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Impact Analysis on the Variations of the Thermo-physical Property of Building Envelopes and Occupancy in Building Energy Performance Assessment

Jaehyuk Lee[a] and Youngjib Ham[b]

[a]*Graduate Students, Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 205 N. Mathews Ave., Urbana, IL 61801; PH (217) 419-9242; FAX (217) 265-8039; email: lee156@illinois.edu*

[b]*Assistant Professor, OHL School of Construction, College of Engineering and Computing, Florida International University, 10555 West Flagler Street, Miami, FL 33174; PH (305) 348-8410; FAX (305) 348-6255; email: yham@fiu.edu*

Abstract

Understanding the impact of uncertainty in modeling the thermo-physical property of building envelopes and building occupancy on energy analysis has recently received attention. This paper evaluates the impact of the variations of the thermo-physical property of building envelopes and occupancy on building energy analysis. As the data format for accessing and updating building information for energy analysis, gbXML-based BIM is leveraged. We first studied the impact of reflecting the as-is thermo-physical properties of different building envelopes from thermographic sensing on building energy load calculation. Then, the response of energy simulation model with respect to the variations of building occupancy is explored. Finally, the impact of each variation on building energy use intensity is analyzed through the regression analysis. Several experiments were conducted on a building located in six different climatic zones in the U.S. The perceived benefits of continuous updating of energy profiles for model calibration for reliable energy analysis under uncertainty and the related open research challenges are discussed in detail.

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Keywords: Building Energy Load Calculation; BIM-based Energy Modeling and Analysis; Thermographic Sensing; Building Energy Diagnostics

1. Introduction

Building Information Models (BIM)-based energy modeling and analysis enable building information in BIM (e.g., geometry, construction types, and material properties) to be directly used for energy analysis, which can save

* Corresponding author. PH (217) 419-9242; FAX (217) 265-8039; email: lee156@illinois.edu

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energy modelers' time and efforts to create energy models [1]. In the current BIM-based energy modeling process, it is assumed that each building element has a constant surface-wide thermal property, which is typically obtained based solely on industry standard databases available in BIM-authoring tools [2, 3]. However, such assumptions are not always applicable for modeling existing buildings to support retrofit decision-makings, since the as-designed building condition is not always maintained over the whole building life cycle. Fig. 1 illustrates the changes in thermo-physical property of building envelope elements captured by thermographic sensing and analytics [3, 4]. Very recently, Ioannou and Itard [5] assert that such thermo-physical properties (e.g., thermal resistance (R-value)) of building envelopes is one of the most influential factors to accurately estimate energy loads. That is because thermal conditioning in buildings is basically attributed to heat transfer through building façades, affecting occupants' thermal comfort and the associated energy use for space conditioning that accounts for around 21% of the energy consumption in the U.S. [6] For example, deteriorated building façades will increase the amount of unnecessary heat transfer and in turn adversely affect occupants' thermal comfort and energy load. Hence, to model such energy-related phenomena in a real-world building for energy analysis, reflecting the as-is building conditions in BIM-based energy modeling process is vital since it can reduce modeling errors. To explore how much it can influence on BIM-based energy analysis, this paper aims to examine the response of building energy simulation models with respect to R-value variations of building envelope elements through several case studies in six different weather zones in the U.S. In addition, the response of energy simulation models with respect to building occupancy variations is also studied for the relative local sensitivity analysis.

