THE IMPACT OF OCCUPANT MODELING ON ENERGY OUTCOMES OF BUILDING ENERGY SIMULATION

A Dissertation
Presented to
The Academic Faculty

by

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In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Architecture

Georgia Institute of Technology
August, 2016

THE IMPACT OF OCCUPANT MODELING ON
ENERGY OUTCOMES OF BUILDING ENERGY SIMULATION

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To my beloved parents,
In-Kyung Kim and Ran-Sook Huh

ACKNOWLEDGEMENTS

Not only the completion of this thesis, but also my long journey of Ph.D. could not have been made without a full support from Professor Godfried Augenbroe, who has always been patient and encouraging with my life as well as my research. I feel greatly lucky to have him as my advisor and would like to return the favor for lifetime. I am indebted to Professor Jason Brown for the valuable teaching experience that provided me a chance to learn how to guide students in a variety of courses. I would also like to extend my deepest gratitude to Dr. Tianzhen Hong, Professor Pieter de Wilde, and Professor Cheol-Soo Park for their unwavering supports and constructive advice on my thesis work even in a long distance.

I am extremely grateful to Professor Seung-Bok Leigh and Professor Taeyeon Kim who provided me insightful knowledge during my master's degree and valuable advices for a new journey in Georgia Tech.

This study would not have been possible without the support of POSCO Engineering and Construction and Dr. Hye-Soo Suh who allowed me to utilize energy consumption data of their actual buildings and gave me practical suggestions. It has been greatly useful and helpful while developing research ideas for this thesis. I also would like to acknowledge the help of Qinpeng Wang and Qi Li for my thesis, who willingly cooperated with me and offered their extensive knowledge.

Without my colleagues and friends I met in Atlanta, this long course of study would not have been this blissful. Many thanks to Jinsol, Jaeho, Sangwoo, Hyun-Kyung, Seunghyun, Sean hay, Huafen, Paoloa, Atefe, Yuming, Roya, Yiyuan, Gustavo, Michael, Chaehee, Alya, Min-Jeong, Lisa, Bona, Justin, Han Jun, Yong Woo, Dr. Honjun Moon and all others for the precious memories we had together and a lifelong friendship we expect to have together. I would like to thank Yeonsook, Sang Hoon, Youjong, Seungyeon, Eunhwa, James, and Yuna for their endless moral supports when I needed it most. Thanks should also go to my brothers, Jinho, Sungho, and Dongho for their invaluable contributions that cannot be underestimated. My sincere thanks to Hye-Jin and Sung Jun who provided me with encouragement, patience, and their trust in me even when we were physically distant.

Lastly, I would like to express my deepest appreciation to my parents, In-Kyung Kim and Ran-Sook Huh, who taught me valuable lessons and gave me all supports throughout my life while enduring a long wait during my Ph.D.

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SUMMARY

The reported performance gap between predicted and real building energy consumption has drawn keen attention from the building simulation community and related stakeholders. Alongside other research efforts to identify, quantify, and close this gap, the most recent attempt is the development of occupant behavior models that generate more "realistic" occupant inputs (occupancy, lighting and appliance use, as well as actions) in the building energy simulation used for energy prediction. These new occupant models are typically realized by stochastic methods. To date, the newly developed models focus on mimicking real life variability. In spite of that, they have not necessarily led to more accurate consumption predictions than previous methods. The reasons for this are not always obvious.

Rather than adding yet another occupant behavior modeling approach, this thesis emphasizes the need to understand the impact of occupant behavior models on building energy outcomes in real life applications. To accomplish this, we investigate two distinctive approaches to occupant modeling: top-down and bottom-up. We build the argument in the thesis that the top-down approach is suitable in highly variable situations where relatively little information about actual occupant variables can be known. This is usually the case in residential applications. By introducing a so-called "Life Style Factor," we conclude that the use of this factor is promising to capture the variability of occupant-related parameters in residential buildings. It covers the energy consumption over a broad spectrum of household composition, life style and other behavioral factors better than any of the current behavioral models. Embracing the top-down approach as

most adequate is based on the hypothesis that no detailed occupant behavior simulation is capable to capture the full spectrum across households.

For commercial buildings, a fundamental analysis is conducted to identify the impact of occupant-related inputs on the performance gap while explicitly considering the level of modelers' knowledge about occupants' presence and actions at the time of prediction. The results of a sensitivity analysis reveal that even in the case where the modelers' ignorance of actual occupancy is significant and hence occupant parameters become important contributors to the performance gap, the resulting disparity could be fairly well quantified without introducing complex occupant behavior models. It is also found that the randomness of occupant behavior with respect to actions, such as window opening has no significant role in the performance gap, at least in typical building simulation practice, i.e. when the objective of simulation is to predict monthly cooling and heating energy consumption of a building design. This finding is significant as it advises us to rethink our pursuit of accuracy by developing new occupant behavior models, such as the ones that aim to explicitly model the human reasoning, perception and action related to the opening of windows. This thesis will enable energy modelers to adequately acknowledge the role of occupancy inputs in building energy simulation, and provide the research community with an analytical basis for the proper inspection of the role and need of (improved) occupant behavior models.

CHAPTER 1

INTRODUCTION

1.1 Building Performance Gap

The performance gap between the reality and the estimation of the building energy simulation has drawn keen attention from the building simulation community and related stakeholders. One obvious concern for building owners is that this shows that their building does not work out as expected, in the worst case it could consumes 50 percent more energy than predicted [1]. Figures 1 through 3 show examples of the performance gap as acknowledged in literature [2, 3 and 1]. The first graph is drawn from a case study of Korean apartment housing which is further explored in this thesis [2, Chapter 2]; the green bar represents the deterministic prediction of the current building simulation practice, and the red one shows the variation of the actual cooling energy consumption of apartment housing units, which spreads wide and is in general far from the predictions. The second graph depicts the median predicted and consumed electricity for three building sectors, schools, offices, and university campus in the U.K. [3]. It shows up to 85% higher energy consumption than predicted. Lastly, Figure 3 is extracted from the report published by the New Buildings Institute in 2008 [1] shows the performance gaps among LEED-certified [4] buildings. The black dotted line in the figure depicts where measured energy consumption is equal to design prediction.

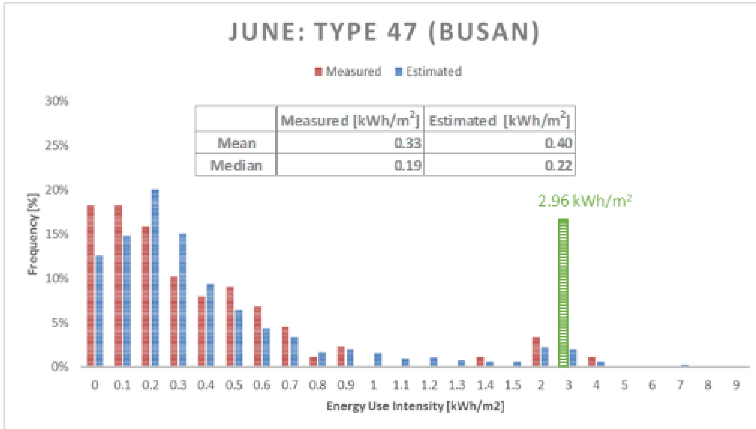

Figure 1 The Performance Gap: Korean Apartment Housing Case Study [2]

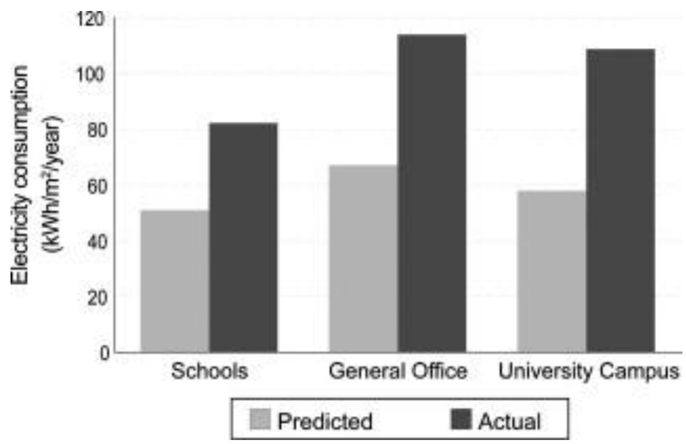

Figure 2 Median Predicted and Consumed Electricity in U.K. [3]

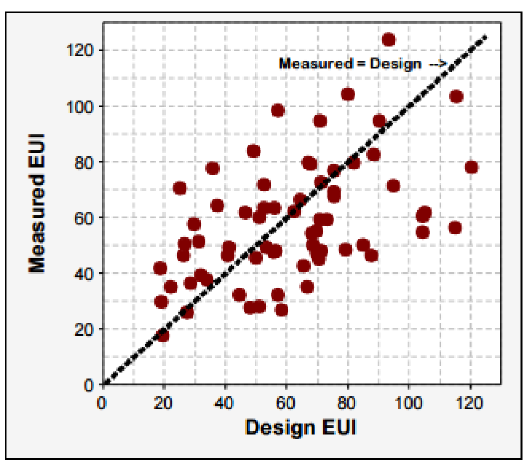

Figure 3 Measured and Deigned EUI in U.S. [1]

Approximately, half of the buildings performed better than expected, but the rest performed worse than their design prediction (Figure 3). As none of these studies provide conclusive answers to the origin of the performance gap, many speculations have been offered as possible explanations.

The performance gap represents “the difference between deterministic energy predictions at the design stage and the actual energy consumption during operation”. There has been an increasing number of research efforts to identify, quantify, and close the performance gap [3, 5, 6, 7, 8, 9, and 10]. One recent paper [7] relates the gap to the lack of knowledge about four major areas in building simulation practice: imprecise knowledge of input parameters, a modeler’s lack of experience, insufficient validity to apply simulation to represent the real-world, inherent errors in simulation tools, from coding errors to errors in embedded assumptions. These model deficiency sources are present at five different systems scales: meteorological, urban, building, system, and occupants. Recent work has tried to quantify all sources through an uncertainty analysis of properly quantified sources of uncertainty. Notably, Sun [7] and Wang [10] prove that proper quantification of all sources of uncertainty can quantitatively capture the magnitude of the performance gap over a population of buildings.

In parallel, the most recent attempt towards closing (at least part of) the performance gap is the development of occupant behavior models, recently coordinated through the launch of IEA-EBC Annex 66 [11]. Recognizing the potentially large influence of occupant behavior on building energy performance, its objectives are to define uniform and standardized descriptions of occupant behavior, develop better simulation methodologies to process them, and implement the resulting occupant models within current building energy simulation tools.

1.2 Occupant Behaviors and Building Simulation

1.2.1 Current Practice

People in buildings influence building energy performance in two ways: their presence in and movement through building zones and their interactions with human operable building systems. To describe these occupant "behaviors", the major occupant-related inputs in current building simulation that should most relevant are occupancy, lighting-use, and appliance-use schedules. In addition to these non-intrusive (from a simulation perspective) occupancy outcomes, there can be a more intrusive occupant role in the operation and state of the building. The latter will be considered as "active" participation or "occupant actions". The prime example of the latter is occupants' operation of operable windows.

People's behavior must be considered as stochastic, cognitively complex, reacting to multiple stimuli, and therefore behaviorally uncertain. This is confirmed by measurement as we observe that patterns of building energy consumption often show a wide variability even with similar or even identical building characteristics and climate conditions. Figures 4 and 5 show the frequency of heating and cooling energy use intensities (EUIs) of 161 Korean apartment units [12] that have identical design characteristics such as floor area and thermal properties of the building envelope. Even when the extreme cases are excluded, the heating EUI varies from 6 kwh/m^2 to 111 kWh/m^2, showing a maximum of more than 100 kWh/m^2 of difference between units.

Similarly, the source EUIs of 297 office buildings in Chicago, IL [13] show around 940 kWh/m^2 of difference (from 25 kBtu/ft^2 to 325 kBtu/ft^2), even when the cases with less than 3% of occurrence are excluded, as Figure 6 shows.

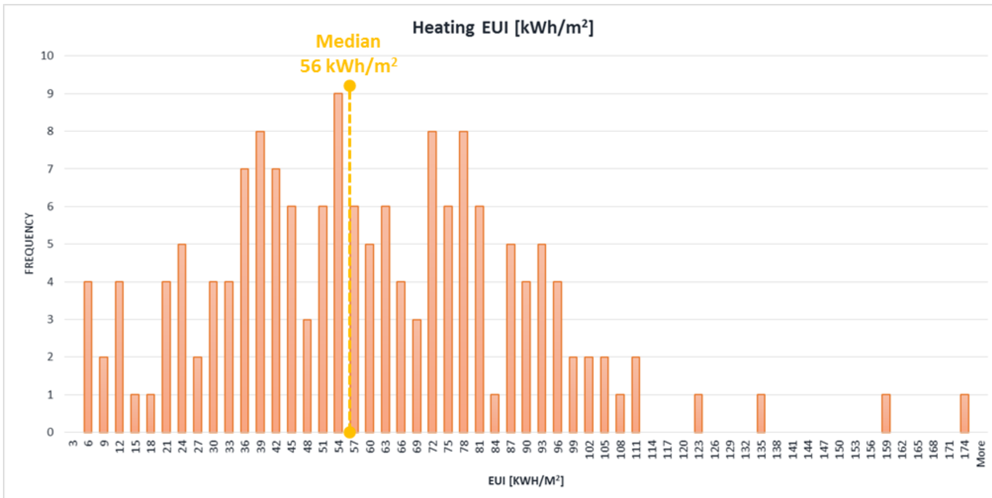

Figure 4 Distribution of Heating Energy Use Intensities of 161 Apartment Units in Gyeonggi, South Korea

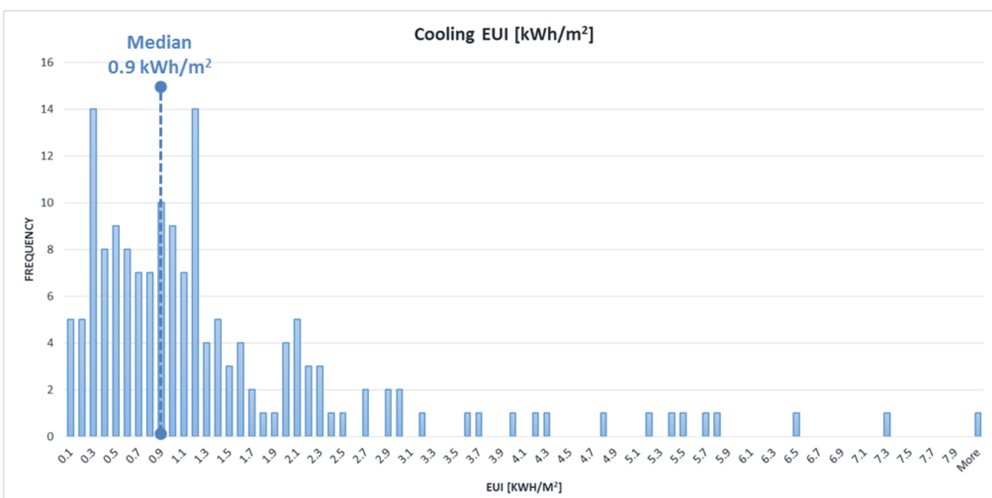

Figure 5 Distribution of Cooling Energy Use Intensities of 161 Apartment Units in Gyeonggi, South Korea

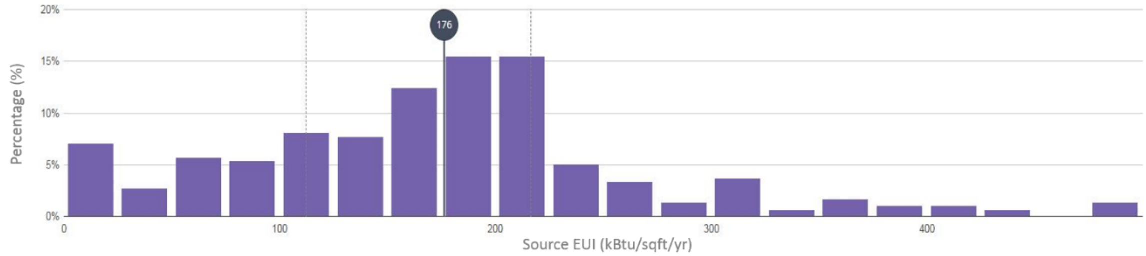

Figure 6 Distribution of Source Energy Use Intensities of 297 office buildings in Chicago, IL [10]

This confirms that more attention to occupant models is justified. In current building simulation practice, however, occupant-related inputs are commonly pre-determined as a default according to a building or occupant organization type, and a corresponding "standard hourly occupancy profile" is assumed. This is usually assumed identical per time of the day (e.g. based on a 9 to 5 office schedule) and per day of the week (only differentiating between weekdays and weekends). This typically results in poor representation of actual occupancy and its variability, and potentially an incorrect energy outcome estimation especially when the accuracy of the prediction, often measured as the discrepancy between predicted and measured data (the performance gap), is in question. It is a debatable issue whether the prime objective of a simulation should be the accurate prediction of actual energy consumption. Many energy studies in the design phase focus on comparative analyses, where it can be readily acknowledged that the delta in the outcomes of two design options is hardly affected by the choice of the occupancy model, as long as it is equal in both simulations. This is also true for code compliance such as those according to ASHRAE 90.1 [14] and ISO 13790 [15]. In both cases the outcome is based on comparative analysis (ASHRAE 90.1) or a normative energy model (ISO 13790). We argue that it is insufficiently recognized in energy modeling practice that occupant modeling does not influence much of our current "retail" simulation work, with the one exception where a "best" prediction of actual energy consumption is the prime objective. The latter is indeed relevant in a number of cases where a target for actual energy consumption has to be guaranteed in the design stage. A good example of this can be found in countries that have adopted an energy code that mandates limits on actual energy consumption, rather than design energy performance based on a normative approach. Sweden [16 and 17] is a good example of this newer practice; they measure the energy consumption of a building in the 2nd year of operation. To guarantee that the maximum energy consumption target is met in the 2nd year, the design prediction must focus on the best possible estimate of the actual consumption in the 2nd year. Other examples closer to home can be found where a risk-associated decision needs to be made based on information about the actual energy consumption that is expected, e.g. in a retrofit analysis linked to energy savings performance contracts. But these considerations come at an extra cost in that we have to explicitly consider the uncertainty in our predictions, both in the occupancy models and in other parts of the building energy model. This will therefore be an important factor in the studies conducted for this dissertation.

