Proceedings of the 2016 Winter Simulation Conference
T. M. K. Roeder, P. I. Frazier, R. Szechtman, E. Zhou, T. Huschka, and S. E. Chick, eds.

QUANTIFYING THE IMPACT OF UNCERTAINTY IN HUMAN ACTIONS ON THE ENERGY PERFORMANCE OF EDUCATIONAL BUILDINGS

Elie Azar
Ahmed Al Amoodi

Department of Engineering Systems and Management
Masdar Institute
PO Box 54224
Abu Dhabi, UAE

ABSTRACT

Actions taken by building occupants and facility managers can have significant impacts on building energy performance. Despite the growing interesting in understanding human drivers of energy consumption, literature on the topic remains limited and is mostly focused on studying individual occupancy actions (e.g., changing thermostat set point temperatures). Consequently, the impact of uncertainty in human actions on overall building performance remains unclear. This paper proposes a novel method to quantify the impact of potential uncertainty in various operation actions on building performance, using a combination of Monte Carlo and Fractional Factorial analyses. The framework is illustrated in a case study on educational buildings, where deviations from base case energy intensity levels exceed 50 kWh/m^2/year in some cases. The main contributors to this variation are the thermostat temperature set point settings, followed by the consumption patterns of equipment and lighting systems by occupants during unoccupied periods.

1 INTRODUCTION

In most developed countries, the building sector accounts for more than one third of overall demands for energy (IEA 2015). This has motivated significant research efforts to develop energy efficient building design and technologies (e.g., building materials, heating and cooling systems, lighting fixtures, and appliances), as well as energy management and automation systems (ASHRAE 2011; Granderson et al. 2011; Levine et al. 2007). Despite the large-scale adoption of such systems, buildings consistently consume more energy than the predictions made by engineers when designing those buildings. Discrepancies between actual and predicted energy levels are in fact commonly observed, reaching up to 100% in some cases of buildings with high electric loads such as research facilities (Turner and Frankel 2008). In order to address or mitigate the mentioned performance gap, there is a growing interest in literature to understand key drivers of building energy consumption, and consequently devise proper and targeted energy conservation strategies. Literature on the topic is particularly divided between investigating building design related drivers of energy consumption on the one hand, and operation or human related parameters on the other.

Stating with the first, various studies investigate the influence of technical or physical building parameters on energy performance (Afshari et al. 2014; Wang et al. 2011; Lam et al. 2008; Lee and Chen 2008). Examples of parameters include building envelope and thermal characteristics (e.g., U-values, infiltration rates), chiller Coefficient of Performance (COP), air flow rates, window glazing characteristics, to name a few. For instance, Lam et al. (2008) conducted a sensitivity on 10 key building parameters to identify their impact on energy consumption levels. Results indicate that Chiller COP and lighting intensity have the highest influence for the particular buildings under study. Similarly, Afshari et al. (2014) studied both the impact of building design and air conditioning settings on building performance of one commercial and one residential building. They evaluated retrofit options such as wall and roof insulations, glazing, chiller COP, envelope air-tightness, and cooling set-point temperatures. Their study concluded that changing cooling temperature set-point by a couple of degrees is extremely effective with the next best factor being the enhancement of wall insulation. Other similar studies have evaluated influential building design parameters and used them to propose building retrofitting options (AlAwadhi et al. 2013; Yalcintas 2008; Tavares and Martins 2007).

On the other hand, recent research efforts have focused on quantifying the impact of human actions on building energy consumption (Azar and Menassa 2014, 2012; Peschiera et al. 2010; Sanchez et al. 2007). For instance, Azar and Menassa (2012) studied the impact of occupancy-related parameters on energy models of office buildings. Parameters included equipment and lighting energy use patterns, cooling and heating set points, hot water consumption, and building schedule. Results indicate that occupancy operational parameters have a significant influence on the results of building energy models, confirming the need to better account for them during the design phase. As another example, Sanchez et al. (2007) studied the energy consumption patterns of plug-load usage in commercial buildings. They found that occupants consistently leave more than half of equipment in their buildings running during unoccupied periods, resulting in unnecessary use of energy.

