OCCUPANT BEHAVIOR MODELING FOR IMPROVING COMMERCIAL BUILDING
ENERGY USE SIMULATION

By
MENGDA JIA

A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

UNIVERSITY OF FLORIDA

2018
To my family
ACKNOWLEDGMENTS

I would like to express my sincere appreciation to my advisor Dr. Ravi Srinivasan, for his guidance and help in both academic world and real life. I am always inspired by his continuous passion and hardworking spirit, which gave me motivation to learn and explore in the scientific ocean. It is my great honor to work with him for my Ph.D. studies, and his support to my scholar development is priceless fortune that will benefit me forever.

I also would like to thank the other members of my doctoral committee, Dr. Robert Ries, Dr. Ian Flood, Dr. Sanjay Ranka, Dr. Damon Allen, and Dr. Gnana Bharathy. Their comments and feedback on my dissertation consistently provided me important insights and helped me improve my research work. Thanks to their contributions in different aspects, I would be able to proceed my dissertation research smoothly and complete it successfully.

In addition, I would like to extend my gratitude to all faculty, experts, and peer colleagues who have helped me with my research. Particularly, I want to acknowledge the faculty members who participated in the survey for the study. Also, special thanks to Nathan Weyer who developed the application for me time after time with full patience.

Finally, I would like to express my deepest gratitude to my family for their endless love and support, especially my parents who are always there for me. I dedicate this work to my mother, who believes in me and encourages me for my whole life, and my father, my role model, who is in the heaven, blessing me.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACKNOWLEDGMENTS</td>
<td>4</td>
</tr>
<tr>
<td>LIST OF TABLES</td>
<td>8</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>9</td>
</tr>
<tr>
<td>LIST OF ABBREVIATIONS</td>
<td>12</td>
</tr>
<tr>
<td>ABSTRACT</td>
<td>14</td>
</tr>
<tr>
<td>CHAPTER</td>
<td></td>
</tr>
<tr>
<td>1 INTRODUCTION</td>
<td>16</td>
</tr>
<tr>
<td>Background</td>
<td>16</td>
</tr>
<tr>
<td>Problem Statement</td>
<td>19</td>
</tr>
<tr>
<td>Research Aim and Objectives</td>
<td>22</td>
</tr>
<tr>
<td>Research Scope</td>
<td>23</td>
</tr>
<tr>
<td>Contributions</td>
<td>24</td>
</tr>
<tr>
<td>Structure of Dissertation</td>
<td>24</td>
</tr>
<tr>
<td>2 LITERATURE REVIEW</td>
<td>26</td>
</tr>
<tr>
<td>Overview</td>
<td>26</td>
</tr>
<tr>
<td>Data Acquisition Technologies for Occupant Behavior Modeling</td>
<td>26</td>
</tr>
<tr>
<td>Data Collection Equipment and Devices</td>
<td>27</td>
</tr>
<tr>
<td>Commonly Used Data and Variable Types</td>
<td>29</td>
</tr>
<tr>
<td>Occupant Behavior Modeling Methodologies</td>
<td>30</td>
</tr>
<tr>
<td>Simulation-based Methodologies</td>
<td>32</td>
</tr>
<tr>
<td>ABM for interactions between occupants and buildings</td>
<td>32</td>
</tr>
<tr>
<td>ABM for interactions between various occupants</td>
<td>36</td>
</tr>
<tr>
<td>Others</td>
<td>37</td>
</tr>
<tr>
<td>Data-driven Methodologies</td>
<td>38</td>
</tr>
<tr>
<td>Statistical analysis</td>
<td>38</td>
</tr>
<tr>
<td>Data mining</td>
<td>41</td>
</tr>
<tr>
<td>Stochastic modeling</td>
<td>43</td>
</tr>
<tr>
<td>Comparison of Major Methodologies</td>
<td>45</td>
</tr>
<tr>
<td>Coupling Mechanisms</td>
<td>50</td>
</tr>
<tr>
<td>Introduction of Agent-Based Modeling</td>
<td>57</td>
</tr>
<tr>
<td>Common ABM Tools and PMFserv</td>
<td>58</td>
</tr>
<tr>
<td>3 METHODOLOGY</td>
<td>61</td>
</tr>
<tr>
<td>Overview</td>
<td>61</td>
</tr>
</tbody>
</table>
Modeling Principles of the Proposed ABM

Occupant Behaviors in Commercial Buildings

Modeling Functions and Rules

Function 1: agent physiology, stress, and coping style
Function 2: agent emotions and value systems
Function 3: agent perception and object affordance
Other optional functions

Decision Making Algorithm Based on the Model

Data Collection and Validation Study of the ABM

Data Collection

Sensor devices, methods, and parameters for indoor environment monitoring
Paper-based survey for recording occupant behavior
Outdoor environmental data
Data collection scale
Performance Test of the ABM
Explanation of data use
Validation method

Integration of Occupant Behavior Model with EnergyPlus™

Co-simulation Method Development

Simulation Scenarios Design

4 CASE STUDY AND RESULTS

Development of ABM based on Actual Building

Descriptions of Case Study Building

Occupant Behavior Model Units

Discussion of the Model

Model Testing and Validation Study

Data Collection Scope and Preprocessing

Results and Analysis of Individuals’ Behavior

Results and Analysis of Overall Performance

Summary and Discussion

Simulation Experiments

Default and Survey-based Settings of Building Energy Model

Co-simulation Data Exchange Schema

Application and Results

Energy use and cooling/heating demand differences
Occipant comfort level differences

Summary

5 DISCUSSION AND CONCLUSIONS

Summary and Conclusions

Limitations of the Research

Development Barriers of Occupant Behavior Model

Case Study Scale Limitations
Co-simulation Function........................................................................................................ 128
Recommendations for Future Study .................................................................................. 129

APPENDIX

A  DETAILED INTRODUCTION OF PMFserv MAIN FUNCTIONS................................. 131
   Agent Physiology, Stress, and Coping Style................................................................. 131
   Agent Emotions and Value Systems .............................................................................. 132
   Agent Perception and Object Affordance ...................................................................... 134