There have been many articles already that investigate the influence of the current way of representing occupant behaviors in building simulation. Eguaras-Martinez et al. [18] proved that the inclusion or exclusion of occupant behaviors in building simulation resulted in up to 30% of difference of energy use predictions. In addition, Hoes et al. [19] show that the influence from the uncertainty of occupant behavior becomes even larger in a case of a building with passive design features such as heavy thermal mass and air-tight façade. The IEA EBC Annex 53: Total Energy Use in Buildings [20] recognized the impact of occupant behaviors as one of six driving factors of energy use in buildings including climate, building envelope, building energy and services systems, indoor design criteria, and building operation and maintenance.

Considering that the performance gap is the result of many factors besides the potential deficiency of occupant-related inputs (and any underlying occupant behavior models), it is therefore important to distinguish and quantify the role of the different factors causing the performance gap. In other words, occupant-related inputs in building simulation need to be considered as one of many sources of uncertainty including meteorological, urban, building, and systems [7]. Any assessment of the true role of occupancy models should therefore be based on a well-founded uncertainty analysis, rather than deterministic analysis as employed in some of the mentioned studies that have gone before ours.

1.2.2 Recent Research Efforts and Remaining Challenges

To represent more realistic occupant behaviors within the limitations of current practice, i.e. deterministic and hence mostly over-simplified occupant-related inputs in building energy models, research has largely focused on new occupant behavior model development using monitor, sensor, and survey data from observational studies. The hypothesis that drives this work is that the data reveals the relationships between the indoor and outdoor environmental factors and occupant behaviors under consideration [21]. Hong et al. [22] reviewed published simulation models and identified major types of occupant behaviors in building simulation as operation of windows, blinds, lighting, thermostat, space occupancy (presence), and plug loads. As we argued earlier, occupant behavior is a combination of multi-stimuli, impacted by a variety of cultural and social factors and the ability to derive true occupant behavioral models from such observations should be regarded as suspect or at least doubtful. Nevertheless, in commercial buildings where narrowly defined work related occupancy scenarios govern the workplace utilization, certain reductionist models of occupancy could be derivable from measurements. Current studies lack however a clear framework to define the approach and significance of these models in a larger framework of human behavior. As part of IEA-EBC Annex 66, Yan et al. [21] outlined the current state of occupant behavior research for building performance simulation and addressed future challenges. After studying these and other literature [21, 22, and 23], the main challenges we are facing in occupant behavior modeling and its inclusion in building simulation are summarized as follows:

- <u>Validation of occupant behavior models</u>

  In recent studies, by using the same occupant-related data to both develop and assess their models, they often fail to validate their models properly. Originally, occupant monitored/sensor data are scattered throughout different use cases and limited to observed buildings and their context is most often characterized by "controlled" experiments. For these reasons the fundamental difficulty is the generalization of the models as elaborated in the following bullets.

- Generalization of occupant behavior models

  It's hard to generalize the occupant behavior model, since it demands "long-term high-resolution empirical data [23]" on occupants and their actions in different cultural, geographical, and climate conditions. Moreover, the data needs to be gathered in the least intrusive way (uncontrolled experiments), and their correlation with individual preferences, cultural and social influences, individual differences in perception of comfort and mental models of potential actions needs to be stablished.

- Selection of proper occupant behavior models

  Even if we take all above factors into account, it is not well supported in the literature what implementation approach is adequate, i.e. what proper form and format of occupant behavior models should be used, for various building simulation cases. The applicability of newly developed models are not generally defined and validated for specific building energy simulation scenarios.

The first two challenges arise from the unavailability of a common database of occupant behavior and its public sharing within the research community. This is one of the prime targets that IEA-EBC Annex 66 strives for in addition to standardized definitions and descriptions of occupant behaviors and underlying modeling methods. Meanwhile, there is another dimension that needs to receive central focus. It concerns the explicit determination of the modelers' lack of knowledge on the future occupants in their target buildings. This does not concern our ability to model, but the modeler's ability to know or predict. There will in all cases be an unavoidable level of ignorance of what the future usage scenarios, occupant population and their specific occupancy parameters will be, and not to mention, how they can evolve over time. Therefore, we still demand more studies that classify use cases, examine various models, and ultimately provide building energy modelers with the proper, i.e. "better" occupant behavior models than available in current practice.

Firstly, there have been a few attempts to classify the models in different resolutions and suggest preferred models for different simulation contexts. To distinguish the appropriate modeling resolutions, Melfi et al. [24] presented three dimensions of occupant behavior modeling: temporal, spatial, and occupancy resolution. Similar to this, IEA-EBC Annex 53 [20] also denotes the importance of understanding how much detail is necessary to reach the defined purpose of the building energy model. In this regards, they suggest preferred occupant behavior models based on four criteria: single or group of buildings, aim of simulation, typical time scale, and typical time step. Even though the need of clarification has been addressed in these previous studies, there is no conclusive answer to what type of model is necessary in terms of its building energy simulation purpose. A simulation for peak load assessment obviously has different requirements than the prediction of monthly aggregated energy consumption.

Secondly, a couple of recent articles [23, 25, and 26] compared different modeling methods and verified whether any of considered models would have a superior merit on providing better approximation than other methods. These articles point out that stochastic models do not necessarily produce better results than other simpler and/or non-probabilistic models of occupancy [23], for instance, when it comes to annual building energy consumption [25]. In other words, once the model is trained using actual occupant data of a target building no matter which modeling method is adopted between probabilistic and deterministic, they yield similar energy outcomes at a certain level of aggregation even if input values differ on an hourly basis. Along with the challenge we have faced for selecting a proper occupant behavior model, this finding evokes several relevant research questions: *when do we really need new occupant behavior models?; how does a specific level of modelers' knowledge (based on previous occupant-related data availability to modelers) influence energy outcomes of building simulation?; more fundamentally, what is the actual role of occupant behavior models (and resulting occupant-related inputs of building simulation) in closing the performance gap?*

We argue that any forthcoming study needs to address these first before supporting the claim that the new occupant model contributes toward closing the performance gap even if it makes a substantiated claimed that it is a more accurate model of actual occupancy. This will enable us to identify where the new occupant model could be properly applied and thus improve confidence in predictions. The objective of this thesis is to provide an analytical basis for the inspection and proper analysis of the role of occupant models.

1.2.3 New Nomenclature: Occupancy Models

In this thesis, we argue that the term occupant <u>behavior</u> models is a misnomer for reasons expounded earlier. That is, we, the building energy modelers are not capable of and not interested in defining the complexity of human behavior in buildings with so many influential factors including biological, social, intellectual, cultural, emotional, ethical, moral, environmental and genetic factors. By using the term “behavior” in our domain, we confuse ourselves as if we could identify these by developing computational models with data. Rather, our aim is to develop occupancy models (a reductionist version of true occupant behavior models) as this reduced form contains only these parameters that have any influence in building thermal studies, i.e. occupant presence and action. In this case, the “behavior” is not necessarily identifiable or even observable but understandable in a statistical sense with enough observational data. As a result, we presume that the occupancy models are primarily driven by (1) monitored data processing and (2) sensitivity analysis, circumventing the need for human behavioral studies.

1.3 Occupant Behaviors and Building Types

To answer the research questions introduced in 1.2.2 within the argued approaches, this study will claim that two distinctive approaches are appropriate for two different types of buildings: residential and commercial. In the design stage, for both residential and commercial buildings, one uses pre-assumed use scenarios such as a number of people and schedule of activities. There is no doubt however, as supported by many studies that the actual occupancy and use of residential space and the systems installed within them varies substantially more than in commercial buildings. One clear example of this is the study referenced in the previous chapter, the heating energy use intensities of 150 Korean apartment units for one heating month, which share the same floor plan, thermal properties of its envelope and a heating system. The major differences between units are the occupants (in residential contexts better addressed as households) who actually live inside and their actions (controls) over a variety of systems including window and blind (inside curtains) operation, lighting and appliance use, heating set-point temperature, etc. As presented in Figure 4, in its dispersion, heating energy use intensity varies from 6 kwh/m^2 to 100 kwh/m^2 even when excluding outliers. One additional context that separates residential from commercial is the role of personal economic conditions (e.g. spending power) of inhabitants in the residential case.

The question arises how can we reproduce such a large spread through an explanatory (bottom-up) occupancy model with the purpose to serve current building simulation purposes? In other words, should we aim for new development of occupant models to adequately represent this apparent large variability in occupancy parameters, as other sources of variation have been eliminated by studying only identical or near identical apartments?

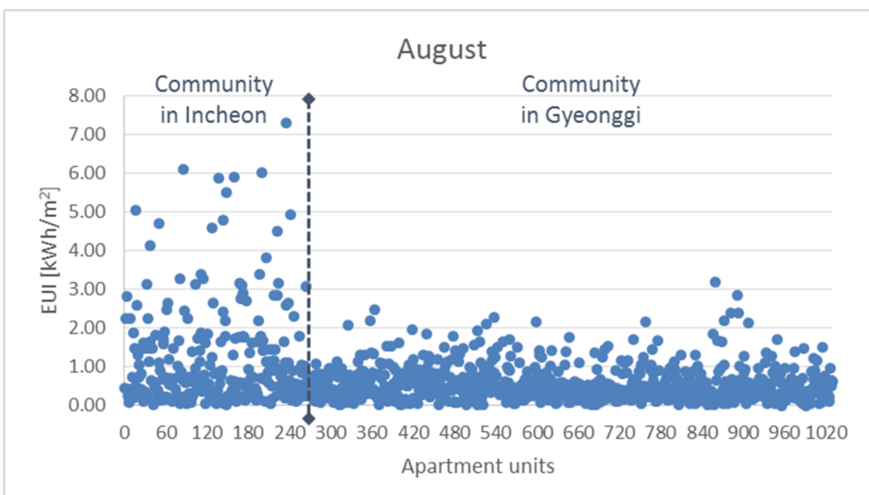

Figure 7 Cooling EUIs of Incheon and Gyeonggi Communities in Korea

The second example (Figure 7) compares cooling energy consumption between the units in two high-rise apartment blocks in the same climate zone. On the left of Figure 7 (the left side of the blue bar), all the units in Incheon have default cooling systems installed inside when the families moved into their units. On the right side of the bar, the units in the Gyeonggi community do not have pre-installed cooling device so that it is left to each household to cope with hot summer days themselves (probably by opening windows) or make the personal decision to install an air-conditioner. Mainly due to this variation in cooling system option in two communities, we can see the distinguished trends of cooling energy use in Figure 7. Higher cooling energy consumption in the Incheon community. Without having house-by-house inspections, we will not know whether and what kind of cooling system a household installed in the Gyeonggi community. Even if we would have this information, getting the information of their preferences, comfort desires, economic consideration, and any other relevant details, it would still be a major challenge to capture this in explicitly modeled variability of occupant parameters, in the hope to generate the observed variability in yearly and monthly energy outcomes. Even with additional information, we just would not know how they actually behave inside of their house.

This wide variability of energy consumption in residential buildings stems mainly from the dependency of system controls in the housing and the difficulty of generalizing compounding factors such as cultural, social, psychological, economical and physical backgrounds of occupants in private homes. This gives a weak underpinning of the claim that building energy simulation will benefit from any detailed occupant modeling, since there are so many factors that influence occupants, their actions, and ultimately energy consumption, as we realize that those are often not measurable, generalizable, and/or describable in the current tools. The next chapter (Chapter 2) will show failed attempts to do so. Given the lessons from that exercise, the complex context of housing and the large observed discrepancy of energy consumption, this study proposes a way to capture the aggregated impact of occupants and their behavior by introducing a so-called *"*Life Style Factor*"* and verify whether the data driven (top-down) approach using this factor is adequate to estimate the variability of future energy use appropriately for the residential case without modeling any details of occupants.

In contrast to residential buildings, commercial buildings have relatively regular schedules of working days and hours and provide less control and interaction options to occupants over the systems even though the inhabitance and implied work cultures of certain occupant organizations will likely lead to more or less some variability. In certain modern workplace cultures, aimed at millennials and a volatile (less controlled) work setting, one could expect that some extreme variability between individual workers and work spaces will result. For the time being it is hard to predict which trend will prevail in future commercial buildings. If we limit our treatment to the current building stock in the U.S., we conclude that commercial buildings tend to become more occupant-centric but centrally controlled rather than relying on individual occupant control. Even if the automated controls will be influenced by the preferences of organizations, once energy modelers know the control strategies, it is quite clear, straightforward, and easily describable in current building simulation tools. This leads to relatively less uncertainty in occupant-related inputs for commercial building simulation and hence it seems promising to try out "better" occupancy models for building energy simulation, i.e. ones that lead to a prediction that is closer to the actual energy consumption. The term "closer" in the previous sentence needs special considerations. As all predictions can only be as good as their assumptions allow, one must be able to quantify the role of all uncertainties, in the occupancy models and all other uncertainties, e.g. in assumed values of input parameters. This then leads to a better way of inspecting the closeness of predicted and actual outcomes, which takes the role of uncertainties as the basis of the comparison. In this regard, more rigorous examinations will be conducted for the commercial type, to answer the following research questions: *1) what's the relative importance of occupant-related inputs in reducing the uncertainty of building energy simulation in general?; 2) how does a particular input uncertainty, i.e. the one that associated with a certain level of modelers' knowledge (or ignorance) on expected occupancy influence the energy outcomes of building energy simulation?* By answering these two questions, this thesis will enable the energy modelers to adequately acknowledge the role of occupant inputs and their impact on energy outcomes, hence properly choose the occupant modeling for their simulation purposes. As a corollary, this study will inform the research community when there is a valid reason to pursue or continue research in better occupancy models.

1.4 Organization of Thesis

This thesis is outlined as follows;

- Chapter 1 has presented motivations and backgrounds of occupant behavior modeling and by elaborating the current research findings, some fundamental research issues are raised to be explored in this thesis. It is argued that these research questions need have a distinctively different setting in residential versus commercial buildings, warranting a different approach to either.

- Chapter 2 elaborates the claim that residential building types require a special aggregate treatment of occupancy and occupant actions. It introduces a “Life Style Factor” that captures the aggregated impact of occupants and their behavior in residential buildings leading to the overall conclusion that relying on standard occupancy modeling for energy predictions of residences is untenable.
- Chapter 3 gives the details of the sensitivity analysis and sets up a comparative study that can identify the roles of occupant-related inputs in building energy simulation.
- Chapter 4 summarizes this thesis with conclusions, expected contributions and possible future research.