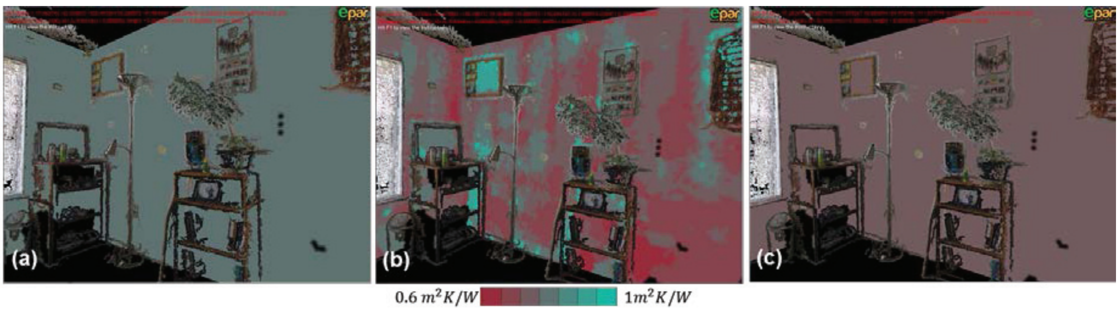


Fig. 1. Changes in thermal resistances of building envelope elements. (a): notional value (designed value), (b): distribution of actual thermal resistances from indoor thermographic sensing, (c): averaged actual thermal resistance [3].

2. Methodology

2.1. Reference building (base case) and energy simulation engine

In this paper, modeling the reference building for energy simulation builds upon the gbXML Test Case Documentation [7] that has similar properties with the real-world residential building in Illinois for analysis. This building model consists of a single space, and the details on the dimension are illustrated in Fig. 2. For simulation, we used the cloud-based building energy simulation tool, AUTODESK Green Building Studio (GBS), which builds on the industry standard DOE-2.2 dynamic thermal energy simulation engine to estimate building energy use based on the effects and interrelationships of building's geometry, materials, systems, usages, and climate [8]. This engine rapidly yields output, enabling us to compare performance variations depending on different building specifications through iterations [9]. For sensitivity analysis, we directly update the gbXML file and vary design parameters.

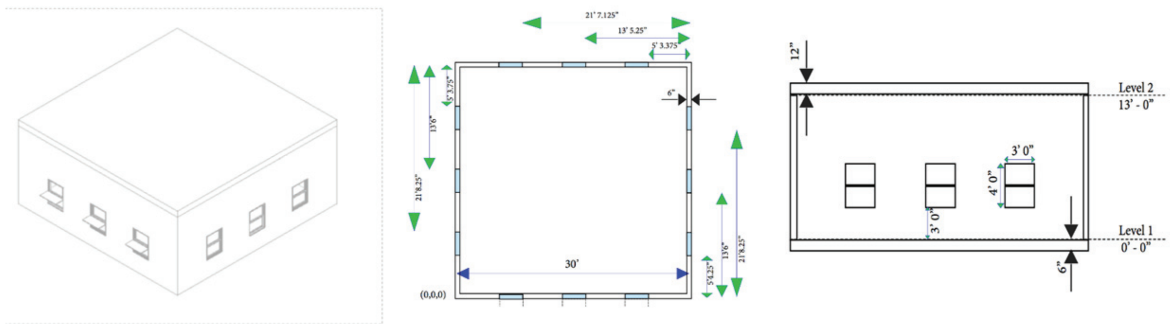


Fig. 2. From left to right: 3D view of a reference building; Floor plan with dimensions; Elevation with dimensions.

2.2. Design parameters

For several case studies of energy simulation, each design parameter of interest is hypothetically varied with respect to the baseline by increasing or decreasing within a given range as shown in Table 1. The range for entire envelope, wall, and roof was from 1 to 60 because the highest R-value recommended by U.S. DOE is about 60, while from 1 to 11 for the window component since typical windows' R-value on market does not typically go over 11. Then, six locations (i.e., Miami, Houston, LA, Washington, Chicago, and Minneapolis) were selected from different climate zone based on the R-value recommendation [10] shown in Fig. 3 (a). For the reference, variations of outdoor air temperature of selected locations throughout a year are illustrated in Fig. 3 (b) and (c).