B  PMFserv SCREENSHOT SAMPLE ............................................................................ 136

C  PMFserv SUPPORTED INFORMATION ....................................................................... 138

D  DATA COLLECTION CODE FOR SMART SENSOR..................................................... 139
   Data Collection Code.................................................................................................. 139
   Data File Upload Code............................................................................................... 140

E  IRB APPROVAL LETTER............................................................................................... 143

F  BEHAVIORAL RECORD SURVEY SHEET................................................................. 145

G  DEFAULT GSP TREE ARCHITECTURE .................................................................... 146

H  CODE FOR PERCEPTUAL RULES DEFINITION......................................................... 148

I  SAMPLE DATASHEET FROM SMART SENSOR......................................................... 155

J  CONFIGURATION OF ENERGYPLUS EXTERNAL INTERFACE ............................... 156

K  BCVTB CONFIGURATION FILE AND SCREENSHOT ............................................... 157

LIST OF REFERENCES ...................................................................................................... 158

BIOGRAPHICAL SKETCH................................................................................................. 167
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-1</td>
<td>51</td>
</tr>
<tr>
<td>2-2</td>
<td>56</td>
</tr>
<tr>
<td>2-3</td>
<td>60</td>
</tr>
<tr>
<td>3-1</td>
<td>62</td>
</tr>
<tr>
<td>3-2</td>
<td>73</td>
</tr>
<tr>
<td>3-3</td>
<td>81</td>
</tr>
<tr>
<td>4-1</td>
<td>87</td>
</tr>
<tr>
<td>4-2</td>
<td>102</td>
</tr>
<tr>
<td>4-3</td>
<td>115</td>
</tr>
<tr>
<td>4-4</td>
<td>116</td>
</tr>
<tr>
<td>4-5</td>
<td>117</td>
</tr>
<tr>
<td>4-6</td>
<td>118</td>
</tr>
<tr>
<td>4-7</td>
<td>119</td>
</tr>
<tr>
<td>I-1</td>
<td>155</td>
</tr>
<tr>
<td>Figure</td>
<td>Description</td>
</tr>
<tr>
<td>--------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>1-1</td>
<td>U.S. energy consumption by sector</td>
</tr>
<tr>
<td>1-2</td>
<td>Problem statement for existing building energy modeling</td>
</tr>
<tr>
<td>1-3</td>
<td>Overview of research pipeline</td>
</tr>
<tr>
<td>2-1</td>
<td>Typical data acquisition technologies for occupant-related research</td>
</tr>
<tr>
<td>2-2</td>
<td>Overview of ABM simulation process</td>
</tr>
<tr>
<td>2-3</td>
<td>Proposed DNAS ontology for occupant behavior modeling</td>
</tr>
<tr>
<td>2-4</td>
<td>Characteristics of agents in ABM</td>
</tr>
<tr>
<td>3-1</td>
<td>Research workflow overview</td>
</tr>
<tr>
<td>3-2</td>
<td>Projection of ABM structure to the context of built environment</td>
</tr>
<tr>
<td>3-3</td>
<td>Decision making process of agent</td>
</tr>
<tr>
<td>3-4</td>
<td>Customized smart sensor node</td>
</tr>
<tr>
<td>3-5</td>
<td>Flow path of validation study</td>
</tr>
<tr>
<td>3-6</td>
<td>Co-simulation method development</td>
</tr>
<tr>
<td>3-7</td>
<td>Simulation scenarios for building performance analysis</td>
</tr>
<tr>
<td>4-1</td>
<td>Case study building in 3-D model</td>
</tr>
<tr>
<td>4-2</td>
<td>Screenshot of “Built_Environment” object in PMFserv</td>
</tr>
<tr>
<td>4-3</td>
<td>Causal relation between environmental parameters, perception types, and</td>
</tr>
<tr>
<td></td>
<td>behavior options</td>
</tr>
<tr>
<td>4-4</td>
<td>Selected sample rooms for validation study</td>
</tr>
<tr>
<td>4-5</td>
<td>Simulation results and survey record for window blinds operation for</td>
</tr>
<tr>
<td></td>
<td>occupant A in a selected day, with illumination level showing underneath</td>
</tr>
<tr>
<td>4-6</td>
<td>Simulation results and survey record for door operation for occupant A in a</td>
</tr>
<tr>
<td></td>
<td>selected day, with indoor temperature and CO₂ concentration showing</td>
</tr>
<tr>
<td></td>
<td>underneath</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Full Form</td>
</tr>
<tr>
<td>--------------</td>
<td>-----------</td>
</tr>
<tr>
<td>ABM</td>
<td>Agent-Based Modeling</td>
</tr>
<tr>
<td>AHU</td>
<td>Air Handling Unit</td>
</tr>
<tr>
<td>ASHRAE</td>
<td>American Society of Heating, Refrigerating and Air-Conditioning Engineers</td>
</tr>
<tr>
<td>BCVTB</td>
<td>Building Controls Virtual Test Bed</td>
</tr>
<tr>
<td>BDI</td>
<td>Belief-Desire-Intention</td>
</tr>
<tr>
<td>BEM</td>
<td>Building Energy Modeling</td>
</tr>
<tr>
<td>EUI</td>
<td>Energy Use Intensity</td>
</tr>
<tr>
<td>FMI</td>
<td>Functional Mock-up Interface</td>
</tr>
<tr>
<td>FN</td>
<td>False Negative</td>
</tr>
<tr>
<td>FP</td>
<td>False Positive</td>
</tr>
<tr>
<td>GHG</td>
<td>Green House Gases</td>
</tr>
<tr>
<td>GSP</td>
<td>Goals, Standards, and Preferences</td>
</tr>
<tr>
<td>GUI</td>
<td>Graphical User Interface</td>
</tr>
<tr>
<td>HMM</td>
<td>Hidden Markov Model</td>
</tr>
<tr>
<td>HVAC</td>
<td>Heating, Ventilation, and Air Conditioning</td>
</tr>
<tr>
<td>IDF</td>
<td>Input Data File</td>
</tr>
<tr>
<td>IEA</td>
<td>International Energy Agency</td>
</tr>
<tr>
<td>IRB</td>
<td>Institutional Review Board</td>
</tr>
<tr>
<td>LEED</td>
<td>Leadership in Energy and Environmental Design</td>
</tr>
<tr>
<td>MAS</td>
<td>Multi-Agent System</td>
</tr>
<tr>
<td>MC</td>
<td>Markov Chain</td>
</tr>
<tr>
<td>MDP</td>
<td>Markov Decision Problems</td>
</tr>
<tr>
<td>MLE</td>
<td>Maximum Likelihood Estimation</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>-----------------------------------------------</td>
</tr>
<tr>
<td>OOP</td>
<td>Object-oriented Programming</td>
</tr>
<tr>
<td>PIR</td>
<td>Passive Infrared</td>
</tr>
<tr>
<td>PMFserv</td>
<td>Performance Moderator Functions Server</td>
</tr>
<tr>
<td>PMV</td>
<td>Predicted Mean Vote</td>
</tr>
<tr>
<td>RFID</td>
<td>Radio Frequency Identification</td>
</tr>
<tr>
<td>TN</td>
<td>True Negative</td>
</tr>
<tr>
<td>TP</td>
<td>True Positive</td>
</tr>
<tr>
<td>USEIA</td>
<td>United States Energy Information Administration</td>
</tr>
<tr>
<td>UWB</td>
<td>Ultra-wide Band</td>
</tr>
<tr>
<td>VAV</td>
<td>Variable Air Volume</td>
</tr>
<tr>
<td>WSN</td>
<td>Wireless Sensor Networks</td>
</tr>
<tr>
<td>XML</td>
<td>Extensible Markup Language</td>
</tr>
</tbody>
</table>
Abstract of Dissertation Presented to the Graduate School of the University of Florida in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