In summary, the interest in human and operation related drivers of energy use has increased over the past years. However, important gaps can be found in the literature, which motivate the need for this work. First, studies on human drivers of energy use are in general scarce in literature, when compared to studies on parameters related to building design and systems' characteristics. Consequently, the true impact of human actions on overall building performance remains understudied and unclear. Second, the few studies on the topic are mostly focused on commercial or residential buildings; other building types such as educational buildings, which can have different energy consumption patterns, have not been specifically studied. Finally, and most importantly, existing studies have typically evaluated the impact of parameters on energy consumption individually (i.e., single parameter effect). As a result, it is currently unclear how simultaneous uncertainty in various parameters, can affect energy consumption and put the efficient performance of buildings at risk.

This study addresses the aforementioned gaps in the literature by proposing a building modeling and analysis framework that evaluates the impact of uncertainty in human actions on building energy performance. More specifically, the framework quantifies the magnitude of the performance risk when accounting for a certain randomness in how people (e.g., building occupants and facility managers) operate and control various building systems. It is important to highlight that this study does not investigate particular drivers of people actions (e.g., economic, social, psychological, etc.). It rather focuses on how uncertainty in the operation of various building systems affects energy consumption levels.

2 METHODOLOGY

The proposed methodology is illustrated in Figure 1 and detailed in the next sub-sections. While the method is general, it is illustrated through an application on typical educational buildings located in Abu Dhabi, United Arab Emirates (UAE). Two types of typical, or prototype, buildings are considered, namely an office and a classroom building.

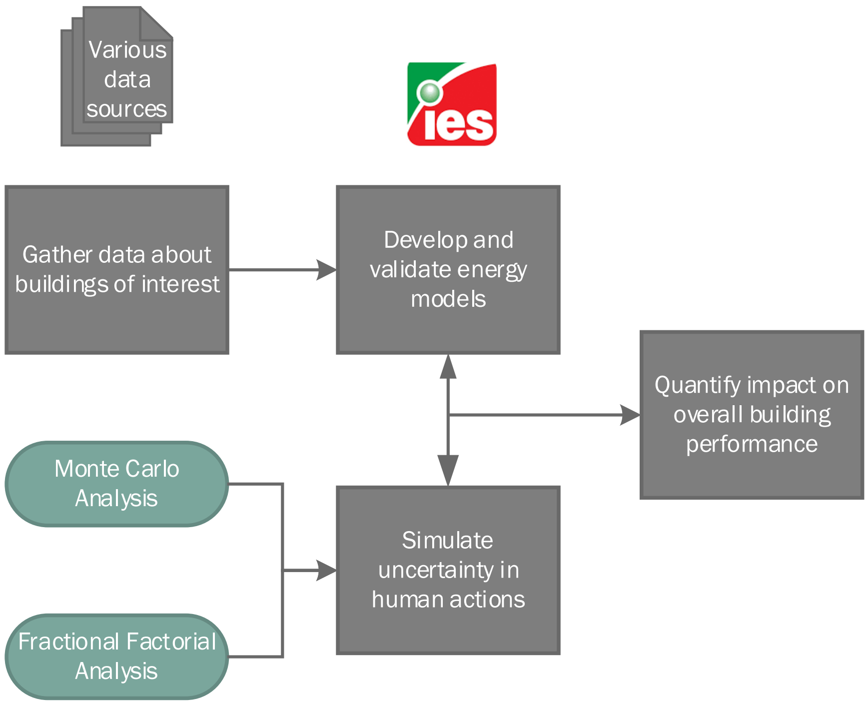

Figure 1: Proposed methodology.

2.1 Data Gathering and Model Development

The first step in the methodology is to gather information about the typical office and classroom buildings considered in this study. Modeling such typical, or prototype, buildings is a common practice in energy modeling studies, ensuring that the results of the study are general and not limited to specific individual buildings (Azar and Menassa 2014, 2012). Therefore, data was gathered from a multitude of sources to assemble characteristics of typical educational buildings in the UAE. The sources included a report prepared for a governmental entity in the UAE (Arup 2010), a local building benchmarking effort (Afshari et al. 2014), building standards such as ASHRAE (2013), as well as other studies on the development of prototype commercial buildings (Deru et al. 2011; Gowri et al. 2009). Examples of the collected information are presented in Table 1.

Following data gathering, BPS models are developed to emulate the performance of the considered typical office and classroom buildings. The BPS software used in this study is the IES-VE software (DOE 2011), where two models are developed, one for the office and another for the classroom building. In general, BPS models require inputs regarding building geometry, construction material and building systems characteristics, building and end-use schedules, as well as outdoor weather conditions corresponding to the location of the modeled buildings. Therefore, the data from Table 1 are used to define these parameters for the modeled office and classroom buildings. As for the weather data, by setting the location of the buildings in IES_VE to Abu Dhabi, UAE, the software automatically fetches local weather data information from meteorological sources. A 3D representation of the models is shown in Figure 2.