Table 1. Designed input values for thermal resistances of building envelope elements for experimental simulations

Envelope				Wall		Roof		Window	
Δ R-Value	R-value (Wall)	R-value (Roof)	R-value (Win)	Δ R-Value	R-value	Δ R-Value	R-value	Δ R-Value	R-value
				-6.5000	0.5033	-4.0000	0.4535	-1.4000	0.5437
				-6.0000	1.0033	-3.5000	0.9535	-1.0500	0.8937
-1.5	5.5033	2.9535	0.4437	-4.0000	3.0033	-3.0000	1.4535	-0.7000	1.2437
-1	6.0033	3.4535	0.9437	-2.0000	5.0033	-1.5000	2.9535	-0.3500	1.5937
0	7.0033	4.4535	1.9437	0.0000	7.0033	0.0000	4.4535	0.0000	1.9437
2	9.0033	6.4535	3.9437	2.0000	9.0033	5.0000	9.4535	0.7500	2.6937
7	14.0033	11.4535	8.9437	7.0000	14.0033	10.0000	14.4535	1.5000	3.4437
12	19.0033	16.4535	13.9437	12.0000	19.0033	15.0000	19.4535	2.2500	4.1937
17	24.0033	21.4535	18.9437	17.0000	24.0033	20.0000	24.4535	3.0000	4.9437
22	29.0033	26.4535	23.9437	22.0000	29.0033	25.0000	29.4535	3.7500	5.6937
27	34.0033	31.4535	28.9437	27.0000	34.0033	30.0000	34.4535	4.5000	6.4437
32	39.0033	36.4535	33.9437	32.0000	39.0033	35.0000	39.4535	5.2500	7.1937
37	44.0033	41.4535	38.9437	37.0000	44.0033	40.0000	44.4535	6.0000	7.9437
42	49.0033	46.4535	43.9437	42.0000	49.0033	45.0000	49.4535	6.7500	8.6937
47	54.0033	51.4535	48.9437	47.0000	54.0033	50.0000	54.4535	7.5000	9.4437
52	59.0033	56.4535	53.9437	52.0000	59.0033	55.0000	59.4535	8.2500	10.1937

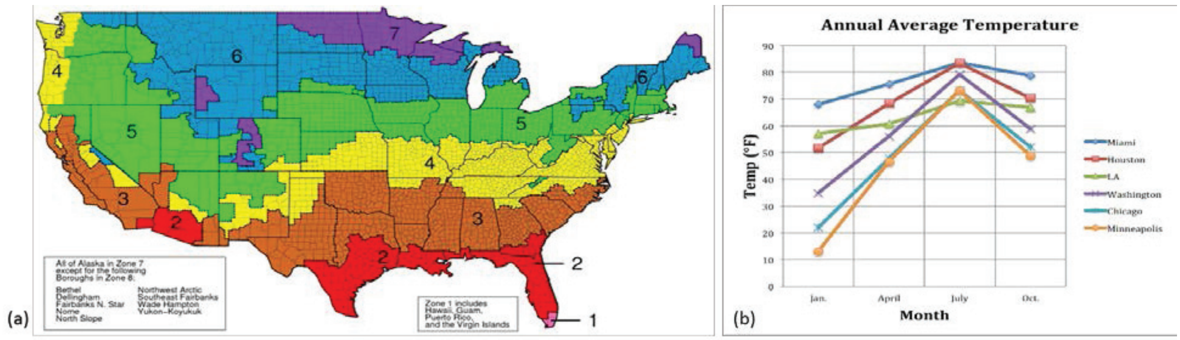


Fig. 3. (a) R-value recommendation zone map by U.S. Department of Energy [10]; (b) Monthly average temperature for the selected six different locations

2.3. Data analysis – Local sensitivity analysis

Once energy simulation is done, a regression analysis is performed to explore the sensitivity based on the relative magnitude of regression coefficients, called 'impact coefficient' in this paper. The linear-log regressions are performed on the collected data for positive (+) variations to obtain the regression coefficients, along with the linear regressions for negative (-) variations. The sensitivity analysis is to explore how the variation in the output of a model depends upon the input information, enabling to examine the relative impact of various input variables on the model output and study the uncertainty of the model results originating from the uncertainty of input parameters [11]. It encompasses both parametric studies, in which input parameters are systematically changed to determine the influence on program predictions [12]. Sensitivity measures are usually calculated using on the OAT approach (one-parameter-at-a-time), in which the impact of changing the values of each design parameter is evaluated [13].