CHAPTER 2

OCCUPANCY MODELS FOR RESIDENTIAL BUILDINGS

2.1 Introduction

Recent studies have devoted a great deal of effort to developing better occupancy models for building energy simulation, especially in terms of their time dynamics implementation, using stochastic and agent-based approaches [27 through 39]. The common goal of these studies is to produce estimates of energy use that are close to measurements by accounting for more realistic occupant behavior in building simulation. However, without massive data gathering about occupancy variables such as presence and actions in different types of buildings, it is still hard to generate general and comprehensive occupancy models that accurately represent the role of occupancy variability in current buildings. In this chapter, we suggest a way of utilizing building energy consumption data to predict energy use in future buildings without knowing the detailed occupancy variables.

While using the normal modeling approach based on building energy model parameters, we introduce a new factor, not found in building energy models, i.e. “Life Style Factor” into our calculation as an additional input in order to capture the combined effect of occupancy variables, such as presence, the operation of set-point temperatures, lighting schedules, and appliance use. This LSF is thus a rolled-up macro version of a fully descriptive occupancy model, representing cumulative impacts of occupant behavior as related to energy consumption. This factor is particularly relevant in cases where we are unable to adopt a detailed occupancy model. Previously we argued that especially in residential buildings, the variability over households, attitude, affordability, and many special personal circumstances usually results in a very wide range of stochastic occupancy models that requires extensive data gathering and analysis to model. For that reason, we postulate a factor that is easier to derive and may capture all the influences sufficiently for the purpose of a project developer. Along with the LSF, we introduce other parameters to test which ones have the power to explain the variability over the observed consumption. This leads to a set of calibration parameters (including LSF) that we treat as stochastic variables that will enable us to estimate not only the means, but also the range (variability) of energy consumption over apartment households in future projects.

To test this proposed method, we utilize monthly cooling energy consumption data for 2,182 Korean apartment housing units with a support of POSCO E&C [12]. More details of buildings and data are elaborated in the following section.

2.2 Case Study

2.2.1 Case Buildings and Energy Data

Energy Consumption Data

With the support of POSCO E&C [12], this study utilizes cooling energy consumption data of 2,182 POSCO E&C apartment units located in Asan, Incheon, Gyeonggi , Busan, and Geoje in South Korea including two climate zones.

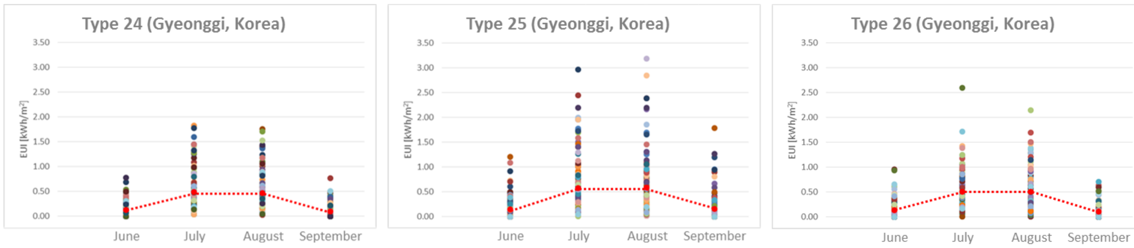

Figure 8 Energy Use Intensities of Type 24, 25, and 26 (Gyeonggi, Korea) and its Averages (Dotted line)

Table 1 Cooling Energy Data Sources: Building Location, Unit Type, Number of Units, and Units for a Cross-Validation

Climate data used	Climate Data: In-Cheon, South Korea									Climate: Ulsan, South Korea					
Location	Incheon, South Korea			Asan, South Korea			Gyeonggi, South Korea			Geoje, South Korea			Busan, South Korea		
Floor plan type	Unit Type	Floor Area (m^2)	No. of unit	Unit Type	Floor Area (m^2)	No. of unit	Unit Type	Floor Area (m^2)	No. of unit	Unit Type	Floor Area (m^2)	No. of unit	Unit Type	Floor Area (m^2)	No. of unit
	Type 1	142	37	Type 13	118	55	Type 21	94	85	Type 27	93	34	Type 35	94	41
	Type 2	145	36	Type 14	161	19	Type 22	94	91	Type 28	91	33	Type 36	94	12
	Type 3	145	20	Type 15	161	17	Type 23	97	104	Type 29	132	49	Type 37	94	15
	Type 4	122	17	Type 16	160	14	Type 24	108	143	Type 30	132	51	Type 38	116	98
	Type 5	122	8	Type 17	160	16	Type 25	108	139	Type 31	132	35	Type 39	116	14
	Type 6	140	8	Type 18	160	15	Type 26	112	137	Type 32	132	35	Type 40	116	19
	Type 7	140	8	Type 19	185	26				Type 33	157	59	Type 41	135	19
	Type 8	158	33	Type 20	185	34				Type 34	157	60	Type 42	135	18
	Type 9	158	30										Type 43	135	15
	Type 10	158	8										Type 44	135	19
	Type 11	180	18										Type 45	137	88
	Type 12	180	20										Type 46	137	26
													Type 47	137	44
													Type 48	134	41
													Type 49	134	41
													Type 50	134	41
													Type 51	134	47
													Type 52	156	46
													Type 53	182	22
													Type 54	182	22
Data used	Step 1 (optimization)		207	Step 1 (optimization)		196	Step 1 (optimization)		699	Step 1 (optimization)		264	Step 1 (optimization)		600
	Step 2 (cross-validation)		36	Step 2 (cross-validation)		NA	Step 2 (cross-validation)		NA	Step 2 (cross-validation)		92	Step 2 (cross-validation)		88
													Total number of units		2182

Table 2 Known and Unknown Parameters from the POSCO E&C Apartment Unit Data

EPC Input Type	**Known parameters**	**Unknown parameters**
Building General	- Building location (Two climate zones) - Terrain class - Total building volume - Building height - Envelope heat capacity	N/A
Building System	- HVAC system type - Fan power - Pump - Building energy management system type	1) Building air leakage level 2) Cooling system COP
Zone	- Zone floor area	3) Internal gain 4) Set-point temperature 5) Occupant/Appliance/Lighting schedules
Envelope Materials	- Opaque/Transparent area - Shading type - U-value - Absorption Coefficient - Emissivity - Solar transmittance	N/A

These five apartment communities have unique floor plans according to the size of their units. Each community consists of at least 8 units with the same floor plan and as many as 143 units. That is, the units share the same floor plan, thermal properties of the building envelope and orientation. Therefore, these data can be utilized for the analysis of the impact of occupant behavior only on energy consumption while eliminating other possible factors such as parameters related to building thermal designs.

Figure 8 illustrates the patterns of cooling energy use intensities during the cooling months (June through September in South Korea) for units with the same floor plan and the same orientation. The floor areas of Types 24 and 25 are 108 m^2 and that of Type 26 is 112 m^2, and the numbers of the units for Types 24, 25, and 26 are 143, 139, and 137 units, respectively. All of these types are located in Gyeonggi, South Korea. As captured in this figure, the cooling energy consumption is widely dispersed from 0 kWh/m^2/month to 3.19 kWh/m^2/month. Even though the units have the same floor plan and envelope thermal properties, they exhibit a large discrepancy between their actual and average (red-dotted line) uses (Figure 8), which originates from the unique occupant behavior in each unit such as occupant schedules, temperature set point control, appliance and lighting uses, and natural ventilation use. Figure 8 also shows that the deviation from the average is wider in the hottest months (July and August) than in the intermittent months (June and September). For example, the standard deviations in August for Types 26, 27 and 28 are 35.61%, 56.06%, and 37.08% and in June, 15.38%, 21.23%, and 18.15% respectively. When we introduce a Life Style Factor in the energy calculation in the later section, we expect that this factor will be able to capture the unknown impact of occupant behavior and its wide variability on energy consumption captured in these data.

Table 1 shows the number of units of each floor plan, its location, floor areas, and in step 1 or step 2. The gray-colored units in Table 1 are utilized for the estimation step (Step 2).

Building design parameters

Table 2 shows the categories of the modeling parameters of the apartment units, separated into known and unknown parameters based on the data that was available in this study. Known parameters are treated as deterministic in all models because either we are able to collect the information or make good guesses throughout the construction data. On the other hand, five unknown parameters including building air leakage level, cooling system COP, internal gain, occupant/appliance/lighting schedules, and cooling set-point temperature are treated as stochastic parameters since those values are potentially different in each apartment unit due to occupant behavior such as their household particulars. Since internal gain, schedules, and set-point temperature largely depend on occupants' presence and control actions in real life, we decide to calibrate them to make the closest match with the measurement, instead of using typical occupancy schedules used in current simulation tools. In the case of occupants, appliances, and lighting schedules, which are defined based on the time of the day and the day of the week, it contains more than 140 unknown input parameters (i.e. 24 hours X 2 weekday/weekend X 3 schedules for occupancy, lighting, and appliance). Instead of calibrating all of 140 schedule parameters inputs, first we input standard schedules for residential buildings defined in commercial reference buildings (mid-rise apartment) of the U.S. Department of Energy [40] and then estimate (calibrate) the total internal gain alternately. Because of this simplification, we only have one unknown input parameter accounting for the internal gain (occupants, lighting, and appliance).

Unlike typical residential buildings in the United States, cooling systems are not installed by defaults in South Korean housing; heating systems such as a radiant floor heating system with a boiler, however, are typically installed when the units are built. For instance, the data set of this study include only one apartment community in Incheon, South Korea, with built-in air-conditioning systems inside the units. Consequently, without a housing inspection, we do not know if a unit has a cooling system.

Furthermore, even if a unit has a cooling device such as a floor-standing air-conditioning system, its actual use may be occasional [41]. In Korean housing, natural ventilation through open windows is a more common way of creating an acceptable level of indoor thermal comfort [42] and as a result, the use of the cooling system will be significantly reduced. In this study, we consider the cooling system COP unknown as different systems may be installed in the units, and the use of the systems at different part load fractions may vary significantly between different households. In addition, we consider the average outside air infiltration as an additional calibration parameter to account for a random use of natural ventilation in the units, which obviously may differ significantly across the households.

2.2.2 Analytic Model

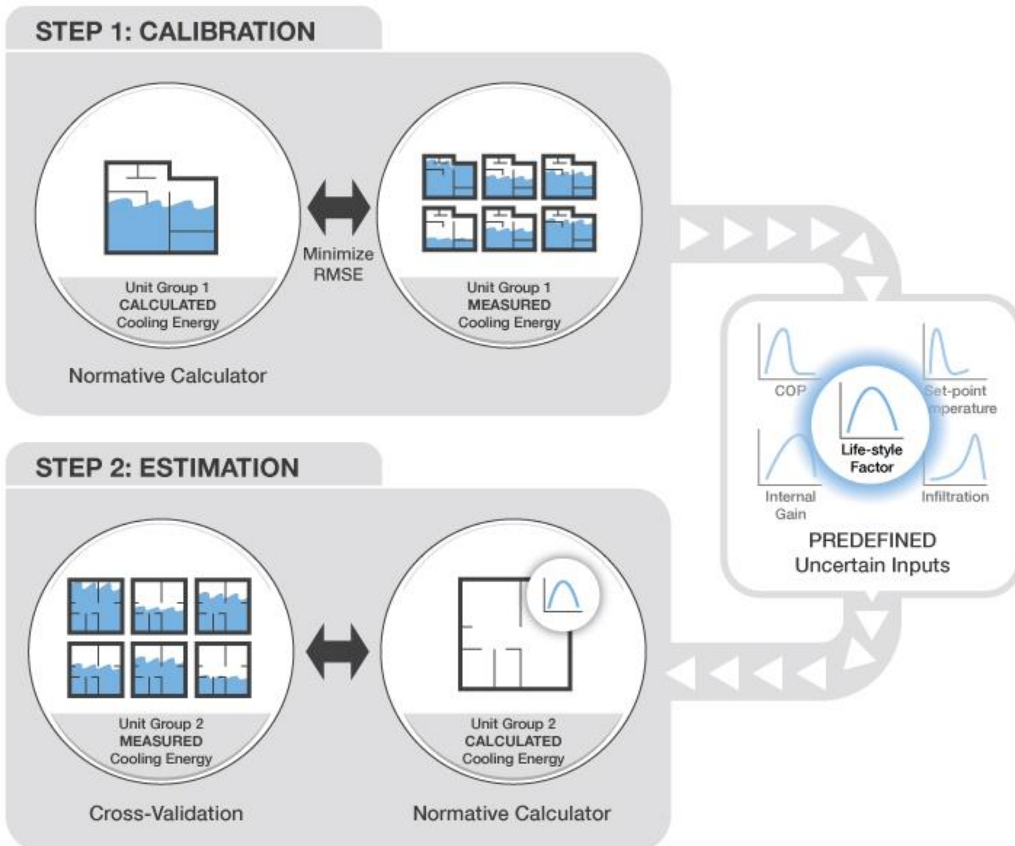

Figure 9 Calibration and Estimation Procedure

The method used in this study consists of two steps (Figure 9). In Step 1, we construct 50 distinct apartment unit models in a normative calculator with known inputs presented in Table 2. The calculated results from each apartment model are compared with the measurement data from identical units. We use the comparison to calibrate five selected input parameters that we regard as uncertain or unknown: cooling coefficient of performance (COP), set-point temperature, internal heat gain, infiltration, and Life Style Factors.

The calibration method is as follows: compare the results for each apartment from the normative calculator with the measurements and run simulations to minimize the root-mean-square error (RMSE) by calibrating five unknown parameters using MATLAB coding [43]. Once we find the optimum values for the calibration parameters (Step 1) for each apartment with an acceptable resulting average of the RMSE (20.1% on average), we generate cumulative distribution functions (CDFs) for each unknown parameter. In Step 2, we construct and simulate other six apartment models (independent from Step 1) for cross-validation, but this time using the five calibrated parameters with the CDFs from Step 1. We then compare the results of these results with measurement data to check if the estimation results from Step 2 are adequate and close enough to the measured energy use data.

Reduced order energy calculation tool

This study uses a reduced order building energy calculation tool developed by the Georgia Institute of Technology based on CEN-ISO standard 13790:2008, the Energy Performance Coefficient (EPC) calculator [15]. It should be noted that the EPC calculator is an "open" version of the normatively defined energy calculation in the ISO standard. The open version deviates for the normative approach in that it allows user chosen inputs for certain parameters that are closed in the normative model. As such the EPC calculator constitutes an easy to use reduced order calculation tool. This lightweight and Excel-based calculator is widely adopted and recognized as an adequate tool especially for large-scale building performance analysis [44 and 45] and building rating purposes [46] since normatively-defined modeling assumptions and parameters constrain the number of building inputs and thus circumvent modeler's bias and reduce the chance of modeling errors. Another benefit is the limited computational effort, which is a benefit since we have to perform 50 calibrations that requires optimization with on average of 1,500 evaluations of monthly energy consumption before full convergence. In this study, we use an EPC calculator based on the monthly quasi-steady-state calculation method [15] which has been proven [46] to be perfectly adequate for comparative energy analysis on the monthly aggregation level.

Life Style Factor

In addition to the calibration parameters explained above, we test an alternative approach, based on a Life Style Factor which is deemed to account for all variability across households of all possible occupancy variables, including actions in an apartment. The approach starts from the recognition that it is almost impossible to predict individual variances, because of their randomness in nature and it is impossible to guess personal constraints and intrinsic factors such as demographics, health, age, gender, and household size that are not recorded for the monitored apartments and usually not known in an apartment design project. One additional unknown factor is the accessibility to cooling systems (built-in or optional post-installation) inside units. As we explained in Chapter 1, Figure 7 shows the difference between Incheon and Gyeonggi Communities mostly driven by different cooling system options. From the large-scale data set of 2,182 apartment units in this study, determining actual building use, such as window-opening behavior, seems virtually impossible without a detailed occupant survey and/or monitoring.

