourly temperature)	4.15%	8.02%
November (hourly temperature)	6.04%	8.21%
December (hourly temperature)	-1.83%	4.42%
Full year (monthly energy)	0.10%	15.00%

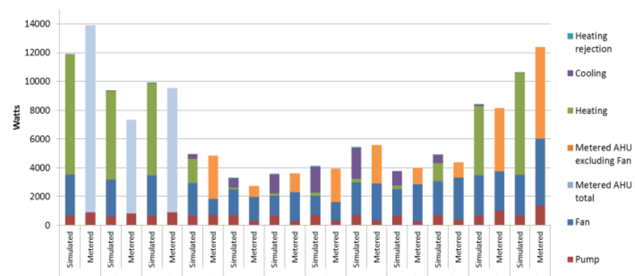

Figure 11 Monthly HVAC energy consumption calibration result

Total building energy calibration result

Figure 12 shows the total annual energy use intensity (EUI) comparison among the AHSRAE 90.1-2007 baseline model, proposed design case model, calibrated model, and the actual metered data of the CSL building. The blue line shows the metered annual photovoltaic energy generation intensity. Table 6 shows the MBEs and CVRMSEs of the 3 models compared to the actual metered data for the year of 2013. The final calibrated model has an MBE of 1.27% and a CVRMSE of 6.01%. The model can be considered as well calibrated.

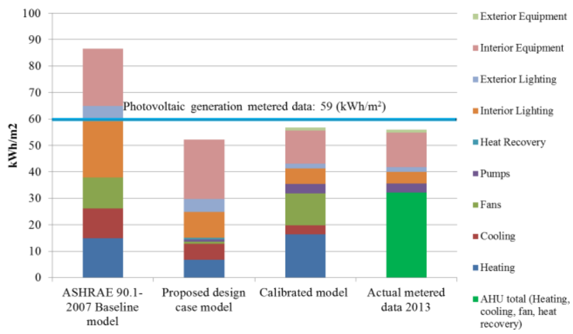

Figure 12 Total annual EUI comparison

Table 6 Errors of total annual EUI compared with measured data for the 3 models

	Baseline	Design	Calibrated
MBE	35.30%	-7.29%	1.27%
CVRMSE	79.88%	93.40%	6.01%

It should also be noted that there are significant variations between the design case assumptions and the actual building operations. The design case model uses the same lighting and equipment power densities and schedules as in the ASHRAE baseline model for comparison purposes. But the actual building lighting and equipment power density is much less than the baseline assumptions. The HVAC energy consumption of the design case model uses night setback strategies to save energy. But the actual building setpoint schedule is more stringent, as seen in Figure 9. This control strategy difference causes a big difference in HVAC energy consumption. The resulting effect is that the MBE of total energy use intensity of the case model compared to the measured data is -7.29%, and the CVRMSE is 93.40%.

CONCLUSION

This paper demonstrates an EnergyPlus model calibration method with occupancy schedule data mining and empirical data in an office building. The occupancy schedule data mining study is novel, practical and effective for office buildings. The lighting and equipment inverse calibration procedure and the HVAC system calibration procedure are also demonstrated in the test-bed building. The overall method provides a scientific and systematic framework to conduct high accuracy EnergyPlus model calibration.

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REFERENCES

ASHRAE. 2002. ASHRAE Guideline 14-2002, Measurement of Energy and Demand Savings. ASHRAE.

ASHRAE. 2007. *Energy Standard for Buildings Except Low-Rise Residential Buildings*. Atlanta, GA: American Society of Heating, Refrigerating and Air Conditinging Engineering, Inc.

Crawley, Drury B., Linda K. Lawrie, Frederick C. Winkelmann, W.F. Buhl, Y. Joe Huang, Curtis O. Pedersen, Richard K. Strand, Richard J. Liesen, Daniel E. Fisher, Michael J. Witte, and Jason Glazer. 2001. "EnergyPlus: creating a new-generation building energy simulation program." *Energy and Buildings*:319-331.

DOE. *Weather Data for Simulation* 2013. Available from http://apps1.eere.energy.gov/buildings/energyplus/weatherdata_simulation.cfm.

Dong, Bing, and Khee Poh Lam. 2011. "Building energy and comfort management through occupant behaviour pattern detection based on a large-scale environmental sensor network." *Journal of Building Performance Simulation* no. 4 (4):359-369.