Building upon the OAT approach, we focus on the effects of uncertain inputs around a point of a base case, a reference building in gbXML schema. In other words, the output variability is evaluated based on the variation of one design parameter within a certain range while the rests are maintained at constant level. Then, the building energy models with input variations are simulated to analyze the effect of design parameter variation on the total energy consumption in terms of *Energy Use Intensity (EUI)*. Here, the input-output relationship is assumed to be linear and the correlation between design parameters is not taken into account [5].

3. Experimental Simulation and Results

3.1. Impact analysis of R-value variations on EUI

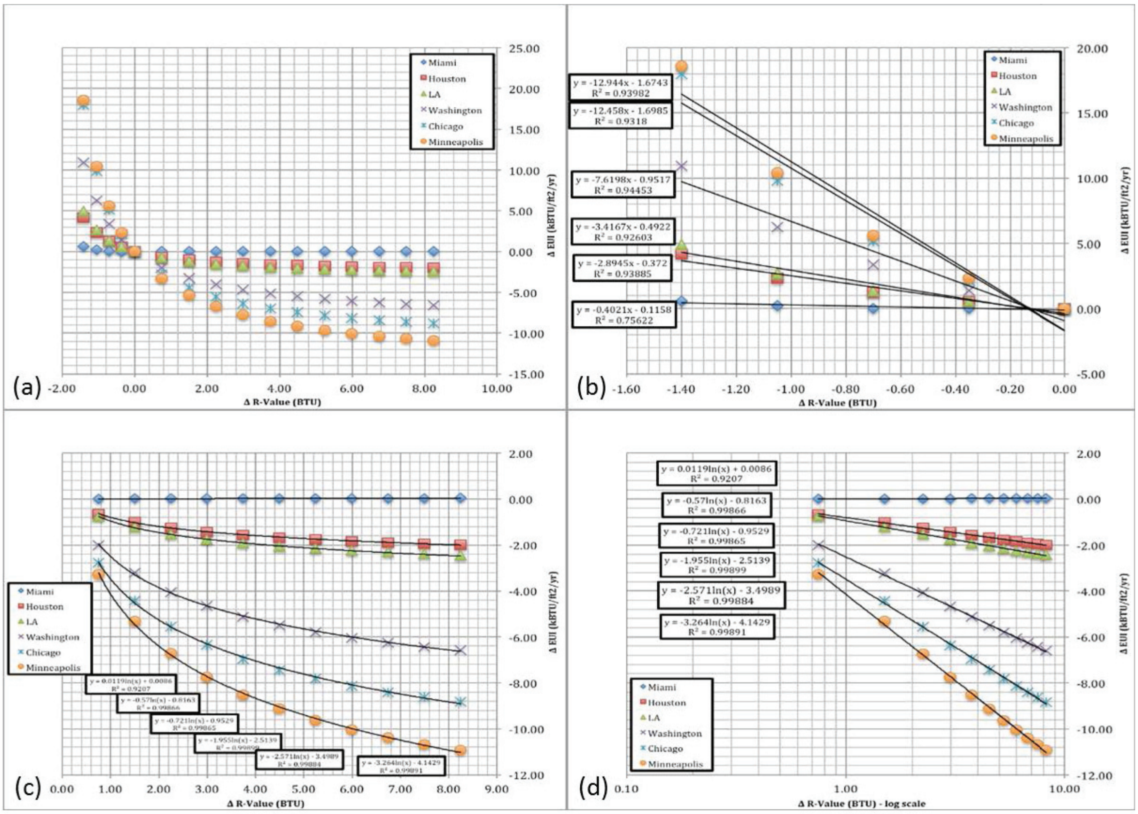


Fig. 4. (a) Δ EUI vs. Δ R-value; (b) Δ EUI vs. Δ R-value (-) and the linear regression; (c) Δ EUI vs. Δ R-value (+) and the linear-log regression; (d) Log-scale representation of Δ EUI vs. Δ R-value and the linear-log regression