Table 1: Typical building characteristics.

Building Characteristic	Values for Office and Classroom Buildings (Respectively)
Floor area	4,982 and 19,592 m^2
Building shape	Square
Number of floors	3 and 2 floors
Window-to-Wall ratio	50 and 33%
People density	18.5 and 3.7 m^2/person
Lighting intensity	10 and 11 W/m^2
Equipment intensity	15 W/m^2
Roof U values	0.53 $W/m^2.K$
Wall U values	1.71 $W/m^2.K$
Air Changes per Hour (ACH)	0.5 ACH
Cooling system type	Packaged air conditioning unit and air-cooled chiller
Air distribution system type	Multizone Variable Air Volume (VAV)
Building, equipment, and lighting schedules	Obtained from ASHRAE (2013), tables 5-J (schedule A) and table G-K, respectively

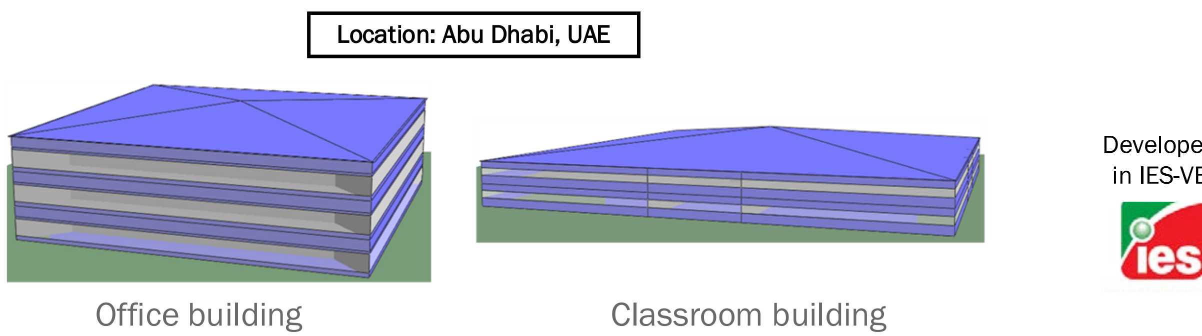

Figure 2: Office and classroom models.

The models are then run, generating base case yearly predictions of 257.1 and 195.1 kWh/m^2/year for the office and classroom buildings, respectively. In order to ensure the validity of the results, they are compared to actual energy consumption levels observed in 4 office and 5 classroom buildings in Abu Dhabi, similar in characteristics to the modeled ones (i.e., type and size). The observed average energy intensities of those buildings are 278.1 and 191.8 kWh/m^2/year, respectively, which are within the 10% acceptable range of error from the predictions of the developed energy models (Azar and Menassa 2012). Furthermore, data was also gathered from a database in the United States (US) (EIA 2003), specifically from 113 buildings of similar characteristics to the modeled ones (i.e., type, size, and weather conditions). Average energy intensities of 278.1 and 191.8 kWh/m^2/year are obtained for the groups of office and classroom buildings, here again falling within the acceptable range for error of 10% from the models' predictions. The developed models in this paper and their predictions are therefore considered valid.

2.2 Simulating Uncertainty in Human Actions

Two parametric variation methods are combined to comprehensively evaluate uncertainty in human actions: Monte Carlo and Fractional Factorial analyses.

2.2.1 Monte Carlo Analysis

Monte Carlo analysis is a method typically used to simulate uncertainty in the input values of a model (e.g., simulation or statistical), and quantify the resulting variability in the outputs of the model (Nguyen and Relter 2015). In this study, the inputs are the parameters of the developed BPS models that reflect how people operate or control various building systems. The output on the other hand is the predicted energy consumption by the models given the changes or uncertainty in input parameters. A total of 60 iterations of the model are performed, as commonly recommended (Nguyen and Relter 2015; Lomas and Eppel 1992). Each iteration is characterized by randomly selected values for the input parameters, generated using uniform distributions. It is important to highlight that while other distributions (e.g., normal, gamma, etc.) can also be used, literature lacks sufficient information on the studied human-related parameters to force a particular distribution when simulating them. Therefore, a uniform distribution was chosen as it avoids making such assumptions and helps capture the overall potential range of variability in these actions. The input parameters studied in this phase, along with their ranges are presented in Table 2.