OCCUPANT BEHAVIOR MODELING FOR IMPROVING COMMERCIAL BUILDING ENERGY USE SIMULATION

By
Mengda Jia

December 2018

Chair: Ravi S. Srinivasan
Major: Design, Construction and Planning

Building energy modeling aids in enhancing building energy efficiency and indoor environment comfort. Among others, occupant behavior is one of the dominant factors that influence building energy use. Existing building energy simulation programs use typical occupant schedules that often do not reflect actual situations. In other words, the dynamic interaction of occupants with the building components is left out in these existing programs. What is needed is a robust occupant behavior modeling approach that utilizes the developments in state-of-the-art behavior models and which seamlessly integrates with building energy simulation programs. Such an attempt will not only improve the building energy simulation by increasing the functioning and estimation accuracy of building simulation programs, but also provides a deeper understanding of occupant behavior itself.

This dissertation develops a novel occupant behavior modeling approach, which follows a pipeline of development, validation, and application of this model, in the context of commercial buildings. Agent-based Modeling (ABM) is used as the foundation of the occupant behavior model, which is implemented in a performance moderator functions’ platform that captures occupant perception based on surrounding
conditions. Specifically, this model explores the occupant’s adaptation to changing ambient environment. The model is tested in an educational building situated in the University of Florida campus. Customized smart sensor nodes and paper-based surveys are developed and implemented to collect data such as the environmental conditions and the open/close status of targeted building components of the office spaces. For validation purposes, the environment data is used as inputs to the ABM. The output of the ABM is compared with surveyed data. Results show satisfactory fit to reality for the model output.

The validated model is, then, applied to investigate the impact of occupant behavior on building energy use estimation. For this purpose, a co-simulation framework is implemented in Building Control Virtual Testbed (BCVTB) to exchange data between the occupant behavior simulator, PMFserv, and EnergyPlus™, a widely used building simulation program. Three simulation scenarios were designed to compare results. Among others, one major contribution of this dissertation is the simulation coupling of the occupant behavior model and building energy simulation model.
CHAPTER 1
INTRODUCTION

Background

Energy conservation and utilization is part of the goals and key component of sustainability according to LEED standard and rating system. The increasing energy demand and consumption in the world will cause a lack of energy resources and production of greenhouse gases (GHG) directly, which leads to enormous living crisis in the future. Based on the estimation by USEIA (Energy Information Administration, 2015), the world energy consumption will grow by 56% from year 2010 to 2040, which emphasizes the necessity of saving energy use from different aspects.

In the United States, buildings are one of the major contributors to the annual energy use, which accounts for more than 40% of the total amount (Energy Information Administration, 2015). From Figure 1-1, it could be observed that for the main sectors that consume energy use, building operations is the largest consumer. Therefore, abundant opportunities exist for energy savings associated with building sector. In the life cycle of a building, six driving factors were identified by International Energy Agency (IEA) that will influence the energy consumption as a whole, including climate, building envelope, building systems and equipment, building operation and maintenance, indoor environmental quality, and occupant behaviors (Yan et al., 2015). From the past decades, research efforts have been addressed on some of the aspects for building energy efficiency. For example, a research study by Cheung, Fuller, & Luther (2005) has shown more than 30% energy savings by adding extruded polystyrene thermal insulation in walls. Zhou, Wu, Li, & Zhang (2014) tested a demand response mechanism in a home energy management system for household economic benefits.
However, among all the controllable factors above, building occupants are considered as the most dominant factor that determines the energy use trend, while the research work on understanding and modeling occupant behaviors in buildings for the general objective of realizing energy-efficient buildings is still being explored. In addition, as one of the main functions of buildings is to provide comfortable context and services to the building occupants, research on the topic of occupant behavior modeling is helpful to develop a “smarter” built environment which is able to improve occupant comfort level and reduce building energy use at the same time (Jia & Srinivasan, 2015).