EVO. 2003. International Performance Measurement & Verification Protocol (IPMVP) Volume III: Concepts and Options for Determining Energy Savings in New Construction.

Fitbit. *Fitbit Flex* 2014. Available from http://www.fitbit.com/.

Haldi, Frédéric, and Darren Robinson. 2011. "The impact of occupants' behaviour on building energy demand." *Journal of Building Performance Simulation* no. 4 (4):323-338. doi: 10.1080/19401493.2011.558213.

Kandil, Alaa-Eldin, and James A. Love. 2013. "Signature analysis calibration of a school energy model using hourly data." *Journal of Building Performance Simulation*:1-20. doi: 10.1080/19401493.2013.838608.

Page, J., D. Robinson, N. Morel, and J.-L. Scartezzini. 2008. "A generalised stochastic model for the

simulation of occupant presence." *Energy and Buildings* no. 40:83-98.
Pan, Yiqun, Zhizhong Huang, and Gang Wu. 2007. "Calibrated building energy simulation and its application in a high-rise commercial building in Shanghai." *Energy and Buildings* no. 39 (6):651-657.
Pedrini, A., F. S. Westphal, and R. Lamberts. 2002. "A methodology for building energy modelling and calibration in warm climates." *Building and Environment* no. 37 (8–9):903-912.
Phipps. *Center for Sustainable Landscapes* 2012. Available from http://phipps.conservatory.org/project-green-heart/green-heart-at-phipps/center-for-sustainable-landscapes.aspx.
Plugwise. 2014. *Circle* 2013 [cited April 27 2014]. Available from http://www.plugwise.com/idplugtype-b/circle.
Python. 2012. *Python Programming Language – Official Website*, January 20 2012 [cited January, 20 2012]. Available from http://python.org/.
Raftery, Paul, Marcus Keane, and Andrea Costa. 2011. "Calibrating whole building energy models: Detailed case study using hourly measured data." *Energy and Buildings* no. 43 (12):3666-3679.
Raftery, Paul, Marcus Keane, and James O'Donnell. 2011. "Calibrating whole building energy models: An evidence-based methodology." *Energy and Buildings* no. 43 (9):2356-2364.
Reddy, Agami T. 2006. "Literature review on calibration of building energy simulation programs: uses, problems, procedures, uncertainty, and tools." *ASHRAE transactions*:226-240.
Turner, Cathy, Mark Frankel, and US Green Building Council. 2008. *Energy performance of LEED for new construction buildings*: New Buildings Institute Washington, DC.
Zhang, Rui, K.P. Lam, Yun-Shang Chiou, and Bing Dong. 2012. "Information-theoretic environment features selection for occupancy detection in open office spaces." *Building Simulation* no. 5:179-189.
Zhao, Jie, and Khee Poh Lam. 2012. "Influential factors analysis on LEED building markets in U.S. East Coast cities by using Support Vector Regression." *Sustainable Cities and Society* no. 5 (0):37-43.
Zhao, Jie, Khee Poh Lam, Omer T. Karaguzel, and Samira Ahmadi. 2012. Design-Build-Operate Energy Information Modeling (DBO-EIM) for Green Buildings: Case Study of a Net Zero Energy Building. In *the 1st IBPSA Asia conference*. Shanghai, China.
Zhao, Jie, Khee Poh Lam, and B Erik Ydstie. 2013. EnergyPlus Model-based Predictive Control (EPMPC) by Using Matlab/Simulink and MLE+. In *13th International Conference of the International Building Performance Simulation Association (IBPSA)*. Chambery, France.
Zhao, Jie, Khee Poh Lam, B. Erik Ydstie, and Omer T. Karaguzel. 2014. "EnergyPlus model-based predictive control within design–build–operate energy information modelling infrastructure." *Journal of Building Performance Simulation*:1-14. doi: 10.1080/19401493.2014.891656.
Zhao, Jie, Ray Yun, Bertrand Lasternas, Haopeng Wang, Khee Poh Lam, Azizan Aziz, and Vivian Loftness. 2013. Occupant Behavior And Schedule Prediction Based on Office Appliance Energy Consumption Data Mining. In *CISBAT 2013 Conference - Clean Technology for Smart Cities and Buildings*. Lausanne, Switzerland: EPFL.