Table 2: Varied input parameters for the Monte Carlo analysis.

Input Parameters	Variation Range
Equipment use during unoccupied periods	From 0 to 30%, 10% increment
Lighting use during unoccupied periods	From 0 to 30%, 10% increment
Window opening	From 0 to 3 hours, 1 hour increment
Shifting HVAC set point temperatures	From 20 ^{0}C to 24 ^{0}C for occupied periods, 1 ^{0}C increment From 22 ^{0}C to 26 ^{0}C for unoccupied periods, 1 ^{0}C increment
Shifting schedules	From – 2 Hours to + 2 Hours, 1 Hour increment

2.2.2 Fractional Factorial Analysis

Fractional Factorial analysis is a method typically used to evaluate the relative effect of individual, or pairs of input parameters, on overall output values. In this study, the relative effect of individual input parameters is calculated to estimate their contribution to the overall variations in outputs observed in the Monte Carlo Analysis phase. In other words, by calculating main effects of individual parameters and normalizing them (i.e., their sum equals to 1 or 100%), the contributions of inputs such as equipment and lighting use, or HVAC set points, to the observed variability in the energy predictions of the BPS models are estimated. Four input parameters are chosen for this stage, where each is varied between a base case value (i.e., used in the base case model), and a test value (i.e., alternative value used to test the impact of change). The choice of two-level fractional factorial design (i.e., base case and test) is commonly used in building energy research (Langner et al. 2012), and is considered appropriate for this study. A total of 4^2 simulations is therefore required at this stage (combinations of base and test values for 4 parameters). The relative impact of a parameter *x*, R_x, is calculated in the equation 1 below, which is adapted from Langner et al. (2012).

$$R_x = \left|\frac{\bar{\mathrm{Y}}_{\mathrm{x\_base}} - \bar{\mathrm{Y}}_{\mathrm{x\_test}}}{\bar{\mathrm{Y}}}\right| \qquad (1)$$

Where, $\bar{\mathrm{Y}}_{\mathrm{x\_base}}$ is the energy intensity (i.e., output) average for all runs where the value of parameter *x* is at its base level, $\bar{\mathrm{Y}}_{\mathrm{x\_test}}$ the energy intensity average of all runs where parameter *x* is at its test level, and $\bar{\mathrm{Y}}$ the average energy intensity of all runs. Table 3 illustrates the varied parameters with their base and test values.

Table 3: Varied input parameters for the Fractional Factorial analysis.

Input Parameters	Base and Test Values Respectively
Combined lighting and equipment use during unoccupied periods	0 and 30%
HVAC set point temperatures	22 ^{0}C and 20 ^{0}C for occupied periods
Window opening	24 ^{0}C and 22 ^{0}C for unoccupied periods
Shifting schedules	0 and – 2 hours

3 RESULTS

The results of the Monte Carlo analysis are shown in Figure 3, illustrating the spread of the energy intensities for the 60 iterations of the office and classroom models. Each circle represents the output of one run, more specifically the energy intensity predicted by the models for a random variation of the input parameters of Table 2. A low spread of the circles indicates a low dependence of the model outputs to changes or uncertainty in their inputs. A large spread on the other hand means that building energy performance can significantly be affected from changes or variations in how people operate the building systems represented in Table 2.

As shown in Figure 3, large spreads are observed for both the office and classroom buildings. Starting with the office building, the values range from 196.9 to 293.9 kWh/m^2/year, with an average of 253.2 kWh/m^2/year. As for the classroom building, the range is from 157.6 to 265.6 kWh/m^2/year. These results confirm the significant influence of human actions on the energy performance of the educational buildings considered in this study.