Figure 1-1. U.S. energy consumption by sector (Source: USEIA)

Occupant behaviors influence building energy use in a various and uncertain manner (Valentina Fabi, Andersen, Corgnati, & Olesen, 2012; Yan et al., 2015). As a consequence, occupant behavior information could serve as a crucial auxiliary element for improving building energy management in various aspects generally. On one hand, to incorporate occupant behavior information into building simulation tools will potentially enhance energy simulation performance with the supplementary input; on the other hand, occupant behavior information could be involved in the realistic building
operations for system optimization and behavior interventions design. Furthermore, occupant behavior is a key factor to evaluate building design and retrofit technologies (Hong, Taylor-Lange, D'Oca, Yan, & Corgnati, 2016; Yan et al., 2015), as different occupant behavior patterns require corresponding technical solutions. In sum, a thorough understanding and modeling of how occupants interact with buildings and behave plays an important role in the building life cycle operations, especially for building energy performance improvement.

Building occupants are the “users” of the building, whose actions vary over time and among different individuals. In the context of built environment, the focus is placed more on the direct interactions between occupants and building, which are usually referred as energy-related behaviors (Hong, Sun, Chen, Taylor-Lange, & Yan, 2016). It may typically include the use of building component (e.g. window opening/closing) and the control of building systems (e.g. HVAC, lighting, appliance). Besides, personal behaviors such as typing, writing, walking and clothing adjustment which affect energy use subtly or indirectly should also be considered under certain cases. Meanwhile, occupants behave differently within different building types because of their emphasis of concerns. For example, physical comfort is the first priority for commercial building occupants, while more factors including time, economic condition, health issues, etc. must be taken into consideration for residential building occupants. Due to the complex mechanism of occupant behaviors, it is difficult to model every single possibility with one methodology. Hence, the modeling approach of occupant behaviors usually depends on the scope and purpose of the research, as well as the available technology and methodology support for the model.
Because of the fact that people spend 80% of their lifetime in buildings (R. Yang & Wang, 2013), needless to say, occupant behavior modeling must be addressed for the purposes of comfortable indoor environment and building energy efficiency. In fact, this problem has attracted numerous researchers’ attention in the past few years (D'Oca, Hong, & Langevin, 2018; Gunay, O’Brien, & Beausoleil-Morrison, 2013; Jia, Srinivasan, & Raheem, 2017; Nguyen & Aiello, 2013), while there still exists research gaps to be explored.

Problem Statement

A number of studies have shown that the uncertainty brought by occupant behavior exerts significant impact on building energy use (Valentina Fabi, Vinther Andersen, Corgnati, Olesen, & Filippi, 2011; Hong, Taylor-Lange, et al., 2016; Yan et al., 2015), which, in turn, renders erroneous estimation of building energy use although often within acceptable error ranges as recommended by ASHRAE (+/- 15% of actual energy use) and other organizations. It is to be noted that these error ranges are sufficiently large. Moreover, existing building energy simulation programs use a relatively complete modeling system for physical and external design factors while oversimplifying the internal ones, particularly the interactions between occupants and building (Figure 1-2). These programs have largely ignored occupant behavior and instead treat occupants as “static.” While an occupant interacts with the building systems in a real world environment, these members are represented as mere numbers in the building energy simulation programs and, therefore, “static” as opposed to their “dynamic” behavior. This leads to large discrepancy between predicted and actual energy use in most of the cases (de Wilde, 2014). This error could be as much as 300% according to (Andersen, Fabi, Toftum, Corgnati, & Olesen, 2013).
(2008) compared the measured and predicted energy use for 62 LEED buildings and found obvious differences for all the buildings. Part of the reasons can be explained by the fact that occupants act and interact with building dynamically, and each individual may behave differently in response to the same ambient settings. This gap needs to be bridged through a robust model that takes into consideration the behavior of occupants. A few inherent issues in representing occupants in building energy simulation programs are discussed below:

Figure 1-2. Problem statement for existing building energy modeling

1. **Occupancy vs. Occupant behavior**

Studies pertaining to building occupants attract attention from many researchers. Related research started by tracking occupant presence/absence status in rooms or buildings, and, then, reduced to number of occupants (Lam et al., 2009; Nasir et al., 2015; Yang, Li, Becerik-Gerber, & Orosz, 2014). This approach is referred to as “occupancy”, a basic data used in building energy use estimation. However, occupancy is a passive data and in contrast to active behaviors of occupants with the building.
components. Although researchers claimed to have modeled occupant behavior, their work lies within the “occupancy” study. For example, Carmenate, Rahman, Leante, Bobadilla, & Mostafavi (2015) claimed that their proposed approach estimates how occupant behavior affect energy use, whereas their work actually counted the number of occupants with energy expenditures of a building rather than attempting to understand and implement the occupant behavior on the building components.

2. Limitation of data-driven modeling approaches

Among the existing research that explored building occupant behavior models, different types of modeling methodologies have been proposed. In general, the methods could be divided into data-driven and simulation-based models. Data-driven model is built based on relevant data of occupant behavior, including environment, weather, and electricity use, etc. However, data-driven model lacks the ability to directly connect to building energy simulation tools and might be only effective and valid for certain buildings and occupant types (Jia & Srinivasan, 2015; Jia, Srinivasan, & Raheem, 2017). Moreover, existing modeling methods, typically, focus on only one particular behavior, which is not holistic in contrast to simulation-based method.

3. Simulation-based research lacks actual data involvement

Simulation-based model tries to mimic the actual occupant behaviors in the building under particular ambient and other boundary conditions. This type of model has a good potential to be integrated with traditional energy simulation tools. However, in most studies of simulation-based model, it often fails to validate the model and no actual data and scenarios are involved, which makes the model less robust and convincing to some extent. Also, there is no agreement yet on the modeling rules for behaviors and impact factors. Since existing conventional building energy simulation tools do not have
an occupant behavior module, either integrated in the simulation algorithm or as an auxiliary system, to account for energy use attributable to the building occupants, there is a strong interest by researchers to develop and implement framework to enable information exchange between heterogeneous simulators.