Fig. 4 (a) illustrates the correlation between Δ EUI (Energy Use Intensity) and the variations on R-values of the window component in six different climate zones. The experimental results show that a strong correlation exists between R-value of building envelopes and EUI with different degrees depending on the geographical locations of the building. To infer the impact coefficients and analyze their sensitivity, the regression analysis is performed on the simulation results as the R-value decreases and increases. Here, to find the best-fit lines, the linear regression is applied for the cases of decrease in R-value (Fig. 4 (b)), while the linear-log regression is used for the cases of increase (Fig. 4 (c)). Lastly, the independent variable is logarithmically transformed to demonstrate the linearity between independent and dependent variables shown in Fig. 4 (d).

3.2. Sensitivity analysis of impact coefficient of different building elements to EUI

Based on the energy performance simulations with respect to the variations on R-value of different building components (i.e., entire envelope, wall, roof, and window) in six different locations, the sensitivity analysis is implemented. Fig. 5 illustrates the magnitude of the impact coefficients (i.e., regression coefficient) to explore the relative sensitivity of R-value variations in each building element for different locations. For example, in the case of Chicago in Fig. 5 (a), it is observed that the wall element is the most sensitive one that can affect EUI (without considering entire envelope here since its variations affect all elements), while the window element is the least. This trend is observed in Washington and Minneapolis, which have the cold winter season than the remaining three locations (Miami, Houston, and LA). Fig. 5 (c) and (d) show Δ EUI and the variations on R-values of entire envelopes, wall, roof, and window in LA and Minneapolis. Interestingly, it is observed that the first three (Miami, Houston, and LA) and last three locations (Washington, Chicago, and Minneapolis) have similar trends respectively.