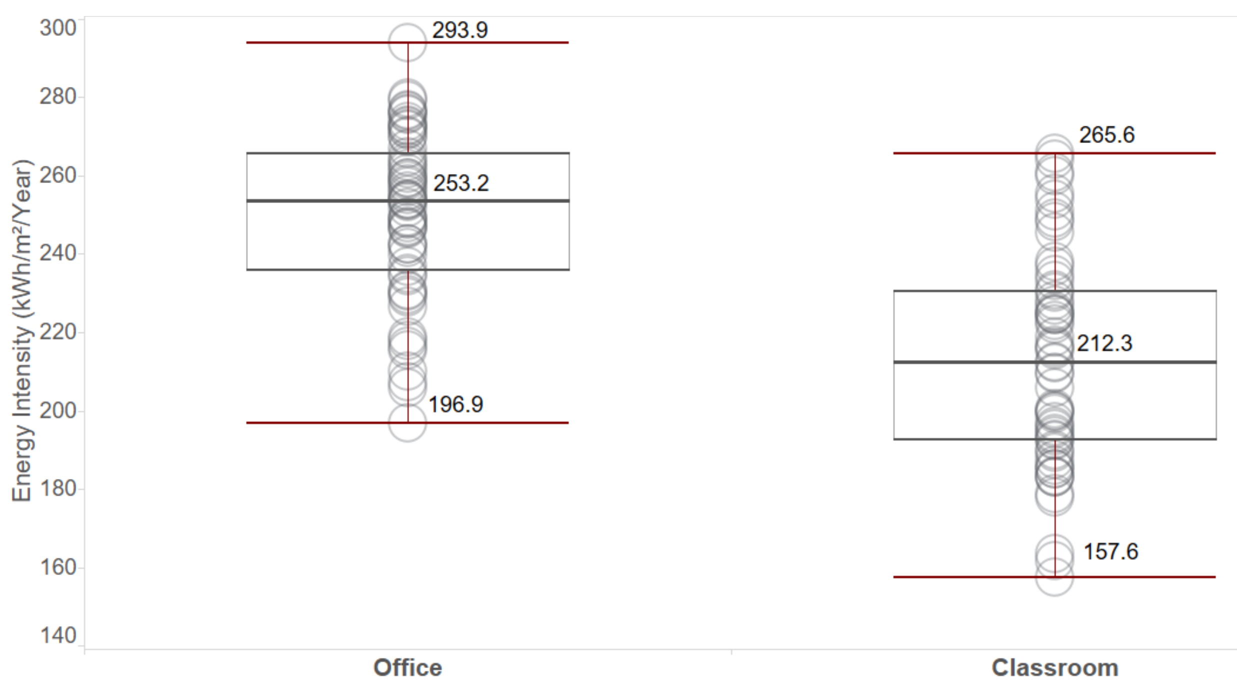

Figure 3: Monte Carlo analysis results.

As for the Fractional Factorial analysis phase, the calculated relative effects of individual parameters are shown in Table 4. The goal of this phase was to explain how much each of the studied parameters contribute to the variability in outputs observed in the Monte Carlo analysis (Figure 3). In order to better visualize the results, the values from Table 4 are normalized and plotted in Figure 4. As shown from the pie charts, for the office building, the most significant contributor to the variability in energy consumption is the "HVAC set point temperatures" parameter. In other words, uncertainty in how people adjust thermostat set point temperatures can explain 53% of the energy intensity range observed in Figure 3 (left side). Window opening and lighting/equipment afterhours use follow with 20 and 17%, respectively. The results confirm the significant effect of thermostat settings on building performance, given the extremely hot weather conditions in Abu Dhabi, UAE (Afshari et al. 2014).

As for the classroom building, the most influential parameter is the equipment/lighting afterhours use with 44%, closely followed by the HVAC set points parameter with 38%. The increase in the influence of equipment/lighting use, when compared to the office building, is mainly attributed to the longer hours per week where the building is unoccupied. More specifically, the classroom building is more often unoccupied (e.g., during evenings and on weekends) than the office building. As a result, changing the afterhours equipment/lighting energy use patterns have a more significant impact on its energy performance.

Table 4: Fractional Factorial relative effects.

Input Parameters	Relative Effect for Office Building	Relative Effect for Classroom Building
Combined lighting and equipment use during unoccupied periods	0.030	0.170
HVAC set point temperatures	0.092	0.147
Window opening	0.034	0.037
Shifting schedules	0.018	0.034