**Research Aim and Objectives**

The overall aim of this research is to develop a novel occupant behavior modeling method to improve building energy use simulation. The specific objectives are as follows:

- **Objective 1:**
  - To develop an occupant behavior modeling method for improved energy simulation by modeling occupant’s interaction with building components owing to indoor and outdoor environmental conditions.
  - **Sub-objective 1-1:**
    - To model occupant’s interaction with building components for the purpose of energy estimation at thermal zone level using PMFserv, an Agent-based Model.
  - **Sub-objective 1-2:**
    - To integrate PMFserv and EnergyPlus™ using a co-simulation platform, BCVTB, which updates activity schedule at each time-step for building energy simulation.

- **Objective 2:**
  - To collect actual environmental data and occupant behavior data to validate the developed occupant behavior model.

- **Objective 3:**
  - To investigate the influences of occupant behavior input to building performance simulation using real-world educational building as a case study.
For sub-objective 1-1, an ABM will be developed with the assistance of a well-tested and widely applied human behavior modeling platform, PMFServ. This is the first-ever attempt to utilize this platform for the built environment domain. This model will use external factors such as indoor and outdoor environmental conditions and internal factors such as personal cognitions into consideration to simulate occupant behaviors on a decision-making basis, thus, providing information that incorporates into energy simulation engine.

For sub-objective 1-2, the developed ABM will be integrated with a widely used building energy simulation engine, EnergyPlus™. This integration is effected by transferring behavior decision information, as inputs, to EnergyPlus™ to generate simulated environmental data, as outputs. For further development, the developed ABM may be implemented as a separate module of EnergyPlus™ to support occupant behavior schedule input to improve final energy use estimation.

To achieve objective 2, relevant data will be collected from selected rooms in a case study building using both custom embedded sensor board and paper-based survey sheets. The purpose is to test and validate the developed ABM.

Finally, for objective 3, after testing the effectiveness of the proposed model, three simulation scenarios will be implemented with EnergyPlus™ to understand and analyze the impact of occupant behaviors to building energy use and indoor comfort level.

**Research Scope**

Because occupant behaviors vary according to building types, occupant types, accessible behavior options, etc., it is impractical to analyze and integrate all potential scenarios in a generic model. Therefore, this research narrows down the scope to one
type of condition using a real-world building as case study. Specifically, this research focuses on commercial buildings and the occupants modeled in the program are all full-time users without long-term absence. Direct interactions with building components are the studied in this research work. The energy impact of occupants owing to their activities such as reading, seating, walking, writing, and other subtle are not studied. Refer to Chapters 3 and 4 for additional details.

**Contributions**

The specific research contributions to the building energy domain are listed below:

1. **Occupant behavior model:** The development of an occupant behavior model in PMFserv platform. This is the first ever attempt to utilize PMFserv for the purposes of studying building occupants.

2. **Co-simulation of the developed ABM and EnergyPlus™:** The development of a simulation coupling method via BCVTB for seamlessly integrating the proposed occupant behavior model and building energy model to improve energy estimation. This development offers a new vision to researchers in the building energy and sustainability areas by providing a new and thorough understanding of the occupant behavior using a sophisticated ABM framework. Besides, this development also increases the functionality of building simulation tools and potentially cuts the discrepancy between predicted and actual energy use;

3. **Validation tools:** The development of data collection, processing, and analysis procedures for model testing and validation. This research fills the gap which the majority of existing simulation-based occupant behavior models ignored, i.e., the use of actual measurement data from the real-world to enhance future implementation capability of the model for better energy use estimation.

**Structure of Dissertation**

This dissertation is organized as follows. Chapter 1 provides a brief introduction to the research background, problem statement, research aims, and expected contributions. Chapter 2 reviews the state-of-the-art occupant behavior modeling methodologies, including data collection technologies and simulation coupling
mechanisms, in the area of building energy efficiency. Chapter 3 presents the research methodology in the dissertation, which follows the sequence of model development, validation and simulation application. Chapter 4 discusses a case study based on an educational building that implements and instantiates the proposed methodology, along with relevant results analysis. Finally, Chapter 5 discusses and concludes the dissertation. In Figure 1-3, an overview of research flow path is illustrated. It should be noted that this is not the writing structure of this dissertation, but the research pipeline of this dissertation.

Figure 1-3. Overview of research pipeline
CHAPTER 2
LITERATURE REVIEW

Overview

This chapter discusses the literature related to occupant behavior modeling in the context of built environment. Many researchers have summarized this topic from different point of views and perspectives (Gunay et al., 2013; Nguyen & Aiello, 2013; Rafsanjani et al., 2015; Stazi, Naspi, & D’Orazio, 2017; Yan et al., 2015), while for the purpose of this research, the main focus is on the state-of-the-art data collection technologies, modeling methodologies and simulation coupling mechanism for occupant behaviors study in the area of building energy efficiency. Moreover, a thorough comparison among the literatures which used ABM for occupant behavior modeling is provided.

Data Acquisition Technologies for Occupant Behavior Modeling

Although occupant behavior modeling methods differ in several forms, data collection and processing approaches are very similar among most studies, which share some of the data acquisition devices and data types. In this section, occupancy modeling technologies as well as methodologies in the later section will be slightly involved for the reasons that 1) occupant-related data collection share the same parameters type and properties, thus the data acquisition technology could be applied to either case; 2) in a similar way, modeling methodologies were usually overlapped, and understanding occupancy modeling methodology could be considered as a prelude to developing subsequent methods for occupant behavior modeling.
Data Collection Equipment and Devices

Advanced technology in the field of electrical and computer engineering has been developing rapidly in the past decade, which helps facilitate data collection and enhance data accuracy. The current collaboration with building energy studies includes not only model-related parameters monitoring but also energy simulation incorporation. Various types of devices such as sensors, cameras or meters are being applied on the basis of research methods and objectives. After collecting the useful data, simulation software could then assist recognizing energy saving potentials.