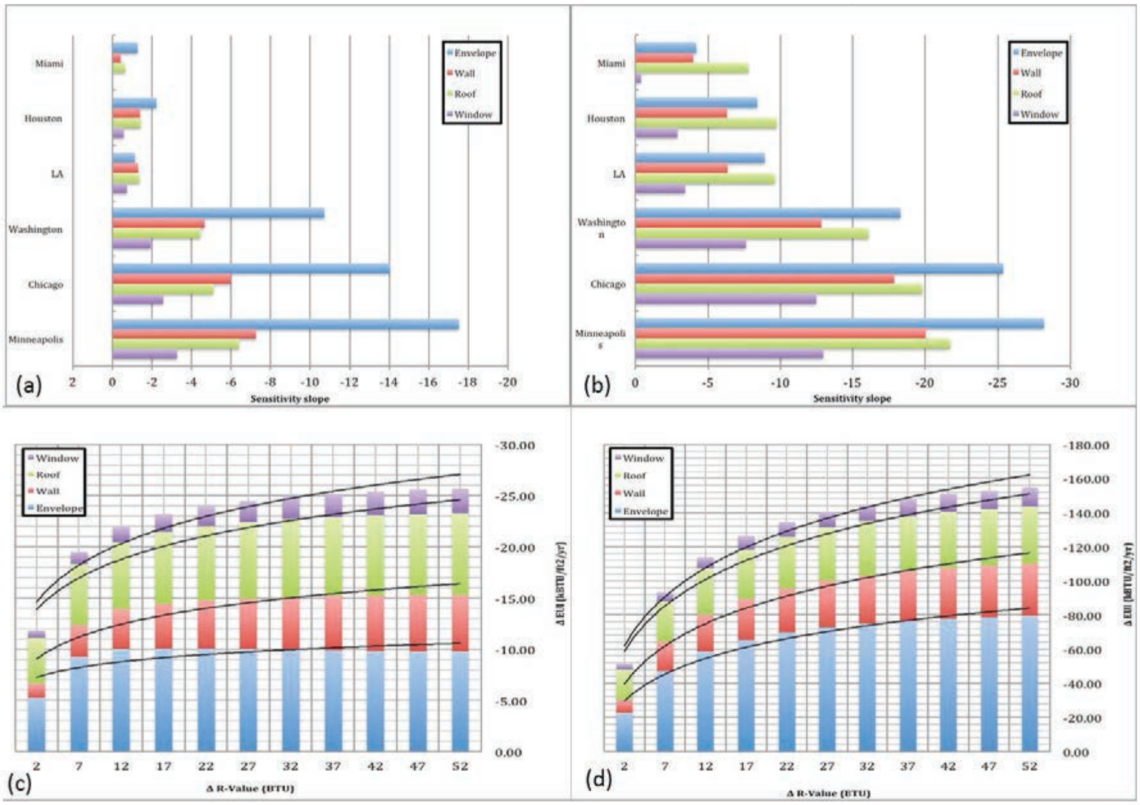


Fig. 5. Impact coefficient of Δ EUI and Δ R-value for entire envelope, wall, roof, and window in six different locations: (a): increase in R-value; and (b) decrease in R-value. Δ EUI vs. Δ R-value for entire envelopes, wall, roof, and window in (c): LA, and; (d): Minneapolis.

Fig. 6 (a) presents the impact coefficient of different building elements depending on different geographical building location. Fig. 6 (b) shows Δ EUI vs. Δ R-value of the window element for six different locations. In our simulation, it is observed that Minneapolis shows the greatest impact, followed by Chicago, Washington, LA, Houston, and Miami respectively. The observations in the relative sensitivity are explicable when considering the monthly average temperature of each location (Fig. 3 (b)). It is observed that the impact coefficient is likely to become greater in the area with lower average temperature. The similar tendency could be observed for other building elements including walls and roofs.

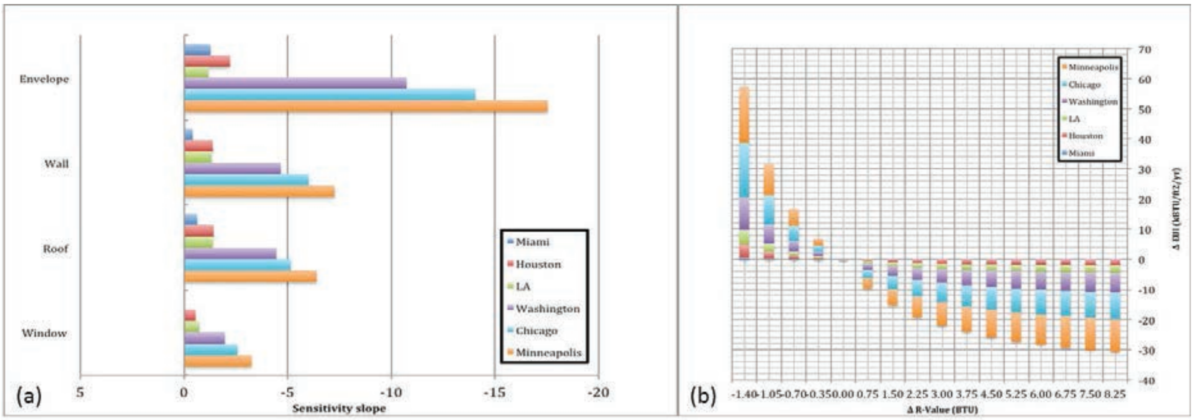
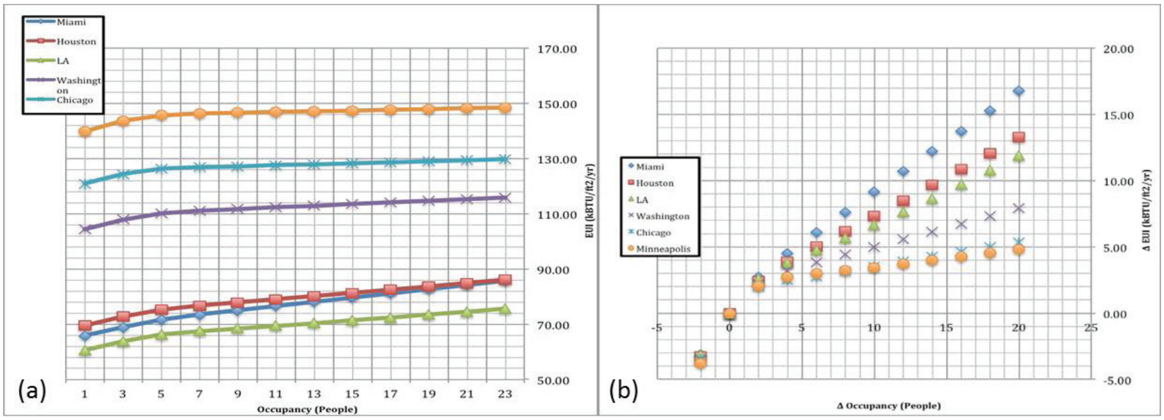