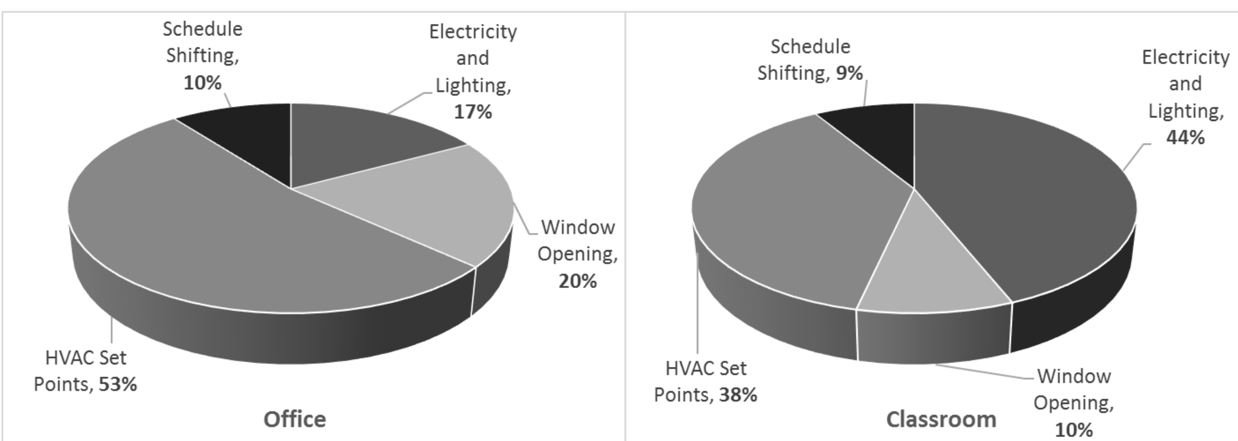

Figure 4: Fractional Factorial analysis normalized results.

4 CONCLUSIONS

This study proposes a comprehensive framework to quantify the impact of uncertainty in human actions on building energy performance. The framework integrates BPS modeling on the one hand, and energy analysis methods, namely Monte Carlo and Fractional Factorial analyses, on the other. The proposed method is general and can be applied on any building. It is illustrated in this study through an application on typical educational buildings in the UAE. Results confirm the significant impact of human actions on building performance, and help explain the commonly observed discrepancies between predicted and actual energy consumption levels in buildings (i.e., energy efficiency gap). Several recommendations can also be made based on the observed results. First, when predicting building energy consumption levels during the design phase of buildings, it is integral to properly account for uncertainty in human-related actions and activities. Such a proactive modeling approach is expected to result in better predictions of life-cycle operational energy consumption and costs, potentially justifying the need for building design features such as advanced energy monitoring systems or smart thermostats. Second, future energy saving initiatives and policies should consider methods that aim to promote energy conservation practices among building occupants and facility managers (e.g., energy education, feedback mechanisms, and game-based conservation campaigns). As shown in this study, simple changes in these stakeholders' actions could lead to important energy savings. Finally, while the main focus in literature has traditionally been on improving building design and technologies, this study confirms that similar efforts are also needed to further improve how people use and operate building systems. Both approaches are complimentary and together, can contribute to effectively reducing the energy intensity and carbon footprint of our built environment.

REFERENCES

Afshari, A., C. Nikolopoulou, and M. Martin. 2014. "Life-Cycle Analysis of Building Retrofits at the Urban Scale—A Case Study in United Arab Emirates." *Journal of Sustainability* 6(1): 453–473.

AlAwadhi, W., A. AlNaqbi, A. Manneh, A. Kazim, and B. Abu-Hijleh. 2013. "Energy Saving Potential Due to Refurbishment of Federal Public Housing in the UAE." *Journal of Engineering* 5(1): 132–136.

Arup Consultants (Arup). 2010. "Pearls Design System New Buildings." Technical Report, *Urban Planning Council*, Abu Dhabi, UAE.

American Society of Heating Refrigerating and Air-Conditioning Engineers (ASHRAE). 2013. "ASHRAE 90.1-2013, Energy Standard for Buildings Except Low-Rise Residential Buildings". *ASHRAE Inc.*, Atlanta, GA.

American Society of Heating Refrigerating and Air-Conditioning Engineers (ASHRAE). 2011. "Advanced Energy Design Guide for Small and Medium Office Buildings". *ASHRAE Inc*., Atlanta, GA.

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: 841–853.

Azar, E., and C. C. Menassa. 2014. "A Comprehensive Framework to Quantify Energy Savings Potential from Improved Operations of Commercial Building Stocks." *Energy Policy* 67: 459–472.

Deru, M., K. Field, D. Studer, K. Benne, B. Griffith, P. Torcellini, B. Liu, M. Halverson, D. Winiarski, and M. Rosenberg. 2011. "U.S. Department of Energy Commercial Reference Building Models of the National Building Stock." Technical Report, *National Renewable Energy Laboratory (NREL)*, Golden, CO. http://www.nrel.gov/docs/fy11osti/46861.pdf [Accessed Mar. 25, 2016].