Wireless Sensor Networks (WSN) are the most common and popular tool for monitoring occupant-related variables such as temperature, humidity, carbon dioxide, sounds, and illumination, etc. Typical WSN consist of sensor nodes that can be distributed throughout the buildings. By using wireless technology, operation and maintenance costs are reduced as no cabling is required. Wireless sensors can be deployed in a remote place where some of the wired devices may not be able to reach. In addition, by forming a network, sensor nodes will be able to communicate and exchange information with each other, and the data could be logged in a more organized way simultaneously. Since occupant behavior usually has a causal relationship with surrounding environment, ambient data sensors are always placed within the research areas. Yang et al., (2014) explored a method to estimate real-time occupancy conditions by monitoring plenty of environmental factors including humidity, temperature, carbon dioxide concentration, light, sound, and motion. A total of 50 sensor boxes were created and deployed with a main controller board and corresponding sensors for the parameters mentioned above. Several machine learning algorithms were applied for the purpose of estimating occupancy without actually tracing
The best performance model can count numbers of occupants at room level with higher accuracy and a lower cost. As a result, HVAC operations can be optimized based on the occupant demand to reach the goal of saving energy while still maintaining user comfort.

Under particular circumstances, self-developed devices are used in combination with corresponding algorithms. HVAC operation schedule was revised by Agarwal et al. (2010) based on real-time accurate occupancy data collected by sensors with a different but more complex method used by Yang et al. (2014). The research study combined a magnetic reed switch with passive infrared (PIR) sensors which were commonly used for occupancy detection, and then developed an algorithm to estimate occupancy in a comparatively accurate and low-cost fashion. That research showed advantages over conventional approaches such as using cameras and vision algorithms, and the simulation results indicated that their system could indeed reflect the presence and absence of people in individual offices, therefore, improvising the HVAC control system based on occupancy data for reducing energy consumption.

In addition to environment data, occupancy/behavior status monitoring is often required for occupant behavior model training and validation. Direct occupancy detection usually relies on cameras or PIR sensors, with each has its own merits and shortcomings. Indirect occupancy detection could be widely different which depends on certain conditions. For example, door or window open/close status change could reflect the user action, thus special devices like reed switch in the study of Agarwal et al. (2010) is used. Electricity meter is sometimes installed for usage pattern recognition as representation of specified occupant behaviors.
Moreover, Chen & Ahn (2014) used Wi-Fi as occupant tracking technology. Their efforts in the research consists of finding correlation between Wi-Fi connection event and electricity consumption using hypothesis tests. The researchers presented the benefits of Wi-Fi network over multiple sensors, as Wi-Fi would be able to track occupancy and the locations of occupants based on access points and signal strength. Besides, smart phones are nearly available for everyone nowadays so cost would not be an issue for this technology. However, Wi-Fi only provides occupant positions without other detailed information that is needed for behavior modeling.

Instead of measuring ambient parameters, Erickson et al. (2009) used self-developed system called SCOPES based on wireless camera networks. The system consists of 16 sensor nodes on the testbed building. Each sensor node is comprised of a camera interfaced with an adapter board. Then the captured images by the system were processed based on the object detection algorithm. The complex image processing algorithm finally generated an array of data containing information needed for occupancy modeling. The cameras used in this study were not for ground truth monitoring.

Commonly Used Data and Variable Types

In general, the data sources of occupant behavior modeling research are from following channels based on types of data: regular indoor environment sensors and outdoor weather stations which are used for ambient parameters measurement associated with occupant behavior (Andersen et al., 2013); electricity use that is collected for understanding energy paths and occupant patterns (Zhao, Lasternas, Lam, Yun, & Loftness, 2014); PIR sensors or cameras that are typically used for grasping ground truth such as occupancy status (Agarwal et al., 2010); and miscellaneous
technologies such as self-developed devices, RFID, Ultra-Wide Band and so on for specific behavior monitoring including window status, occupant locations, reading and walking, etc. (Li, Calis, & Becerik-Gerber, 2012; Masoudifar, Hammad, & Rezaee, 2014). Last but not the least, conducting survey is another data source used for modeling and simulation in many past research studies (Feng, Yan, Wang, & Sun, 2016), which should not be ignored and must be used in coordination with the advanced technologies.

Figure 2-1 depicts the current data acquisition technologies for corresponding data types that are used for modeling purpose. It is noticeable that though technologies provide sufficient convenience for data recording, the most important mission is to identify the key parameters to measure in order to avoid unnecessary and redundant data collection. Moreover, many novel methods, or even some existing methods that are temporarily discarded due to inadequate technical support in the past could be applied in the future due to the improvements in data processing ability and increase of device types and performance.

**Occupant Behavior Modeling Methodologies**

Data collection is the preparation step of modeling occupant behavior. The current technologies provide adequate access for the data that is needed for the research. Nevertheless, there is no common view or requirement that determines the selection and use of collected data. In fact, based on different modeling methodologies, data is not a mandatory element in some cases in that the models are not built based on volumes of data with those methods. However, additional validation work may be required for this type of methods, thus data is still needed for the models.
Figure 2-1. Typical data acquisition technologies for occupant-related research
In general, based on the modeling purpose and structure, occupant behavior modeling in buildings could be classified into two major categories, namely simulation-based methodologies and data-driven methodologies. The main difference between the two categories reflects in the model foundations, where simulation-based models establish a virtual environment with heterogeneous objects that mimic how actual human beings behave, regulated by rules, and data-driven models usually build a mathematical relationship between particular variables and targeted behaviors using behavior-related data from the experimental buildings and occupants.

Simulation-based Methodologies

As a representative simulation-based methodology, Agent-based Modeling (ABM) is a computational model for simulation of objects interaction with each other and the external environment. The model is on the basis of regulated rules which enable assessing the effects on the whole system.