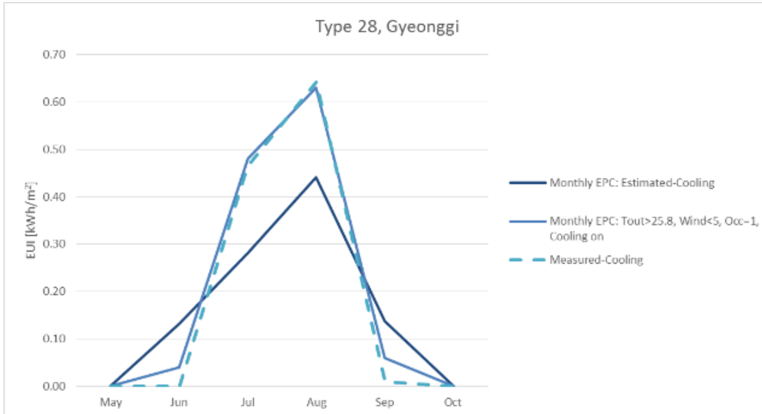

Figure 10 Measured and Calculated cooling EUIs of One Unit in Gyeonggi, Korea

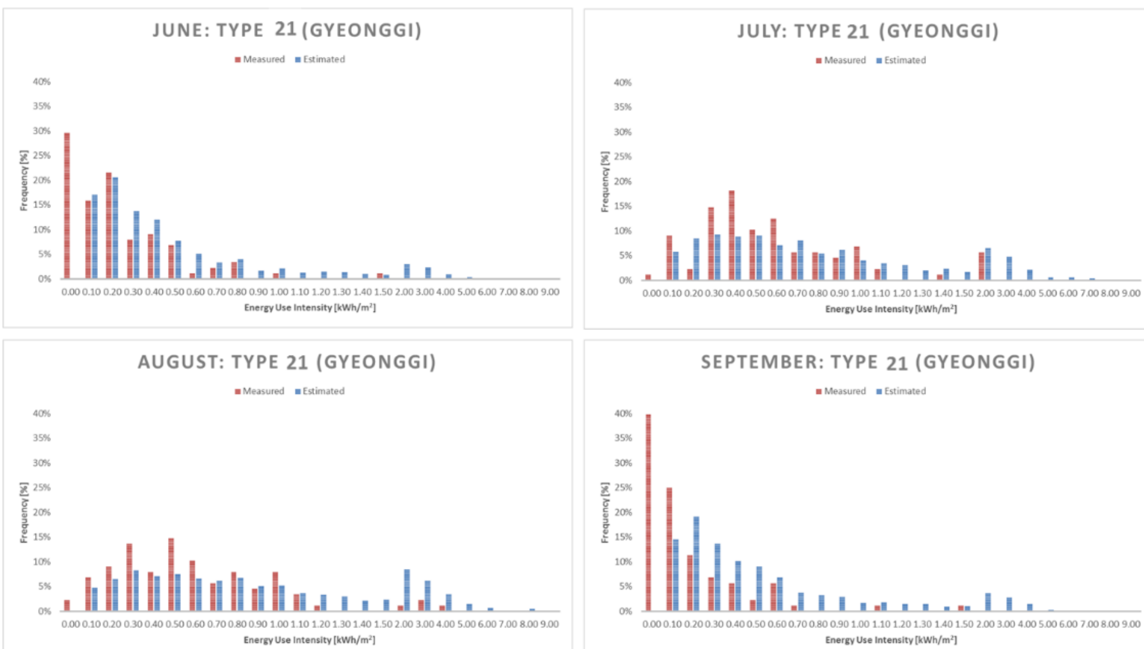

Figure 11 Measured and Estimated Cooling EUIs with a Single Life-Style Factor
(Type 21 in Gyeonggi, Korea)

As seen in Figure 10 for one selected apartment, when we apply standard occupant inputs in the energy model, the results of monthly cooling energy consumption (dark blue) differ markedly from those of the measurements (light blue).

Once we manually set the input conditions, the results (dotted) closely resemble those of the measurements with the RMSE of 14.09%. In this case, we assumed the conditions of cooling system use based on the fact that natural ventilation is a common way of cooling in Korean housing. We set several conditions of natural ventilation use by using outdoor temperature, wind speed, and occupant schedule. These results could indicate that we need a detailed occupant survey and monitoring when targeting the estimation of actual energy use of individual apartments. For our study the individual prediction for a particular apartment-household combination is less relevant as the developer is primarily interested in the prediction of the spread over the apartments in a new targeted development. This is in fact the main purpose of the energy analysis in the design development stage, as the owner wants to generate apartments where a maximum energy consumption guarantee can be given to the prospective renters or owners. As is clear from the data, such guarantee is hard to give as there will always be households that will use more energy and will complain that the guarantee is not met. Given the large spread, this looks inevitable, no matter what guarantee is given. From the developers perspective it is however important to find the guarantee level that will be met by, say, 80% of the households assuming that no other instructions will be given to the new renters. In reality the 80% guarantee will be given to a renter contingent on certain behavioural rules that could be developed from studies discussed in this chapter. This is however beyond the scope of my thesis.

As seen in Figure 11, we found that a single summer long Life Style Factor for four cooling months from June to September was not able to capture the occupant diversity adequately for different months. Figure 11 shows 30% to 40% of units of Type

22 in Gyeonggi have zero cooling energy use in June and September, and one Life Style Factor could not account for this tendency. Therefore, this study introduces two separate Life Style Factors for June and September (the intermittent months) and July and August (the hot summer months) based on the different cooling energy use patterns shown in the measurement data.

2.2.3 Calibration of Unknown Parameters (Step 1)

Among the 54 types of floor plans, 50 units were modeled and calculated in Step 1 and five unknown parameters were calibrated for each unit separately to make the calculated results close to those of the measurement data using the EPC monthly calculator [44] and MATLAB coding [43]. These 50 types of floor plans account for 1,966 units among 2,182 units in the data set. Table 3 shows the lower and upper bounds of unknown parameters, including cooling COP, infiltration rate, internal gain, set-point temperature and Life Style Factors, which we calibrated in MATLAB coding to minimize the RMSE (20.1% on average) for each apartment unit. That is, cooling energy consumption of each unit is calculated for 1,000 times with randomly selected values of five unknown parameters shown in Table 3. Out of 1,000 results, the closest one to the measurement with a minimum RMSE is selected for a corresponding household. Remember that each unit design has at least 8 up to 143 households resulting different cooling energy uses from reality (measured data).

Table 3 Lower and Upper Bound of Unknown Parameters in MATLAB setting

Optimized Parameters	Cooling COP	Infiltration [ACH]	Internal Gain [W/m^2]	Cooling Set-point Temperature [°C]	Life-style factor
Lower bound	3	0.1	15	20	0
Upper bound	4	9	60	28	1

2.2.4 Estimation with Pre-Defined Unknown Parameters (Step 2)

For a cross-validation test, we estimate the cooling energy use of Type 2 in Incheon, Types 28 and 33 in Geoje, and Type 45 in Busan (Table 1) and compare the results of the estimations with those of the measurements (Figures 12 to 15). By utilizing the CDFs from Step 1, we sample the values of the five unknown parameters from these distributions to create 1,500 samples that are subjected to an individual calculation run. The results are used to make a probability distribution of the energy consumption. This is done for all different floor plans. Figures 12 through 15 show both the estimated and measured cooling energy uses with their probabilities in percentages for each unit listed above. The figures also present the deterministic EPC calculation results, calculated without pre-defined parameters, in green. This deterministic prediction did not include a Life Style Factor, whereas the other calibration parameters (cooling COP, infiltration rate, internal gain, and cooling set-point temperature) were for all apartments identically set to their typical values used in current simulation practice based on commercial reference buildings (mid-rise apartment) of the U.S. Department of Energy [40].

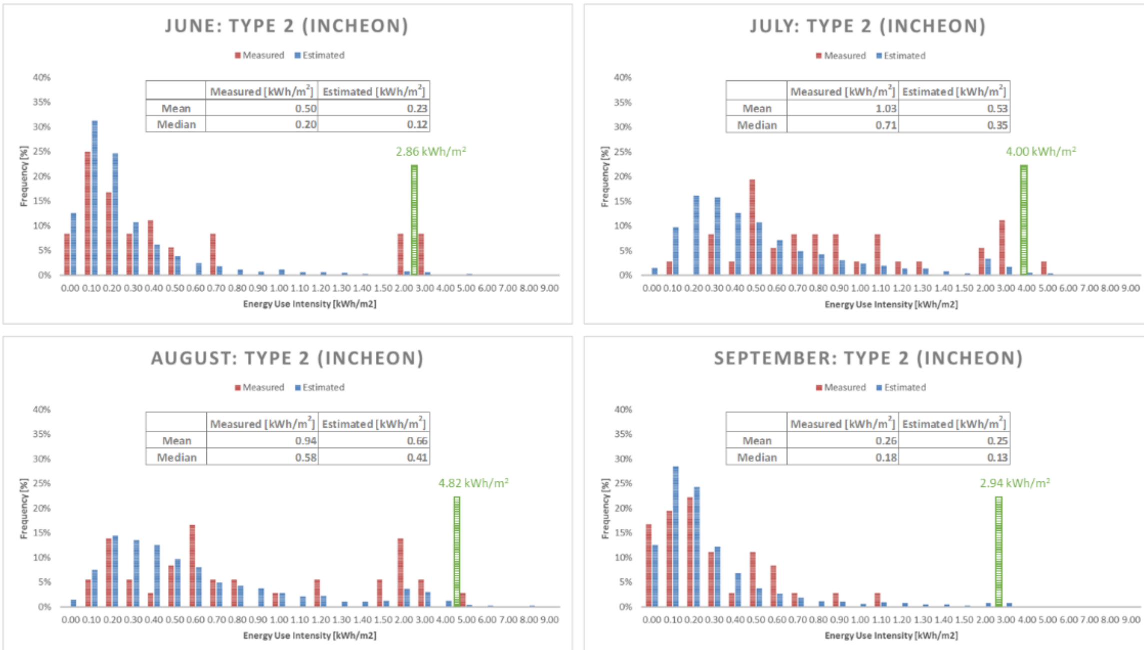

Figure 12 Step 2: Result Comparison (Type 2, Incheon)

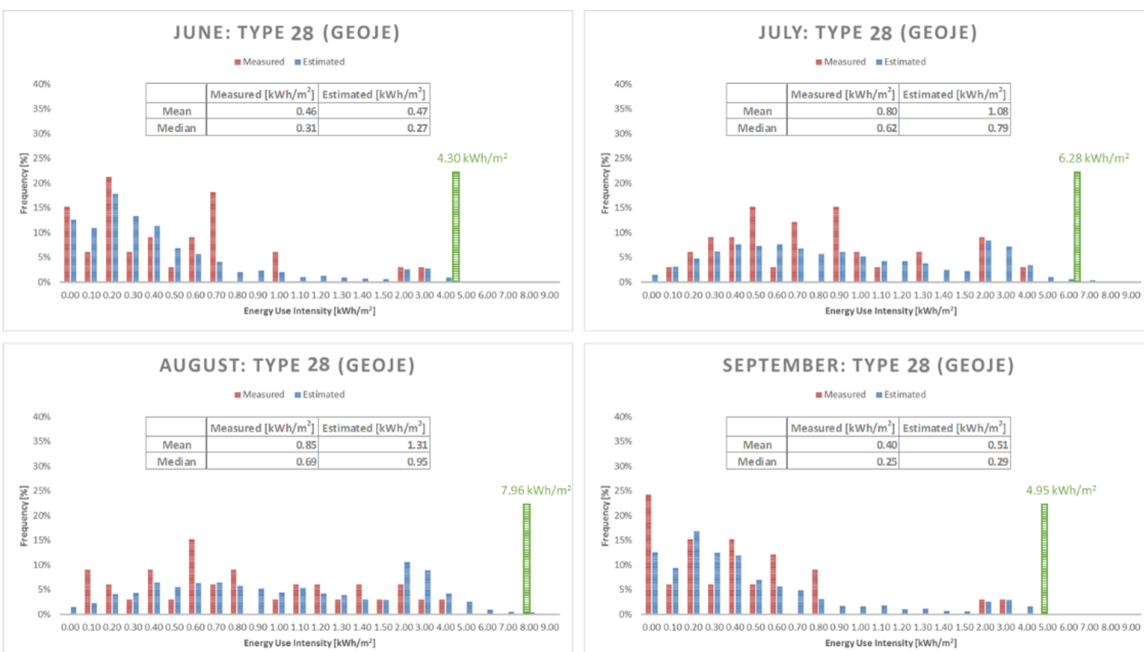

Figure 13 Step 2: Result Comparison (Type 28, Geoje)

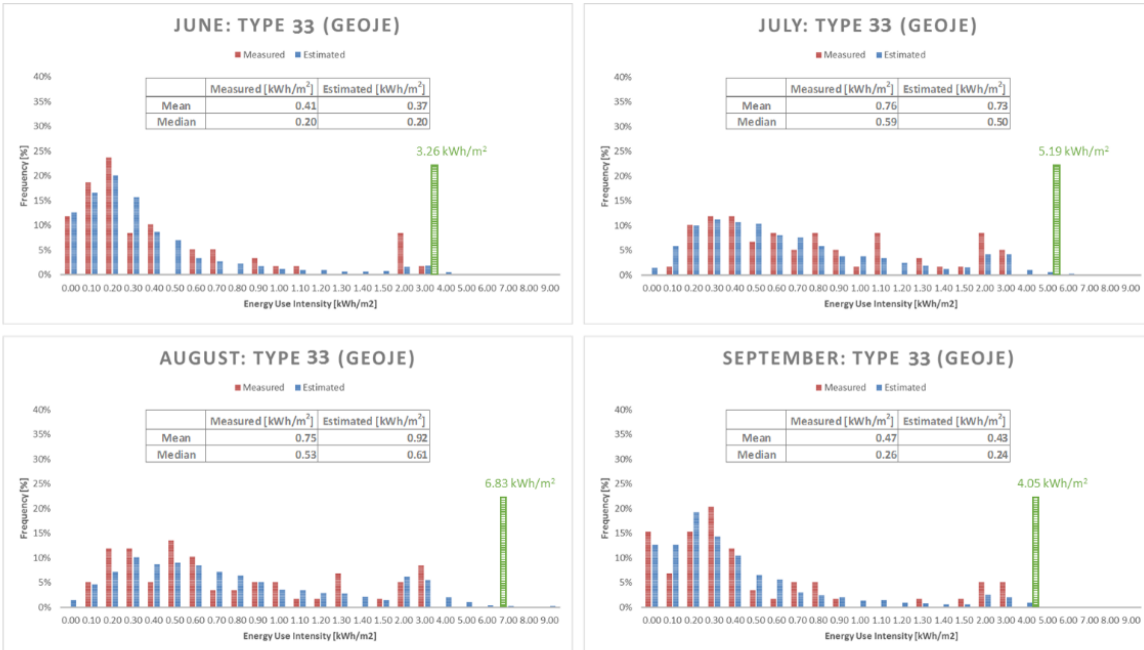

Figure 14 Step 2: Result Comparison (Type 33, Geoje)

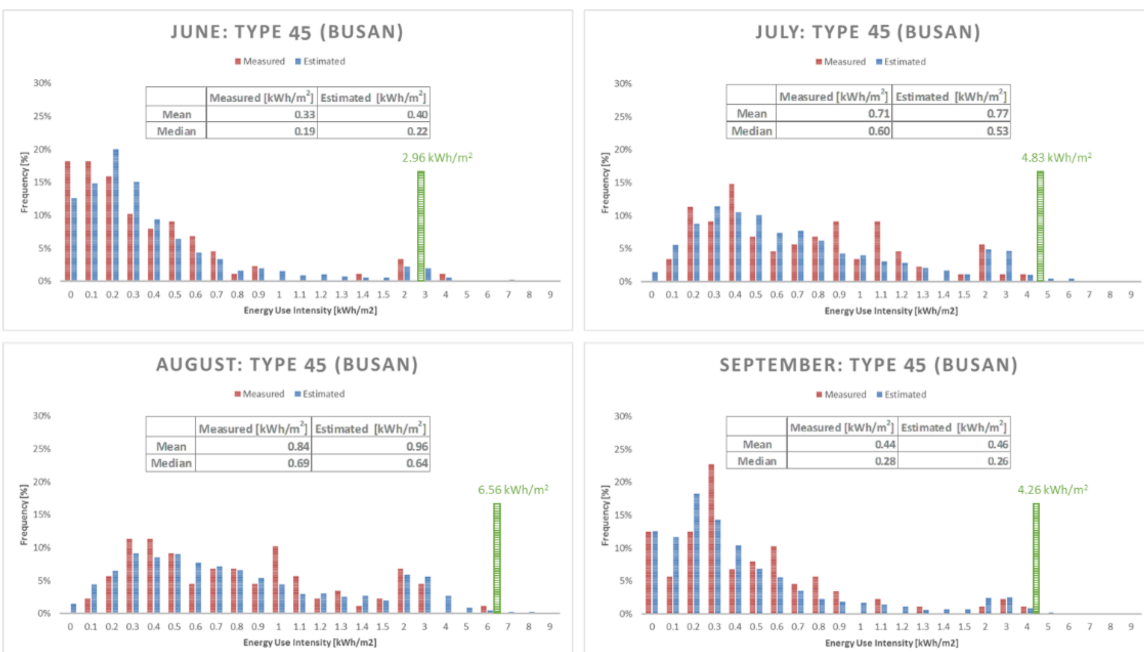

Figure 15 Step 2: Result Comparison (Type 45, Busan)

Table 4 Comparison of mean cooling EUIs (Type 45, Busan)

Type 45, Busan (The best fit)				
Mean Cooling EUI [kWh/m2/month]	June	July	Aug	Sept
Measurement	0.33	0.71	0.84	0.44
Estimated using calibrated parameters and LSF	0.40	0.77	0.96	0.46
Estimated using standard inputs	2.96	4.83	6.56	4.26

Table 5 Comparison of mean cooling EUIs (Type 2, Incheon)

Type 2, Incheon (The worst fit)				
Mean Cooling EUI [kWh/m2/month]	June	July	Aug	Sept
Measurement	0.50	1.03	0.94	0.26
Estimated using calibrated parameters and LSF	0.23	0.53	0.66	0.25
Estimated using standard inputs	2.86	4.00	4.82	2.94

Overall, Figures 12 through 15 show that the estimated variation of the energy use of individual floor types corresponds well to the measured energy use pattern across the data set. In the case of Type 45 in Busan (Figure 15), its probability distribution and mean of cooling energy use have the best match with measurement with 12% of difference in average EUIs. However, when a smaller number of units was available for the energy data, a weaker resemblance of the probability distributions occurred, for example, in Type 2 in Incheon (36 units) (Figures 12). In the same context, the estimated results of Type 33 (Figure 14) in Geoje with 59 units show closer agreement with the measured cooling energy use pattern than Type 28 (Figure 13) in Geoje with only 33 units. Tables 4 and 5 compare the estimated results with measurement both for the best (Type 45 in Busan, Figure 15) and worst (Type 2 in Incheon, Figure 12) fitted results.