Gowri, K., D. Winiarski, and R. Jarnagin. 2009. "Infiltration Modeling Guidelines for Commercial Building Energy Analysis." *Pacific Northwest National Laboratory (PNNL)*, Richland, WA.

Granderson, J., M. A. Piette, B. Rosenblum, and L. Hu. 2011. "Energy Information Handbook: Applications for Energy-efficient Building Operations." *Lawrence Berkeley National Laboratory (LBNL)*, Berkeley, CA.

International Energy Agency (IEA). 2015. "Energy Efficiency". *IEA* http://www.iea.org/aboutus/faqs/energyefficiency/ [Accessed July 4, 2015].

Lam, J. C., K. K. Wan, and L. Yang. 2008. "Sensitivity Analysis and Energy Conservation Measures Implications." *Energy Conversion and Management* 49(11): 3170–3177.

Langner, M. R., G. P. Henze, C. D. Corbin, and M. J. Brandemuehl. 2012. "An Investigation of Design Parameters that Affect Commercial High-rise Office Building Energy Consumption and Demand." *Journal of Building Performance Simulation* 5(5): 313–328.

Lee, W. L., and H. Chen. 2008. "Benchmarking Hong Kong and China Energy Codes for Residential Buildings." *Energy and Buildings* 40(9): 1628–1636.

Levine, M., and D. Urge-Vorsatz. 2007. "Residential and Commercial Buildings." Climate Change 2007: Mitigation, *Cambridge University Press*, Cambridge, UK.

Lomas K. J., and H. Eppel. 1992. "Sensitivity Analysis Techniques for Building Thermal Simulation Programs." *Energy and Buildings* 19: 21–44.

Nguyen, A., and S. Relter. 2015. "A Performance Comparison of Sensitivity Analysis Methods for Building Energy Models." *Building Simulation* 8: 651–664.

Peschiera, G., J. E. Taylor, and J. A. Siegel. 2010. "Response Relapse Patterns of Building Occupant Electricity Consumption following Exposure to Personal, Contextualized and Occupant Peer Network Utilization Data." *Energy and Buildings* 42(8): 1329–1336.

Sanchez, M., C. Webber, R. Brown, J. Busch, M. Pinckard, and J. Roberson. 2007. "Space Heaters, Computers, Cell Phone Chargers: How Plugged in are Commercial Buildings?." *Lawrence Berkeley National Laboratory (LBNL)*, Berkeley, CA.

Tavares, P. F. D. A. F., and A. M. D. O. G. Martins. 2007. "Energy Efficient Building Design using Sensitivity Analysis—a Case Study." *Energy and Buildings* 39(1): 23–31.

Turner, C., and M. Frankel. 2008. "Energy Performance of LEED for New Construction Buildings." *New Buildings Institute*, Vancouver, WA.

US Energy Information Administration (EIA). 2003. "Commercial Buildings Energy Consumption Survey (CBECS)." *EIA*, Washington, DC. http://www.eia.gov/consumption/commercial/data/2003/ [Accessed Feb. 3, 2016].

US Department of Energy (DOE). 2011. "Building Energy Software Directory". *DOE*. http://apps1.eere.energy.gov/buildings/tools_directory/subjects.cfm/pagename=subjects/pagename_menu=whole_building_analysis/pagename_submenu=energy_simulation [Accessed Feb. 3, 2016].

Wang, J., Z. J. Zhai, Y. Jing, X. Zhang, and C. Zhang. 2011. "Sensitivity Analysis of Optimal Model on Building Cooling Heating and Power System." *Applied Energy* 88(12): 5143–5152.

Yalcintas, M. 2008. "Energy Savings Predictions for Building Equipment Retrofits." *Energy and Buildings* 40(12): 2111–2120.

AUTHOR BIOGRAPHIES

ELIE AZAR received his Ph.D. from the University of Wisconsin-Madison, and currently is an Assistant Professor in the Engineering Systems and Management department at Masdar Institute, Abu Dhabi, UAE. His research interests include optimizing the performance of the built environment with an emphasis on human actions and energy use behaviors. His email address is eazar@masdar.ac.ae.

AHMED AL AMOODI received his MSc in Engineering Systems and Management at Masdar Institute. His research interests focus on developing methods to quantifying the impact of human action on the energy performance of buildings. His email address is aalamoodi@masdar.ac.ae.