Fig. 6. (a): Impact coefficient of Δ EUI and Δ R-value on each building envelope elements with weather variations. (b): Δ EUI vs. Δ R-value of window for six different locations

3.3. Impact analysis of occupancy variations on EUI and the comparison with the impact of R-value variations

We further look into Δ EUI vs. Δ Occupancy in six different locations of the building. As can be seen in Fig. 7 (a) and (b), the total amount of energy use and the degree of change in EUI are different depending on the location of the building. Fig. 7 (d) presents the associated sensitivity analysis. Unlike the results shown in above sections, it is observed that the impact coefficient is likely to become greater in the location of higher average temperature. Fig. 8 illustrates the impact of Δ Occupancy and Δ R-value on Δ EUI. Here, for comparison between relative impact of R-value and occupancy variations on EUI, we consider the absolute magnitude of Δ EUI. In our experiments, for instance, it is observed that Δ R-value of 27 for the wall element and Δ Occupancy of 6 would influence Δ EUI of 5.



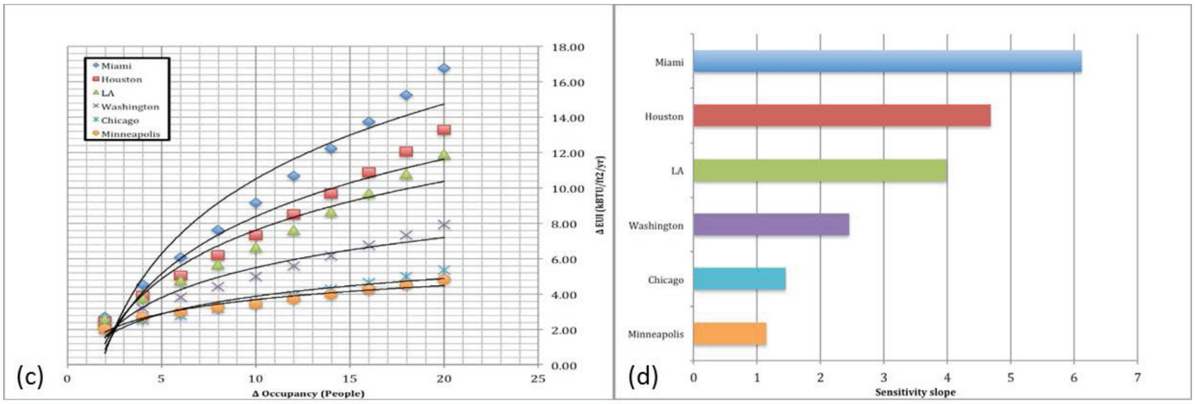


Fig. 7. (a) EUI vs. Occupancy; (b) Δ EUI vs. Δ Occupancy; (c) Δ EUI vs. Δ Occupancy and the linear-log regression; (d) Impact coefficient of Δ EUI and Δ Occupancy in six different locations.