ABM for interactions between occupants and buildings

ABM for occupant behavior study has different emphasis. Many research focused on the interaction of human and building systems. For example, Klein et al., (2012) developed their own multi-agent comfort and energy system to model alternative management and control of building systems and occupants. In their model, devices, occupants and meetings are all simulated as agents. Four distinct control strategies were applied as comparison, which are baseline, reactive, proactive, and proactive-Markov Decision Problems (MDP) for the purpose of building operation as well as intelligent coordination of devices and occupants. They compared the results of energy and comfort and stated that proactive with MDP shows the best result.
The work of Andrews, Putra, & Brennan (2013) showed strong potential capability of ABM as their team have been trying to build a modeling framework for occupant behavior at building level by this method. These researchers created occupant perception and behavior model and integrated it with simulation software for energy simulation. Their whole modeling system is comparatively comprehensive as it includes not only building performance sub-model that modifies the state of indoor environment but also human agent sub-model that simulates decisions and reactions of occupants. As for the occupant module, a procedurally oriented framework called Belief-Desire-Intention (BDI) was introduced which was then enriched for a better version.

Lee & Malkawi (2014) presented a simulation method using an ABM approach that tried to mimic occupant behaviors in commercial buildings while also accounting for the impact on both thermal conditions and energy use. The agent-based model tried to identify six common behaviors that are related to thermal comfort, and then adopted Fanger’s PMV model to identify behavior triggers including its connection to the behavior list and initial values used in the experiment. The decision-making process was based on an assumption that there are three categories of beliefs that will cause different occupant behaviors. The agents in this research were occupants only, the cost function for each agent is expressed in a function consists of beliefs, time, and weight coefficients. The system worked as follows: for each cycle, the bigger the cost $F_{ij}$, the greater probability that behavior $j$ will be performed by agent $i$. The initial coefficients were all decided based on assumptions while actually it should be decided by case studies or measured survey. At time $t$, when an agent was in a place, the whole simulation procedures was as follows: 1) Decision making process. The process
conforms to a rule of “observe, orient, decide and act”. The outside simulator provides environmental parameters to an agent and calculate its PMV to see the comfort level, then cost function will be used to figure out the ranking of behaviors (orient). After that the type and number and incremental changes (decide). Acts mean to send the impact back to outside simulators; 2) in the process, the agent could learn by upgrading the behavioral belief. However, the interaction part in this experiment was decided as fixed, which means they were muted influenced while in the real world it is not the case; 3) simulation coupling was also included. ABM was programmed in MATLAB and linked with EnergyPlus™ with the help of BCVTB architecture, to exchange parameters in a whole loop. The result part explored how different behaviors affect building energy use and occupant comfort level by adjusting relevant parameters to get different kinds of results. Figure 2-2 shows the logical process diagram of their proposed ABM.

Figure 2-2. Overview of ABM simulation process (Adapted from Lee & Malkawi 2014)
Langevin, Wen, & Gurian (2015) presented a detailed ABM using thermal comfort and behavior data from a field study in an office building. This model assigned building occupant agents dynamics for clothing, metabolic rate, thermal acceptability and behavior choice hierarchy. The rules of agent behavior conformed to Perceptual Control Theory to maintain thermal sensation. The performance of prediction was compared to other modeling options for validation. Although the study was limited to an office building, this approach provided a platform for more flexible simulations based on the interactions between occupants and surrounding built environments. The study also showed that ABM can be used to model interactions between different occupants.

Hong, D'Oca, Turner, & Taylor-Lange (2015) proposed an ontology for modeling occupant behaviors from the external drivers to internal needs of people, then to the actions and systems they act on (Figure 2-3). Subsequently, an occupant behavior simulation tool was created with their so-called “Drivers, Needs, Actions and Systems” structure (Hong, Sun, et al., 2016). The software tool is built without the support of any existing ABM tools, but completely invented for the purpose of building energy simulation. The model applied Weibull functions to determine the probability of actions as a function of environmental data, and generated outputs of three common behavior schedules for further use.

The ABM by Kashif, Ploix, Dugdale, & Le (2013) was built via the Brahms modeling software, which is a popular Modular Execution Framework for integrated systems. The researchers focused on the residential building occupant behaviors and described a causal model of behaviors that is analogous but somewhat different to (Hong, Sun, et al., 2016), as two factors (time and environment) were identified as the
triggers of behaviors. However, this research tend to describe the model in a social science perspective and did not cover the internal details and settings of the simulation environment. Moreover, the simulation scenario was purely based on an imaginary home situation which is not convincing enough to be valid.

![Diagram of DNAS ontology](image)

Figure 2-3. Proposed DNAS ontology for occupant behavior modeling (Adapted from Hong et al. 2016)

**ABM for interactions between various occupants**

Azar & Menassa (2012) analyzed the relationships between occupants within their agent-based model to account for different occupant energy use characters and changes. The unique contribution of their model as compared to others is that they considered only energy consumption behaviors and factors that cause behavioral change. Basically, their modeling process started by identify energy-consuming behaviors and determine factors that cause behavior changes. Then an iterative model is created with assumed input. After obtaining energy consumption rate per occupant behavior type using eQuest, the model was simulated for energy use variation. The researchers also tested the reaction to different input parameters by conducting sensitivity analysis, with four scenarios created.
Alfakara & Croxford (2014) used agent-based modeling to explore the interaction between occupants in residential houses and room systems for turning HVAC on/off as well as opening/closing windows. They built the ABM by dividing the objects into two classes: person and room. Each of the classes has their own attributes that were defined by the researchers that are based on probability. At the simulation stage, iterations were conducted combining the model and temperature input. Two cases were considered: a baseline and improved case, in which the improved case increased the temperature threshold of occupants. The results showed a reduction in HVAC used hours and an increase in window opening rate. Also, the cooling load was reduced by 30%. Although some of the parameters used were simplified, the model set the foundation for the future stages of research.