Despite the relatively poorer match for some floor types, it is fair to conclude that all of the estimated results, by considering occupant impact in the way described above, show a much more realistic indication of the cooling energy use than the deterministic prediction which uses a standard household profile. When the number of measurement data is large enough to provide the variability of occupancy, this method, unlike typical simulation tools, is relatively simple and efficient in terms of modeling and computational effort that must be devoted to estimating more realistic energy use of apartments. Moreover, the outcomes allow the developer to make better estimates of the aggregated consumption of the apartment complex, which is used for the proper estimates of long term energy footprint of the new apartment building.

2.3 Discussion

This chapter proposes a way of utilizing monitored energy consumption data of apartment units to predict energy use in future projects. This is accomplished by using the data of realized projects to estimate the cumulative effects of occupant and apply them to future designs in the same demographics area. This study introduced a new additional parameter, “Life Style Factor”, to capture the cumulative effects of occupant behavior and possible but unknown operational constraints, such as accessibility to cooling systems (i.e., built-in or optional post-installation of a cooling system). When we estimate the cooling energy consumption of new designs using the CDFs of the five calibrated parameters in Step 1, we find that this method provides good estimates of not only the means, but also the range (variability) of energy consumption, i.e. far more realistically than typical simulation results based on standard assumptions, and significantly better than calibrated occupancy models without use of a macro factor such as our LSF. The results are significant for project developers of new apartment complexes, as they want to not only guarantee a certain mean energy consumption of the total building but also anticipate the wide range of actual consumption of individual apartment, as this has implications for their tenant leasing agreements as well as energy code compliance and potential electric utility contracting. By examining a larger amount of measurement data including cultural, spatial, and demographical differences of buildings, future research could yield findings that would prompt engineers and architects to apply this method more universally.

A far reaching conclusion of this chapter is that the work on occupancy modeling of households may in many cases be ill-guided, because of the large variability across household usages of their residence that finds its origins in many personal, cultural, social and economic factors that are outside the realm of what will be known about intended occupants of future residential building, or indeed CAN be known about the residents. We argue that the best way forward is therefore the large scale use of residential consumption records in different locations, demographics, building types and income scales to create a database of LSF distributions that can readily be used in predictive energy studies.

CHAPTER 3

OCCUPANCY MODELS FOR COMMERCIAL BUILDINGS

3.1 Introduction

Unlike residential buildings, the characteristics of office buildings and occupants who reside in them, can be assigned in a more formal and systematic way to designated spaces and regular patterns of occupancy based on their working days and hours. Commercial buildings seem therefore amenable to a more detailed treatment of the role of occupancy, which in contrast to that residential buildings can be viewed as a bottom-up approach. This should lead to a refinement of existing or the introduction of new occupancy models, aimed at better representation of occupancy in building simulation for the purpose of predicting building energy outcomes on the monthly scale.

Among other methods used for new occupant behavior models we can distinguish better time series descriptions of temporal variability, i.e. going from deterministic to statistical, agent-based, and based on data-mining. The most recent attempts have been realized by various stochastic methods that claim to provide realistic representation of occupants and hence leading to a closer prediction to the actual energy consumption when integrated with building simulation tools. However, as elaborated in the literature [23, 25, and 26], recently developed stochastic occupant models do not automatically guarantee estimates of energy outcomes that are closer to reality than standard deterministic modeling. This finding demands a fundamental investigation of the actual role of occupancy models (translated into occupant-related inputs in building simulation) on predicted energy outcomes.

The fact that newly developed stochastic models providing “realistic” hourly variations of occupancy do not outperform the standard (deterministic) inputs if derived from the same actual occupancy data of a target building raises two main research questions as followings;

What’s the role of occupancy inputs in the performance gap?

This question implies an investigation into how sensitive the energy outcomes of typical building simulation are to the occupancy inputs. Along with other intrinsic sources of uncertainty in building simulation, the role of occupancy inputs in the disparity between measurement and estimation will be identified in Section 3.3.

What’s the role of modelers’ level of knowledge of actual occupancy in energy outcomes of their interest?

By comparing two contrasting levels of modelers’ knowledge on occupancy, Section 3.4 will reveal not only the impact of modeler’s knowledge on energy outcomes, but also the actual significance of their difference.

This research will present an analytical basis for the inspection and proper analysis of the role of occupancy models in the two major aspects given above, and hence enable the energy modelers to adequately acknowledge the impact of occupant inputs and provide a solid foundation for verifying the proper occupant modeling for various building simulation applications.

3.2 Levels of Modelers' Knowledge

The discrepancy between measured and estimated energy consumption of building designs results from various causes. One of the promising ways to quantify these is uncertainty analysis (UA). The UA of building performance simulation is typically realized by three major sources of uncertainty: parameter uncertainty, model form uncertainty and scenario uncertainty [7, 8, 9, and 10].

The parameter uncertainty refers to the uncertainty in simulation model inputs such as material properties, ground albedo, convective heat transfer coefficients, and wind pressure coefficients that have defined based on standard conditions (e.g. catalogue values), which implies possible variations in unspecified cases. Suppose we are able to acquire the true values of these inputs for our simulation models, uncertainty will still exist since building simulation "models" we use have, by definition, their own assumptions and simplified physical formulae to represent complex processes in the real world. The discrepancy that this causes is categorized as model form uncertainty. The third category is scenario uncertainty, mainly related to the way humans and (control) systems operate the building. The latter category also includes the weather scenario to which the building is exposed. Other possible factors contributing to the performance gap include measurement errors, human errors (bias) in preparing the inputs and processing the outputs. In this thesis we consider the occupant behavior models to be part of scenario uncertainty. Note that we characterize this scenario uncertainty mostly through the parameters with which we have parameterized the occupancy models, which enables a ranking of these parameters with those in category 1.

Similar to other parameters, the uncertainty of occupant-related inputs largely depends on data availability to energy modelers, i.e. how much detailed data related to occupancy they have at their disposal. Such data could for instance come through surveys filled out by designated occupant organizations, or collected data from the same or a similar organization in another, similar building , and if possible similar type of work force composition. These data augment the design brief and specification which are obviously the starting point of the occupancy model. A crude way to indicate the level of modeler’s knowledge about occupancy of a building under design is depicted in Figure 16 [25].

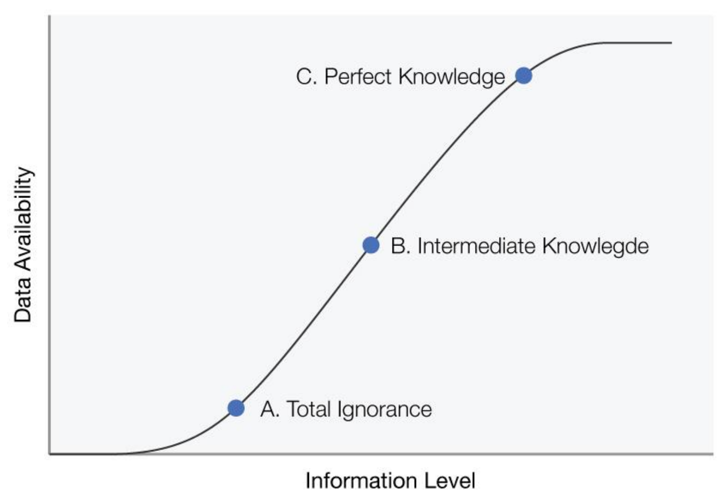

Figure 16 Occupancy information available to the modeler (from low to high)

At the point A (“total ignorance”), we define a typical case during the building design stage where we only have limited information on occupancy before its actual operation starts, such as the intended use of buildings and design brief stating the intended number of people and working hours. In this case, one picks one of the standardized schedules for a corresponding or closest match building of the same type.

The case at point C (“perfect knowledge”) represents the hypothetical case that we have a full access to occupant-related data. This case is indeed hypothetical for buildings under design. For buildings under retrofit, one could imagine that one acquires full knowledge collected through sensors, monitoring, and/or surveys on any spectrum of occupancy in a target building, which means no uncertainty related to occupancy exists, if one assumes that the post retrofit occupancy is the same as pre-retrofit. In most cases, we would be positioned somewhere in between the two extremes, that is, some level of “intermediate knowledge” at which the introduction of an occupancy model with characterized uncertainty could be appropriate.

In order to identify the impact of different levels of modelers’ knowledge on energy outcomes, two tests are conducted. First a sensitivity analysis is carried out to identify the impact of occupant-related inputs on the performance gap along with other sources of uncertainty in building energy simulation. Secondly, we compare the energy outcomes both for the standardized input (still prevalent in current practice) and the actual ones and verify how the outcomes are different from each other. We are interested in finding out whether the impact of increasing levels of knowledge (and thus the impact of more precise occupancy models) needs a full simulation or is quantifiable or predictable by other means.

Since we are aiming to verify the impact of modelers’ knowledge of occupancy on aggregated building energy outcomes, this study focuses on parameter uncertainty in the sensitivity analysis in order to identify dominant parameters and test how much uncertainty of occupancy parameters contribute to the performance gap. By exploring these two tests, we are able to inform the energy modeling discipline about the true relevance of occupant modeling in building energy simulation and set the future research direction to help close the performance gap by enforcing proper occupant modeling.

3.3 Sensitivity Analysis: The impact of occupancy inputs

3.3.1 Sensitivity Analysis

Sensitivity analysis (SA) is conducted with all uncertain parameters of the building energy model in general to rank them based on their influence on energy outcomes generated by a building simulation. For the outcomes, we will focus on monthly heating and cooling energy use in this study.

To put these parameters in order of its influence, an uncertainty analysis (UA) is carried out. The basic approach is that we first quantify the uncertainty in energy outcomes that stems from the uncertainty intrinsic to all parameters, and then execute a statistical method to identify for all parameters, how much of the uncertainty in the outcome they are responsible for. It is clear that the resulting ranking depends strongly on the range of uncertainty of each parameter. However, a parameter with a small range can still end high in the ranking when the outcome is very sensitive to that parameter. The reverse is obviously also true.

Uncertainty analysis is done in this study using the Georgia Tech Uncertainty and Risk Analysis Workbench [GURA-W, 47] which EnergyPlus [48] as its embedded simulation tool. GURA-W provides automated processes for EnergyPlus modelers to quantify the uncertainty using a UQ repository that has prior characterizations of uncertainty in all simulation model parameters. This workbench is realized using EnergyPlus for its building energy simulation engine and ModelCenter [49] for integration of different models, e.g. an excel-based UQ repository, EnergyPlus, and a MATLAB [43] language for Monte Carlo execution and Latin Hypercube sampling.

Along with general parameters of uncertainty already specified in GURA-W, the following occupant-related inputs are added in the SA.

1) Presence of Occupants (impacting metabolic heat loads in the space, as well as direct electricity loads from lighting and appliance use)

2) Window Operation

In the first sensitivity analysis, we use basic occupancy inputs (presence) in the form of current standard practice, i.e. in the form of standard hourly profiles (schedules). Window operation is not considered in this phase of the study.

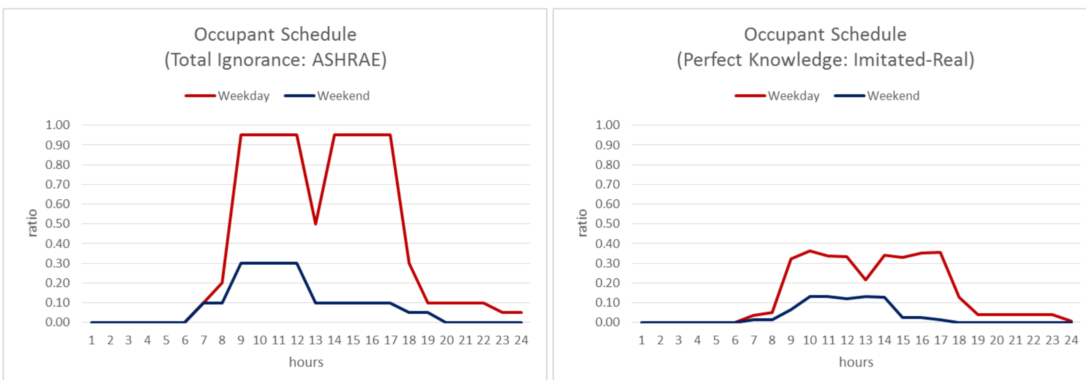

Figure 17 Average Workday and Weekend Occupant Schedules
(Total Ignorance and Perfect Knowledge)

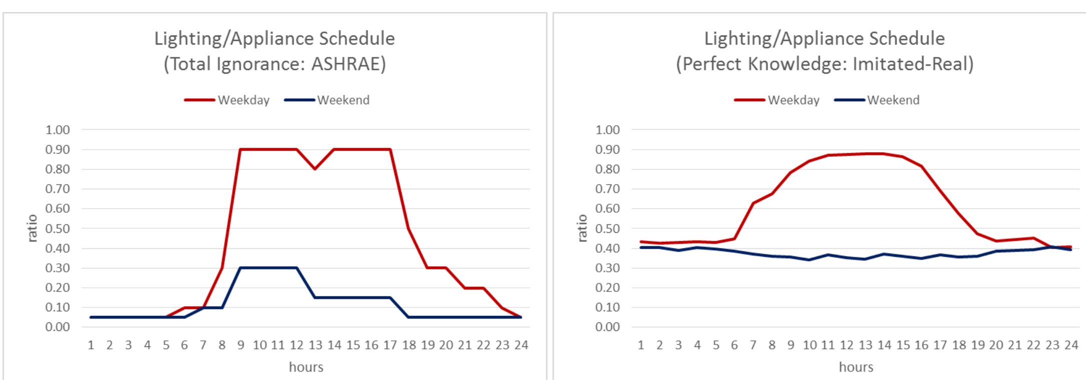

Figure 18 Average Workday and Weekend Lighting/Appliance Schedules
(Total Ignorance and Perfect Knowledge)

In order to distinguish the different levels of modelers' knowledge on the hourly schedules, we use total ignorance and perfect knowledge (refer to Figure 16) by taking ASHRAE typical weekdays/weekends occupancy schedules [14] and imitated real ones, respectively. We deliberately assume quite a large difference between the ASHRAE profiles and our hypothetical perfect knowledge case. Note that whereas the ASHRAE profiles are daily fixed schedules, they are not in the perfect knowledge case, i.e. they vary from hour to hour and day to day. What the figures show as schedules is to be interpreted as the hourly mean of the weekday and weekend schedules. We assume that occupancy parameters that capture the temporal variability will have a quantified uncertainty range and distribution based upon the hypothetical data. In fact, the range and distribution of this uncertainty is of course also related to the level of available data, across the scale from totally ignorant to complete certainty.

The perfect knowledge schedules for both presence and lighting/appliance in this study are fabricated using the LBNL web-based simulator [50, 51, 52, and 53] and once again treated to depict an extreme case (in this case of a clearly under-occupied building) rather than designed for a real life situation. Figures 17 and 18 show the average weekly occupancy profiles (presence and lighting/appliance) for both ASHRAE and the imitated real schedules. In the SA, these two levels of occupancy inputs are treated as a categorical variable with the value 0 or 1. This approach enables the SA method to rank the influence of the occupancy model relative to the influence of other uncertainties.