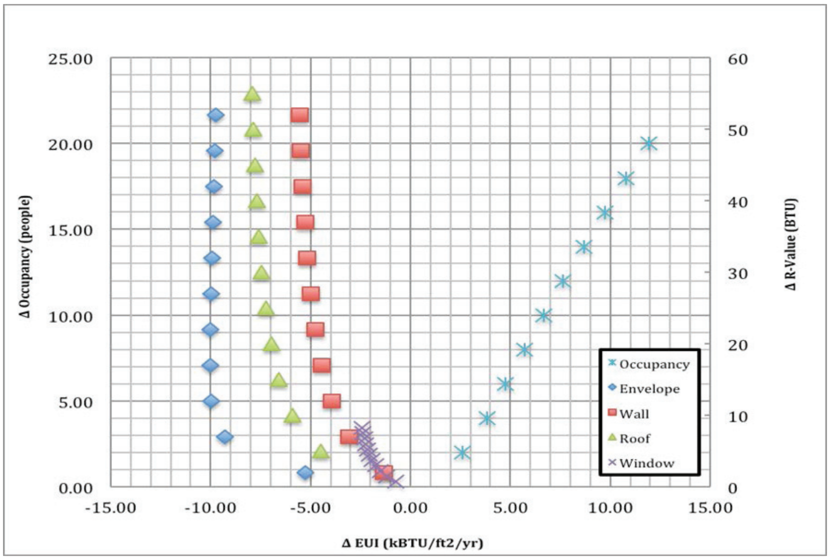


Fig. 8. Δ Occupancy and Δ R-value vs. Δ EUI in Miami.

4. Discussion and Conclusions

In this paper, we experimentally studied the impact of the variations of thermo-physical property of building envelope elements (e.g., wall, roof, and window) and occupancy on building energy performance assessment by several case studies under six different weather zones in the U.S. Each parameter was hypothetically varied with respect to the reference building's values by increasing or decreasing the value within a given range for each building element, and then simulation was iterated for different geographical locations. The local sensitivity analysis was conducted on the simulation results to explore the relative sensitivity and the impact of R-value and occupancy variations for each location.

In our experimental simulation on a typical small office building under different climates, it is observed that with the window component always being the least sensitive building envelope element on EUI, the wall component is typically the most sensitive in Washington, Chicago, and Minneapolis, while the roof component becomes the most sensitive one in the remaining three locations (Miami, Houston, LA). It is also observed that relative magnitude of the impact coefficient have the similar tendency that in the cases of Washington, Chicago, Minneapolis, the wall component has much greater impact than the roof component on Δ EUI with window being the least. However, in the remaining three locations (Miami, Houston, LA), the difference of magnitude of impact between the roof and wall component is likely to become minimal as R-value increases. It is observed that the relative magnitude of the impact does not always correspond to the surface area of each element proportionally, which implies that other significant factors, such as weather conditions and designed (i.e., initial) R-value, have greater influence on EUI than the surface area. Meanwhile, the relative sensitivity and the impact of weather variations is likely to become greater in the area of lower average temperature as R-value increases, while simulation in LA is an exceptional case because the difference between the lowest and the highest average temperatures throughout a year is the least among all observed locations. On the other hand, the relative sensitivity and the impact of occupancy variations is likely to become greater in the location with higher temperature as the number of occupants increases.

The intent of this research is to support to identify the most influential parameter on building energy consumption under environmental uncertainty and facilitate better decision-makings on prioritizing the targets for building envelope inspection and determining the optimal envelope retrofit alternatives for improving energy efficiency, rather than presenting specific simulation results and associated trends that can be generally applied to any universal cases. The reference model used for this paper can be scaled-up or assembled with other units for further simulation. With various simulation engines, further studies on the relationship between two parameters, R-value and building occupancy, are needed for normalization of variables, which allows more accurate comparison of their relative impacts on the building energy performance.

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