In addition to this, a second analysis takes occupants' action, especially window opening behavior, into account to establish its relative importance among the other parameters on the energy outcomes. As we are at this stage most interested to verify the need for a sophisticated “window-action” model, we make no attempt to develop such a model. Rather, a plausible window opening logic is postulated and then perturbed by random actions of the occupant. These random actions can range from totally obedient (no randomness) to totally random. The intention of this “monkey experiment” is to establish the sensitivity of energy outcomes to the rationality of window operation. It is clear that if low sensitivity could be established, the monkey will almost do as well as the rational human, thereby absolving the modeler to use a sophisticated window-operation model. Current research efforts are devoted to formulate occupant behavior in mathematical models and estimate their future behavior even including their probable randomness. The results from the second analysis will give us an insight into the actual importance of modeled (rationalized) behavior on energy outcomes.

For our analysis it is of crucial importance to disaggregate energy consumption into HVAC (the indirect consequence of occupancy through sensible and latent heat release from humans and appliances) and other direct electricity use such as used by electric lighting and appliances. The amount of lighting and appliance use will directly influence the electricity consumption in a building but its calculation is very straightforward, i.e. multiplying the power density of equipment with the number of hours of use. The amount of lighting and appliance use will generate additional heat gain in the space along with occupants’ heat dissipation, which will indirectly increase the cooling demand in summer and decrease the heating demand of the building in winter. It is crucial to distinguish these influences and separate them out in the result analyses. This also means that the real aim of our study focuses on the energy outcomes of heating and cooling energy use as the other direct uses of electricity are not mediated by building behavior and can be directly calculated from the schedules and need no additional models.

As we want to make a quantitative assessment of the role of occupancy we need to set up case studies of actual buildings. The SA is conducted for a medium office building from the U.S. Department of Energy reference buildings [14], which complies with ASHRAE Standard 90.1-2004 [54]. This reference building has three floors with one core and four perimeter zones per floor, and total floor area is 4,982.19 m^2. For cooling and heating, a central packaged air conditioning unit and a gas furnace are equipped with variable air volume terminal boxes with reheat.

It should be noted that the purpose of this study is to identify the influence of occupancy and action models on monthly energy outcomes in general, albeit that our analysis will be limited to one particular case building. It is anticipated that the results show how occupancy variables and action uncertainty rank in importance amidst other parameter uncertainty. This should lead to recommendations to focus further research on this area or conclude that some currently touted research directions can be qualified as red herrings.

3.3.2 Heating and Cooling Energy Results

Sensitivity of Occupant Presence

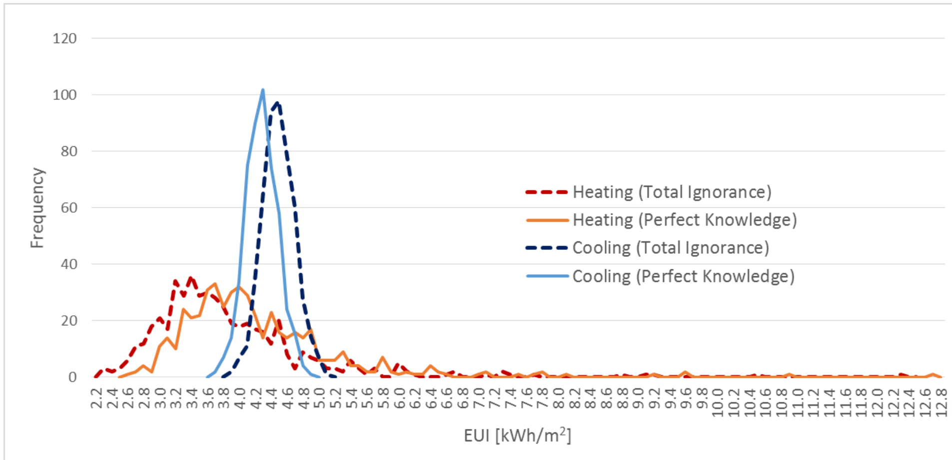

Figure 19 Cooling and Heating EUIs for Total Ignorance and Perfect Knowledge

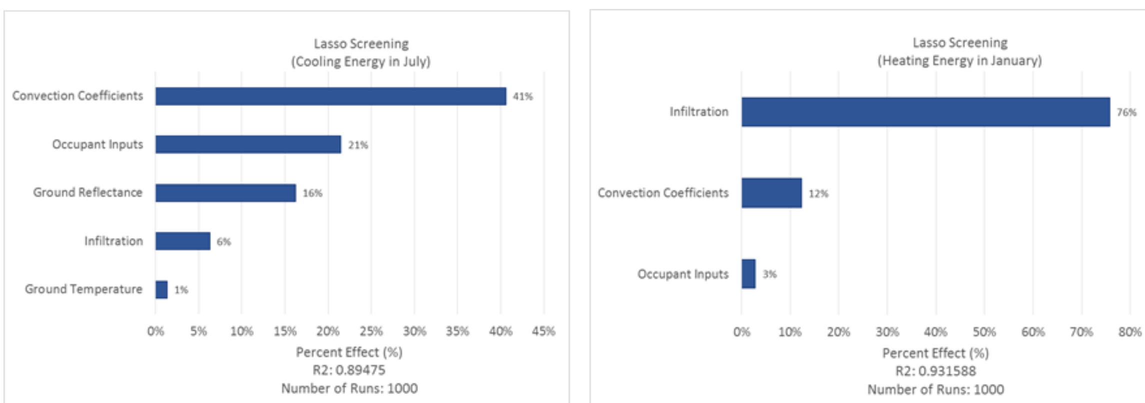

Figure 20 Sensitivity Index Ranking for Significant Uncertain Parameters (1)

Figure 20 presents a ranking of the parameters to which the energy outcomes (monthly heating and cooling energy consumption) are notably sensitive. As described previously, the uncertainty of occupant-related inputs is reflected here as the modeler's choice between two extremes: total ignorance and perfect knowledge about occupants' presence, which depicts the uncertainty pertaining to the modeler's knowledge on occupancy.

For cooling energy use (July in Atlanta, GA), five parameters explain 89.5% of uncertainty with occupancy inputs ranked as second (21%). On the other hand, in case of heating energy use (January in Atlanta, GA), infiltration is the dominant parameter accounting for uncertainty with 76% of outcome variance, while showing occupant-related parameters to have almost no impact with 3%. It should be noted that these rankings reveal only relative importance. If one parameter takes center stage the other parameters obviously become relatively less important. One should always inspect the difference in the outcome distribution (Fig 19) before the assessment of the absolute importance of a parameter. The heating season can be seen to have a large spread which is mostly attributable to the large uncertainty range of the infiltration, driven by uncertainty in wind pressure and ELA (effective leakage area). The large spread (fat distribution) indicates a large uncertainty in the outcome. Note that the difference (shift) between the distributions that we find using the two distinct occupancy models is substantive.

For the cooling season the spread of cooling EUI (Figure 19) is skinny meaning other the overall importance of uncertain parameters is relatively small with use of either occupancy model. The shift between the two distributions is quite "clean", revealing that the shift between the two distributions is quite independent of other factors, as the shapes of both distributions are hardly affected. For both the heating and cooling season the occupancy parameters seem to do little else than shifting the distribution. This expectation is that this is driven by the mean of the hourly presence and hardly influenced by the temporal variability. The impact of occupant-related inputs is found to be feeble in the result of ranking, compared to other parameters such as infiltration, which is as expected.

We should note that even though the occupancy inputs are placed high in a ranking for monthly cooling energy use, we expect that this is caused mainly by the shift which is due to the large difference in presence between ASHRAE schedules and assumed real ones, which results in mainly the shift of cooling EUIs rather than affect the spread in the distribution. As hinted before, this study intentionally creates a large difference (in mean hourly schedule) between LBNL simulator generated “real” and standard ASHRAE such that the combination of the UA and SA enables the separation of mean shift and temporal variability effect. As denoted in previous papers [23, 25, and 26] once modelers have acquired a fair amount of occupancy data of their buildings, this disparity could become negligible. The major conclusion is that the effect of occupant-related inputs seems largely independent from the effect of other uncertainty sources. This leads to the conclusion that the effect of occupancy might be treated through a (simple) calculation of the shift, thus obviating the need of a sophisticated occupancy model. We will come back to this issue later in this chapter.

Sensitivity of Occupant Presence and Window Opening

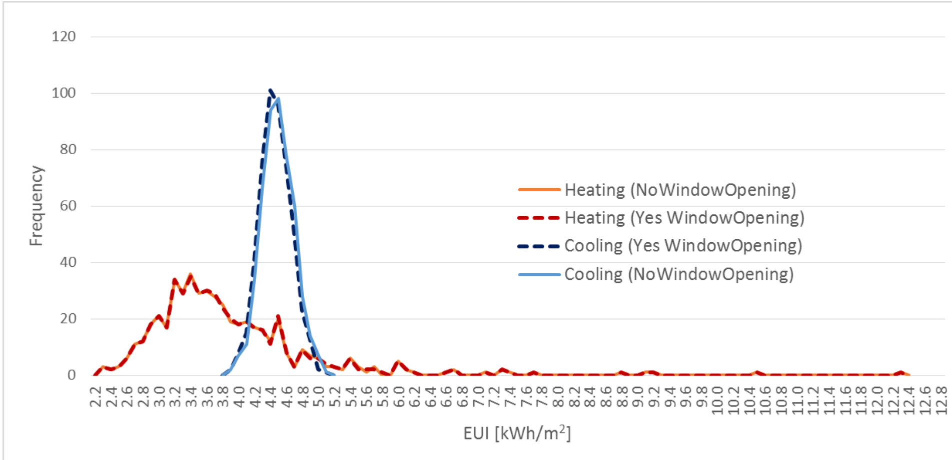

Figure 21 Cooling and Heating EUIs for Including and Excluding Window Opening Action

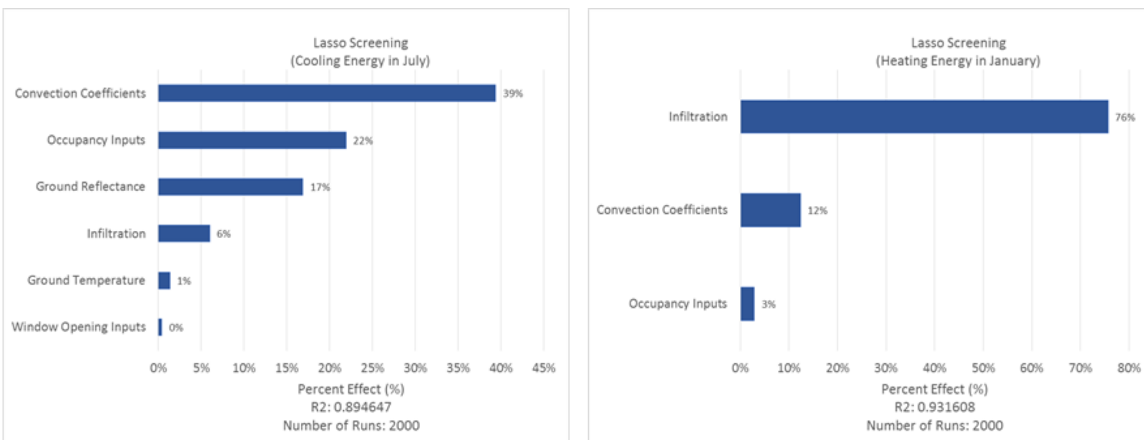

Figure 22 Sensitivity Index Ranking for Significant Uncertain Parameters (2)

In addition to the basic occupancy inputs as used before, a SA is conducted with uncertain window opening behavior as an additional occupants' actions in buildings. Firstly, we treat window opening behavior into two scenarios: no opening action and random opening action. For the window opening logic, we assume that the window will be open, and outside air will be infiltrate at the rate of 20 ACH, once the following conditions are met;

a. the case building is occupied at the current time (i.e. hourly occupant profile is not zero),
b. the dry-bulb temperature of outside air is between 15°C and 30°C,
c. the outside wind speed is less than 15m/s

Note: in the given case these conditions are met for 18% of all hours of the year.

For the purely random case the following condition is added:

d. for all available hours that meet conditions a, b and c, a value of 0 or 1 is randomly generated, 1 meaning that the window is open, 0 meaning that the window remains closed

Based on a reference [55], we identified that a minimum measured air change rate (in houses with open windows) is between 2.5 and 4 ACH and that a reasonable assumption of high flow rate is 10 ACH and above. For the purpose of this study, we assumed a higher flow rate of 20 ACH than the reference, which de facto amplifies the cooling benefit of natural ventilation which increases the sensitivity of window action on energy consumption

As seen in Figure 22, window opening is barely shown in the ranking with less than 1% of outcome variance for cooling EUIs and totally negligible in heating EUIs. This results stem from both the limited hours of natural ventilation in the given climate (Atlanta, GA) and the relatively small impact that natural cooling/heating has in the Atlanta climate for the chosen office building. The next step in the analysis is to consider the role of occupant action modeling. It is important to test whether the randomness of occupant behavior (and different modeling methodologies that create and estimate this randomness) influence monthly energy outcomes significantly. To examine this, we create four different window opening scenarios taking possible biases in real life. For comparison purpose, firstly we have an optimized scenario i.e. rationally-determined window opening actions, which is beneficial for cooling energy reduction while no additional heating energy use is allowed to occur. Next, based on the random schedule used above, we additionally made two scenarios: Bias 0 and Bias 1. Bias 0 represents the case where occupants tend not to open window while Bias 1 depicts the case where they most likely open window. In these three cases including Bias 0, No Bias, and Bias 1, we assume that "usable" outside air temperature can take a wider range than the rational case, for instance to articulate personal preferences. The window opening logic used in these four scenarios and resulting available hours is summarized in Table 6.

Table 6 Window Opening Scenarios

Scenarios		Opt. Scenario	Bias 0 (most likely closed)	No Bias (random)	Bias 1 (most likely open)
Logic	Occupant Presence	Occupied hours only			
	Wind Speed [m/s]	Outside wind speed ≤ 15 m/s			
	Outside Air Dry Temp [°C]	20 ≤ OA ≤ 25	15 ≤ OA ≤ 30		
Total Available Hours		1144 (13%)	591 (7%)	1551 (18%)	2509 (29%)

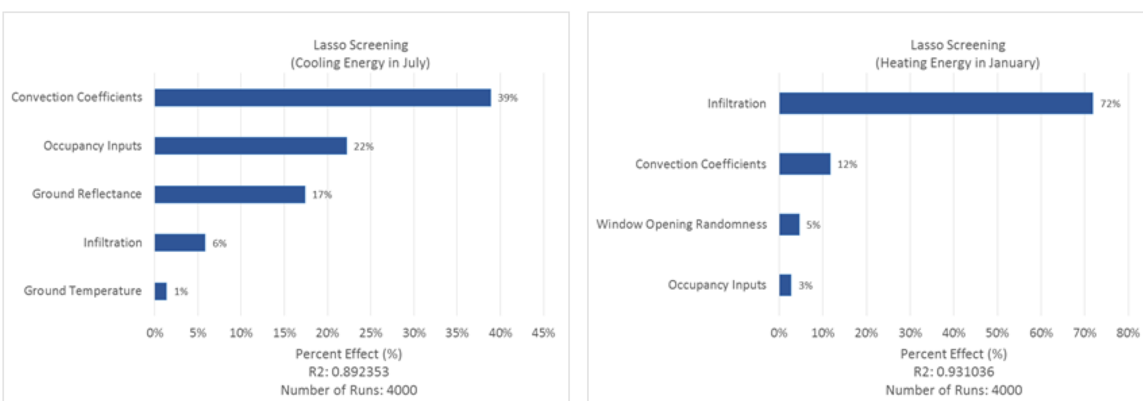

Figure 23 Sensitivity Index Ranking for Significant Uncertain Parameters (3)

As can be seen, the difference between the four window opening scenarios have no significant impact on both cooling and heating EUIs showing barely in the ranking with 3% in heating (Figure 23). Due to the fact that heating energy use is extremely sensitive to the infiltration of outside air, window opening scenarios are ranked third for heating EUIs with Infiltration (72%), nevertheless, its impact reaches only 5%.

3.4 Comparative Analysis: The impact of modelers' knowledge

3.4.1 Comparative Analysis

As identified in the previous section, occupant behavior models, more specifically occupant-related inputs in building simulation have a high rank in the SA results mainly when the modelers' ignorance is large. However, we found out that the levels of modelers' knowledge primarily account for a mean shift of the resulting distributions both in January and July (heating and cooling). This is obviously not surprising as ignorance about the average number of people in a building must lead to significant uncertainty in aggregated energy consumption. But do we need a temporal model of occupancy to predict the EUI shift due to differences in mean occupancy. Wang et al. [25] proved that the actual cooling energy consumption in July (Atlanta, GA) could be predicted using the result of the current practice (standard schedule, i.e. total ignorance) and adding the extra cooling needed for an arbitrary increase in mean occupancy. Moreover, this addition or shift in monthly energy outcomes can be calculated by a simple hand-calculation. This shows that it is possible to calculate the shift between the two occupancy models based on the difference in mean presence. In other words, we can calculate the difference between two cases with the information of how many occupants are on average in the building in a given month. Remember that we are only considering cooling and heating consumption in this calculation because it was already established that the effect of direct consumption of lighting and appliance can be calculated independently of the building. In the following section we will assert that in heating or cooling dominated months the monthly aggregated extra heat load from occupants can be calculated and simply added to the cooling demand or subtracted from the heating demand. The delta in electricity consumption follows simply from multiplying the extra heating or cooling demand with the average COP (close to maximum part load fraction) of the heating/cooling system. The next section will show the calculations and inspect our assertions. Following the reasoning about the shift in heating and cooling one step further we anticipate that during the swing months, e.g. April, see Wang et al. [25], our calculation will not correctly calculate the shift in cooling and heating energy consumption of the building. The reason for this is the fact that in months that are neither heating or cooling dominated, the extra heat load from occupancy may lead to temperature floats within the acceptable comfort range thus not simply increasing cooling or decreasing heating by the by the extra generation. . This recognition also leads to the conclusion that the shift can be climate dependent. For this purpose the uncertainty analysis is expanded to the same building in three different locations including Miami, FL, Atlanta, GA, and Chicago, IL.

3.4.2 Results and Discussion

Cooling Energy Consumption

This section implements the analysis suggested in the previous section. Its purpose is to show that the effect of the difference between the two extreme occupancy models can be represented by the difference in monthly mean presence and heat gain from lighting/appliances alone. If this is indeed confirmed, the conclusion is justified that for monthly energy prediction little else is needed than the monthly mean presence.

First of all, the shift for each month is calculated using the following formulae;

$$\Delta\, Heat\ Gain_{Occupant} = Total\ Number\ of\ People * (Heat\ Gain/Person) * \left(\frac{Total\ Occupied\ Hours_{PK}}{Month} - \frac{Total\ Occupied\ Hours_{TI}}{Month}\right)$$

$$\Delta\, Heat\ Gain_{Lighting/Appliance} = Total\ Lighting/Appliance\ Heat\ Gain * \left(\frac{Total\ Use\ Hours_{PK}}{Month} - \frac{Total\ Use\ Hours_{TI}}{Month}\right)$$

$$Shift\ for\ Cooling/Month = \frac{\Delta\, Heat\ Gain_{Occupant} + \Delta\, Heat\ Gain_{Lighting/Appliance}}{Cooling\ COP}$$

, where PK stands for Perfect knowledge, TI stands for Total Ignorance.

Monthly hand-calculated cooling shifts are summarized in Table 7. Using these values, Figures 24 through 26 are elaborated comparing the distributions of monthly cooling EUIs from the UA results between total ignorant, treated total ignorant with monthly shift, and perfect knowledge.

The light blue color depicts the result of total ignorance using ASHRAE standard occupancy profiles, while the gray color represents the imitated-real case. The result after the hand-calculated shifts added into the total ignorance is presented in a dotted dark blue line. As it approaches to cooling dominated months, the disparity between the imitated-real and the treated total ignorance becomes smaller. Especially June to October in Miami, FL and June and July in Atlanta, GA show close correspondence with each other. For the months that already have a large cooling need, the shifts (i.e. calculated additional heat gains to the total ignorance) directly impact on the increase of cooling loads, while other months would have more hours with free floating indoor temperature between cooling and heating set-points because of this additional heat. This would be hard to calculate by hand.

However, since this resulting disparity between the real and the treated distribution in those swing months, is strongly related to the climate conditions of each month (e.g. cooling-dominated, heating-dominated, and intermittent months based on the weather conditions), we try to relate this disparity (the difference of means) to the number of Cooling Degree Days (CDD) of individual month and test whether this could be quantified by using a linear regression technique.

Table 7 Cooling Shifts for 12 months

Month	**Hand-Calculated Cooling Shift [kWh/m^2]**
January	0.61
February	0.56
March	0.61
April	0.60
May	0.34
June	0.33
July	0.36
August	0.34
September	0.51
October	0.53
November	0.50
December	0.53

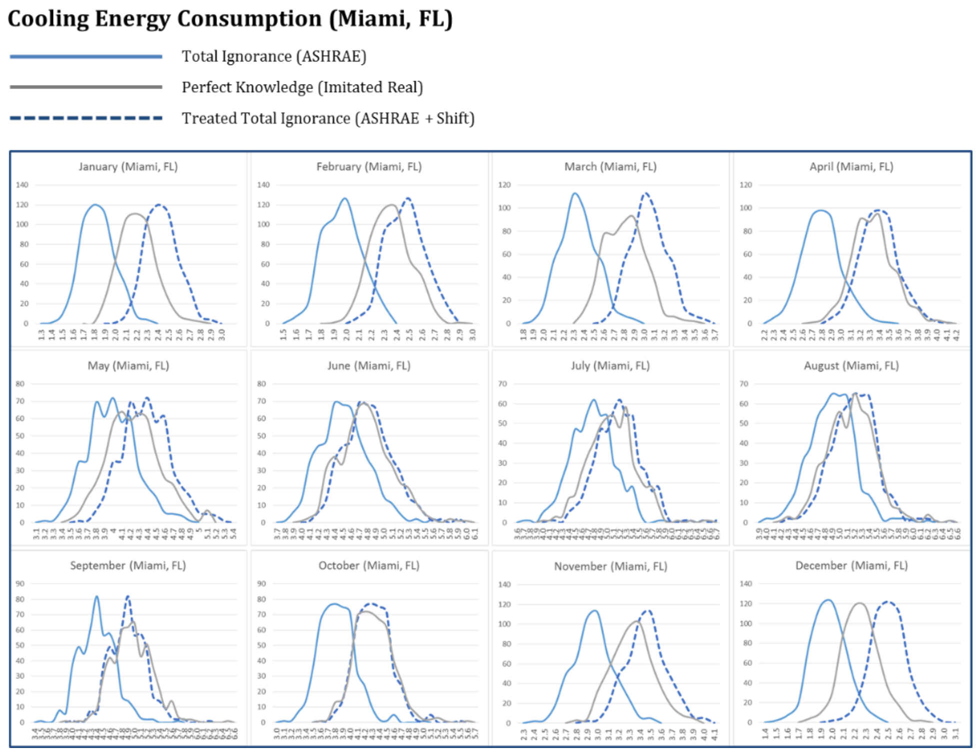

Figure 24 UA Results: Cooling EUI Results (Miami, FL)

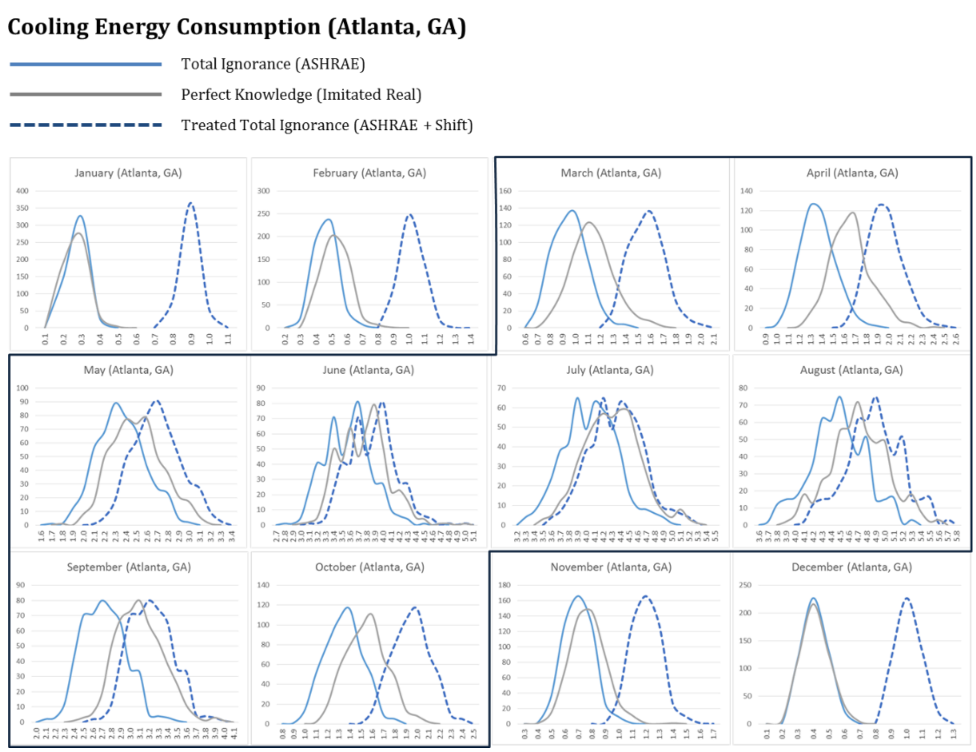

Figure 25 UA Results: Cooling EUI Results (Atlanta, GA)

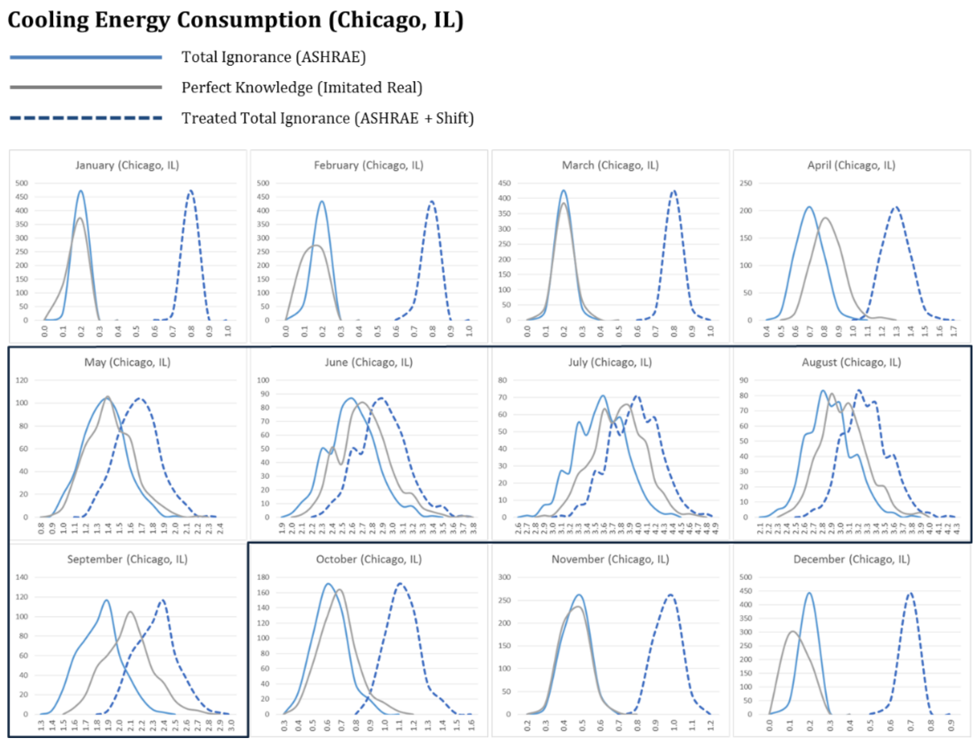

Figure 26 UA Results: Cooling EUI Results (Chicago, IL)

- Cooling and Heating Months

First of all, we classify 12 months into two categories using the monthly heating and cooling energy consumption averages when applying the imitated-real schedules: a cooling and heating season that both include intermittent months where cooling or heating EUI is more than 50% of total heating and cooling EUI of corresponding months. Table 8 shows months sorted into the cooling season in gray color.

Table 8 Cooling Energy Percentage in Total Heating/Cooling Energy Consumption

Cooling Energy Consumption Percentage	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Miami, FL	98%	98%	99%	100%	100%	100%	100%	100%	100%	100%	100%	97%
Atlanta, GA	5%	16%	70%	91%	99%	100%	100%	100%	100%	85%	45%	15%
Chicago, IL	1%	1%	3%	27%	84%	99%	100%	100%	97%	42%	8%	1%

- Calculation of Cooling Degree Days (CDD)

Secondly, we calculate CDD for the case buildings located in three different climate conditions. To do so, the first step is the calculation of the CDD base temperature above that the case building needs to start air conditioning. As shown in Figure 27, we basically draw an equation using averaged monthly dry-bulb outdoor temperature and corresponding cooling energy use from the uncertainty analysis, and calculate the temperature when cooling EUI is zero. Once the base temperature is determined, we calculate CDD for each location using the local TMY3 weather files that we also used in the corresponding uncertainty analysis of monthly energy outcomes in this study. Table 9 summarizes resulting CDD values for 12 months in three locations.

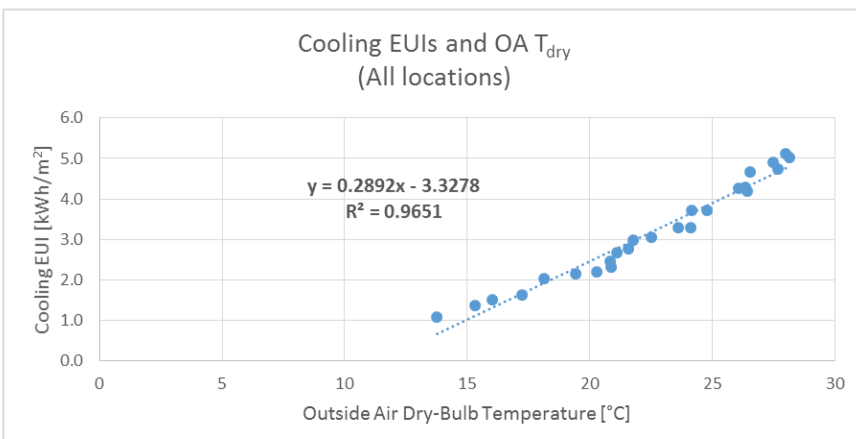

Figure 27 Regression Analysis for the Base Temperature of CDD

Table 9 Monthly CDDs for Three Locations (Miami, Atlanta, and Chicago)

$CDD_{11.51C}$	**Miami, FL**	**Atlanta, GA**	**Chicago, IL**
Base Temperature	**11.51°C**		
January	245.14	9.28	0.00
February	262.04	35.39	0.00
March	311.85	87.70	3.49
April	378.04	178.51	70.57
May	462.06	289.21	126.53
June	485.20	398.62	287.98
July	515.16	451.20	391.37
August	510.35	466.09	318.17
September	479.52	330.38	198.72
October	459.86	145.03	38.48
November	362.34	54.02	26.01
December	272.31	13.60	0.00

- Linear Regression Analysis

Lastly, the monthly CDDs and the mean differences between the real and the treated cases are plotted in Figure 28. In Figures 28, we can clearly note that as CDD becomes larger (more cooling-dominated month), the mean difference decreases as we already expected. The R^2 is more than 90% that implies we can estimate the mean difference using a simple climate indicator, such as CDD in this study.

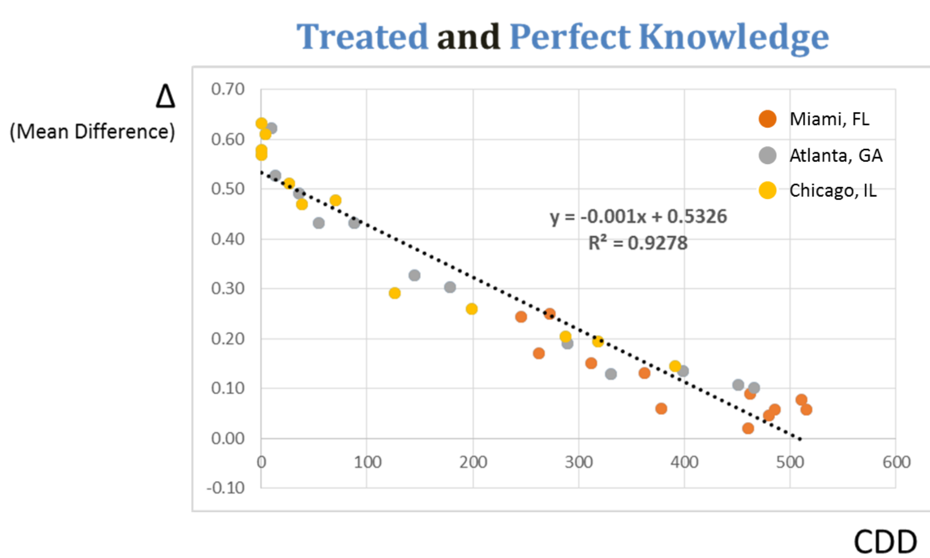

Figure 28 Scatter Plot of Monthly CDD and Mean Difference

It is noteworthy that once this linear relationship is defined for each climate condition, we can even estimate the “proper” shift for all months informed with actual scenarios of use in operation. This would become a novel way to incorporate the impact of occupancy on energy outcomes of building simulation - in other words, a new method to handle the different levels of modelers’ knowledge of occupancy. The procedure would be to start with an uncertainty analysis for the base case (e.g. the total ignorance case) and add the calculated shift to the distribution to reflect the effect of another occupancy model. The magnitude of the shift would be calculated per month and per climate zone using the regression result shown above. This procedure is only tested for the monthly aggregated energy outcomes for heating and cooling energy consumption.

<u>Heating Energy Consumption</u>

The same approach is repeated here for the heating season, and the results are presented in the same manner. Shown in Table 10, hand-calculated heating shifts are larger than the cooling case because of the heating efficiency.

$$\Delta\, Heat\ Gain_{Occupant} = Total\ Number\ of\ People * (Heat\ Gain/Person) * \left(\frac{Total\ Occupied\ Hours_{PK}}{Month} - \frac{Total\ Occupied\ Hours_{TI}}{Month}\right)$$

$$\Delta\, Heat\ Gain_{Lighting/Appliance} = Total\ Lighting/Appliance\ Heat\ Gain * \left(\frac{Total\ Use\ Hours_{PK}}{Month} - \frac{Total\ Use\ Hours_{TI}}{Month}\right)$$

$$Shift\ for\ Cooling/Month = \frac{\Delta\, Heat\ Gain_{Occupant} + \Delta\, Heat\ Gain_{Lighting/Appliance}}{Heating\ Efficiency}$$

Table 10 Heating Shifts for 12 months

Month	**Hand-Calculated Heating Shift [kWh/m^2]**
January	2.48
February	2.25
March	2.47
April	2.42
May	1.37
June	1.33
July	1.43
August	1.37
September	2.07
October	2.13
November	2.04
December	2.15

Table 11 Heating Energy Percentage in Total Heating/Cooling Energy Consumption

Heating Energy Consumption Percentage	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Miami, FL	2%	2%	1%	0%	0%	0%	0%	0%	0%	0%	0%	3%
Atlanta, GA	95%	84%	30%	9%	1%	0%	0%	0%	0%	15%	55%	85%
Chicago, IL	99%	99%	97%	73%	16%	1%	0%	0%	3%	58%	92%	99%

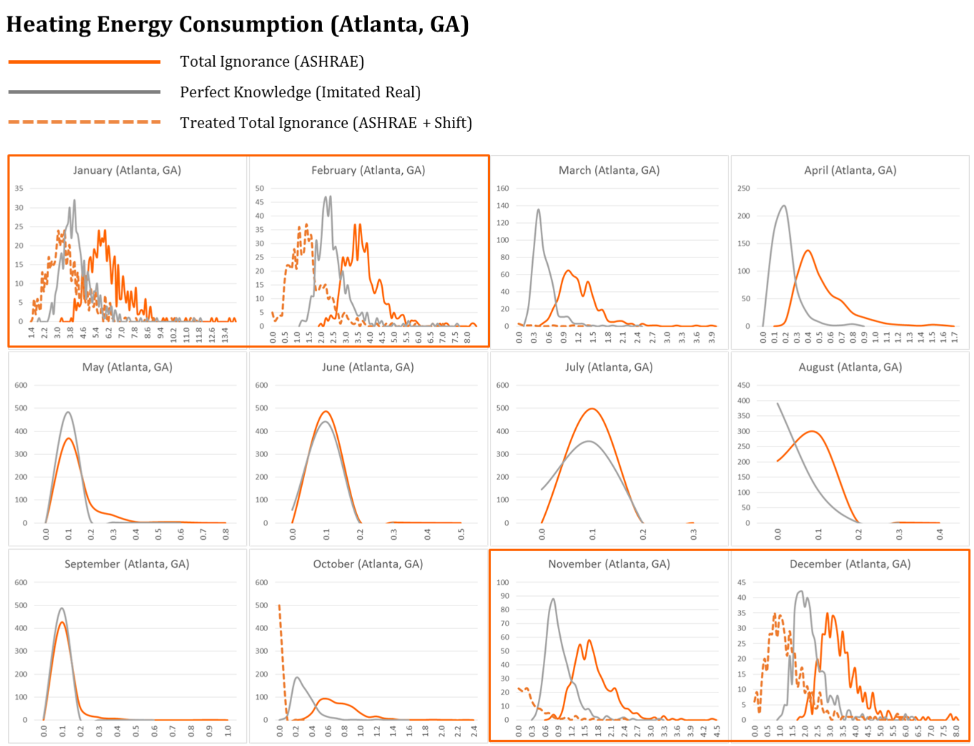

Figure 29 UA Results: Heating EUI results (Atlanta, GA)

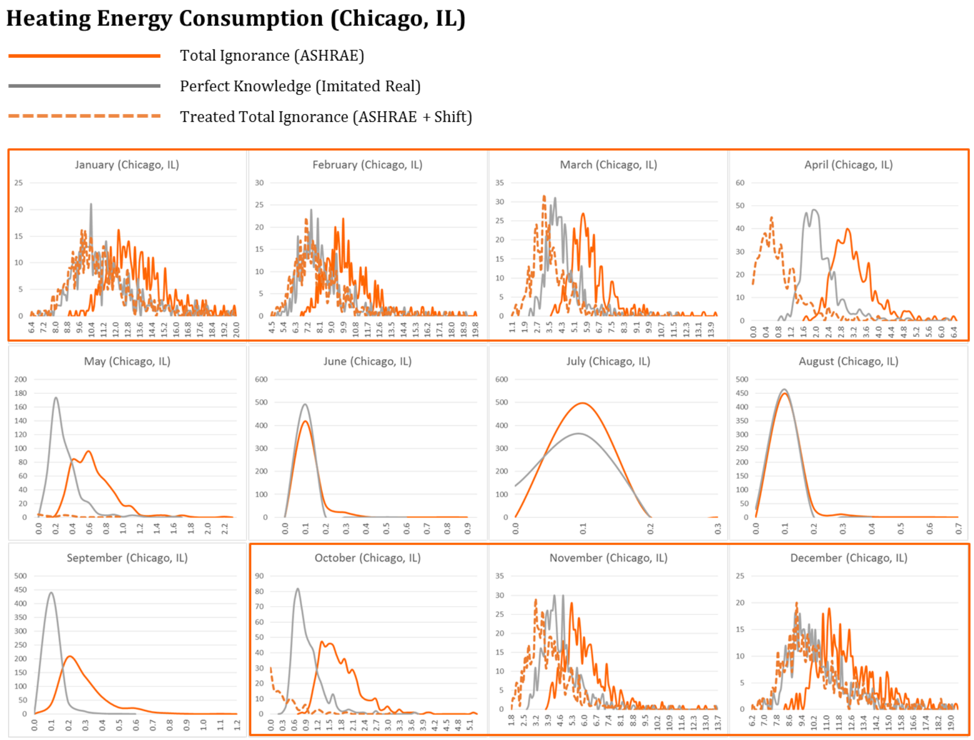

Figure 30 UA Results: Heating EUI results (Chicago, IL)

In case of heating, Miami, FL is excluded because it has barely any heating energy consumption during the year (Table 11). Based on the percentages of heating energy consumption in total heating and cooling energy use, Table 11 depicts the heating season in Atlanta, GA and Chicago, IL in gray color.

In Figures 29 and 30, the solid line of orange color represents the heating EUI distribution with standard occupancy profiles, while the gray line depicts the imitated-real case. The result after the hand-calculated shifts added into the total ignorance is presented in a dotted orange line. Because of relatively moderate winter climate in Atlanta, GA, the treated results are not conforming well to the real ones even in the heating season, while Chicago, IL shows a close agreement.

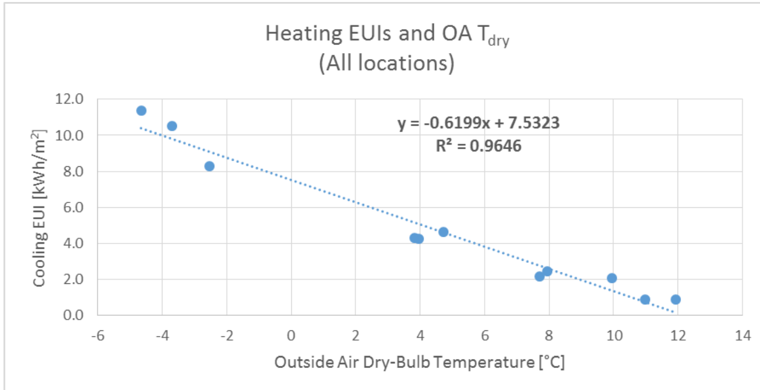

Figure 31 Regression Analysis for the Base Temperature of HDD

Table 12 Monthly HDDs for Two Locations (Atlanta and Chicago)

$HDD_{12.15C}$	Atlanta, GA	Chicago, IL
Base Temperature	**12.15°C**	
January	261.00	520.69
February	146.70	410.77
March	24.53	260.95
April	9.25	130.40
May	0.00	13.86
June	0.00	0.00
July	0.00	0.00
August	0.00	0.00
September	0.00	0.00
October	8.29	66.55
November	49.84	243.11
December	149.09	490.92

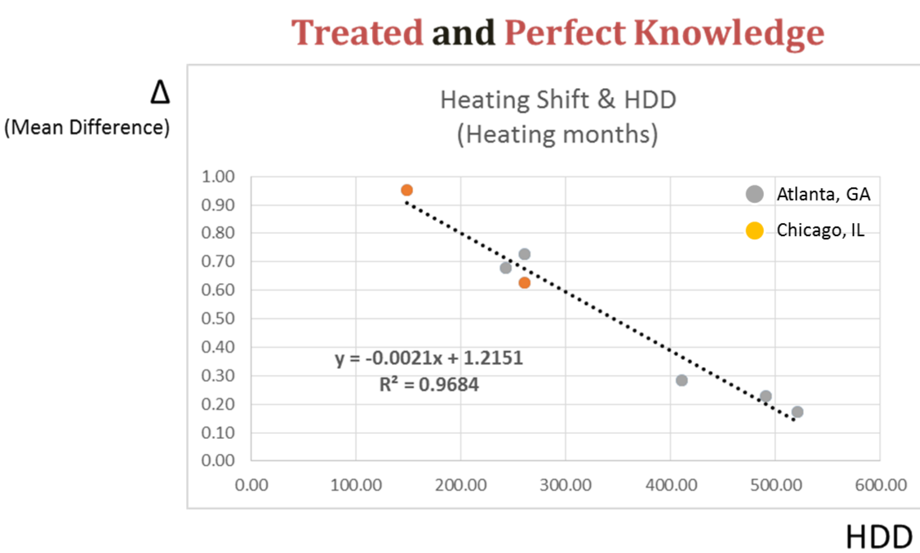

Figure 32 Scatter Plot of Monthly HDD and Mean Difference

The base temperature of HDD and the resulting monthly HDDs are presented in Figure 31 and Table 12. Lastly the regression analysis results are presented in Figure 32. Even with a smaller number of cases (total 11 data points), the R^2 shows more than 95% and in general the trends shown in both graphs still support our argument fairly well.

CHAPTER 4

CONCLUSIONS AND FUTURE WORK

4.1 Summary and Conclusions

This thesis gives rise to a pause in the development of new occupant behavior models and provides an analytical basis for the building simulation practitioners to better comprehend the actual role of occupant behavior modeling and hence guiding them to choose the “proper” modeling of occupants and their behaviors for a given purposes of building simulation. In this thesis we have limited this quest to the case where monthly aggregated energy outcomes are the purpose of the simulation. In addition to this, direct energy consumption, i.e. electricity consumption from the grid, is separated from occupancy factors that impact heating and cooling (and thereby indirectly lead to energy consumption), because of their forthright nature to be quantified.

First of all, this thesis hypothesizes that there is no uniform way to capture occupancy models because residential and commercial applications have few things in common. We therefore introduce two distinctly different approaches, i.e. bottom-up and top-down applied to residential and commercial respectively. By introducing the “Life Style Factor” into the residential building simulation, we prove that LSF is capable to capture a broad spectrum of household composition, their life styles, and other behavioral factors (usually hard if not impossible to be known to modelers) and support energy estimation of future building designs adequately without attempting detailed occupant behavior modeling.

Secondly, in case of the bottom-up approach, the thesis hypothesized that the impact of occupant-related inputs on monthly aggregated energy outcomes of building simulation is explicit, and even quantifiable, which shows that the need to study their role in the performance gap is not compelling. Since occupancy inputs in building simulation depend on what kinds of and how much details of occupancy data is available to simulation modelers, the impact of occupant-related inputs can be rephrased as the impact of the level of modelers' knowledge on occupancy. Through the sensitivity analysis and the comparison study in Chapter 3, we concluded that even in the case where the modelers' ignorance of actual occupancy is significant and hence occupant parameters become important contributors to the uncertainty in monthly outcomes, the resulting disparity could be fairly well quantified without introducing complex occupant behavior models. It is also found that the randomness of occupant behavior with respect to actions, such as window opening has no significant role in the uncertainty of the outcomes. These conclusions can be generalized to the overall building simulation practice, i.e. when the objective of simulation is mostly to predict monthly cooling and heating energy consumption of a building design.

Ultimately, this thesis made a starting point for us to think of the following question when we look into the occupancy modeling;

> *"Are high resolution occupant behavior models crucial for the credibility of building energy prediction?"*

Even within the limitations of this thesis, our work shows that the affirmation of the relevance of occupant behavior models is not likely.

4.2 Future Work

4.2.1 Top-Down Approach

This thesis introduces the "Life Style Factor" into residential building simulation and shows its use in a particular context. In order to support the wide applicability of LSF into building simulation, we need to clarify and/or resolve the following issues:

- Selection of calibration parameters: this thesis chooses four calibration parameters along with LSF based on the data availability of a given case building. Before applying LSF to other cases, we need to examine a target building and carefully determine the calibration parameters in terms of modelers' data availability (knowledge) and possible sources of unknown occupant related factors in the predictive simulation.
- Adequate amount of energy data: this thesis utilized monthly heating and cooling consumption data for more than 1,966 apartment units (54 designs) and tested LSF for 216 units (4 designs). However, this thesis does not provide an assessment of the adequate amount of energy data one needs to yield fair LSF values to capture the variability of occupancy throughout a group of similar buildings.
- Definition of "similar type of buildings": the case apartment buildings used in this thesis have unique cultural, physical, and demographical circumstances. To generalize the use of LSF, we need a further study to define a way to correlate different types of buildings in different cultural, physical, spatial, and demographic contexts with certain LSF distributions.

4.2.2 Bottom-Up Approach

This thesis concludes that the choices of different occupant behavior models become immaterial when we are interested in aggregated energy outcomes i.e. monthly electricity consumption for heating and cooling. To expand these findings the following tasks need to be further investigated:

- Application cases of building simulation: this thesis focused only on the case where we are interested in monthly heating and cooling energy outcomes as the customary “retail” application of building simulation. However, for example, once hourly variations of energy outcomes are in question (e.g. peak load analysis for system sizing), the analysis introduced in this thesis could lead to different conclusions. For a proper inspection of the need for high resolution occupant behavior modeling within building simulation, a broad spectrum of building simulation use cases needs to be identified in terms of outcomes of interest, availability of data, types of buildings, etc.
- Spatial variability of occupants: there are other use cases where the need to analyze the effect of spatial (in addition to temporal) variability of occupants and their actions is crucial, or where group behavior and occupant-to-occupant influence becomes a dominant factor. These cases should be examined in future follow-ups following the same critical inspection done in this thesis.

In all cases the critical assessment of this thesis should be aimed at the question whether high resolution occupant behavior models are relevant and have a significant effect on the outcomes of interest. The answers may surprise the research community and funding bodies alike.

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