Others

Although simulation-based methods (especially ABM) can be generally categorized into two different forms, there is no strict separation line between them. Different types of combination approaches exist in the literature as well. For example, Putra, Andrews, & Senick (2017) built a model that replicated the interactions among occupant/tenant representative/building manager/building systems. In that research, both types of interactions were defined as behavior options to deal with external interruptions. The model showed the importance of heterogeneous occupant perceptions and behaviors in understanding responses to load shedding events. The stimulus of behavioral changes is the energy load shedding instead of environmental conditions, which is an interesting idea, but yet has not been proven to be valid under the circumstance.
The research of (Papadopoulos & Azar, 2016) indicated that ABM can be combined with data-driven methods. That research modeled six human actions that have high energy influence on buildings, and translated changes in human attributes to building energy consumption levels. With 1200 groups of behavior-related variable value settings, the energy use data was obtained for each group using traditional building performance simulation. Then, a linear regression model was developed that associated energy use to the six behavior-related variables, so that a surrogate model was generated to predict energy use that effectively integrated building performance simulation in ABM.

**Data-driven Methodologies**

Data-driven methodologies could be further categorized into three classes, which are statistical analysis, data mining, and stochastic modeling.

**Statistical analysis**

Statistical analysis is conducted to establish a numerical relationship between occupant behavior and other information. Indoor environment, electricity use, or time series where all somehow influence occupant behavior mutually. Using regression model, the probability of studied behavior could be expressed via related parameters input.

A study by Haldi & Robinson (2008) is one of the earlier examples of using the statistical method. That research asked all the volunteer participants to complete an electronic survey with several questions about their activity level, thermal sensation, and adaptive opportunities exercised. At the same time, indoor and outdoor temperatures were recorded by sensors or from the local department (Swiss Federal Office of the Environment). Logistic regression was then applied to analyze the influence of thermal
stimuli on occupants’ behavior to open/close windows, blinds, fans, and doors. Also personal behavior like consuming drinks and adaptations on clothing was also included in the study. The authors found that internal temperature played a more important role than the external temperature on predicting the probability of occupant behaviors.

Due to a comparatively steady relationship between occupant status and ambient characters, researchers tend to search the quantitative triggers of occupant behavior. Indoor environmental data, occupant presence/absence information, and position of shading and windows were collected by Mahdavi & Pröglhöf (2009) in five office buildings located in Austria using weather station, occupancy sensors, and time-lapse digital photography. The statistical relationship was provided among these parameters by depicting trends in the same coordinate and summarized that long-term general patterns of occupant control behaviors on building system could be translated as a function of indoor and outdoor conditions.

Peng et al. (2012) quantitatively described occupant behaviors through various parameters in different ways. They noted that equipment operational status and their energy use might reflect occupant behavior. For their research experiment, equipment energy usage models were divided into three categories, namely time-related, environmentally related, and random, to describe occupant behavior. Similarly, they used probability and time steps to model the first type of behaviors, environment and user feedback data to track the behaviors of second type above. Finally, they assumed three types of typical lifestyle of humans and simulated the energy consumption based on the division type.
Tabak & de Vries (2010) used two methods to predict the frequency of intermediate activities in an office building. Based on the context of that paper, intermediate activities depend on a person's role to a lesser degree but has more correlation with human needs, which in their opinion, are independent of a specific environment and thus could be developed in a generic way. The researchers first identified nine activities and their influencing factors through a survey, and decided to use S-curve method for the behaviors that strongly depend on the time elapsed since the last occurrence. Other behaviors that occur more randomly were assigned a random function to decide the start time. One of the shortcomings of the research is that the data source came from a web-based survey with lots of questions about their activities, frequency and so on. Despite this, the statistical results of effective responses still showed possible behavior time and duration at an average level.

Some research studies are also conducted for specific behavior objects tracking. Li, Li, Fan, & Jia (2015) focused on window opening behavior and collected ambient data of six factors including indoor/outdoor temperature, indoor/outdoor humidity, indoor CO₂ concentration and outdoor wind speed. Window occurrences conditions were then gathered using self-developed window open status recording device. In that research, they used multi-factor variance analysis to find the statistical significance of the six factors to window opening activity. The study concluded that outdoor temperature is the most influencing factor. Base on the results, a logistic regression, was performed to obtain the mathematical relationship between the probability of window opening and outdoor temperature. A second comparative method namely Monte Carlo simulation was also performed to get the probability distribution of window opening activity.
Mahdavi & Tahmasebi (2015) compared two previously developed probabilistic models and a non-probabilistic model by fitting separate training data given their performances on occupancy prediction. The probabilistic models demonstrated the relationship between occupancy and time. The contribution of that research helped to improve the accuracy of training and validation datasets and an evaluation approach that analyzed prediction errors on occupant presence prediction.

**Data mining**

In most of the cases, electricity usage condition of certain equipment may reflect users’ behavior. Therefore, by mining energy usage data, corresponding occupant behavior pattern can be learned, especially for a long-term mode.

In the research of (Zhao et al., 2014), a data mining solution was developed to predict occupant behavior and schedule based on office appliance energy use. Electricity meter was deployed to measure electricity data of appliances including desktop computers, monitors, task light, speaker, laptop computer, hard drive and personal heater. A pedometer was attached to each experiment participant for ground truth data logging for a total of six occupants. The researchers trained and tested these data with three data mining algorithms, and the results had good performance on predicting schedule of appliance application behavior. One of the issues of this study is that occupant behaviors are only defined into four categories that did not cover all the possible scenarios.

D’Oca & Hong (2015) used a three-step data mining schedule learning method to deal with a data set of the occupancy status of 16 offices to provide insights of patterns of occupancy. Before the learning process, raw occupancy data was transformed to pre-processed data representing several predictor attributes (season, day, time, window
state. The authors applied the C4.5 algorithm to generate a decision tree model that aimed to predict the value of a label attribute (occupancy) based on those input attributes. Forty-five decision rules were derived based on the tree model from the root node to a leaf node, which could understand repetitive occupancy patterns. The cluster analysis using k-means was performed to group these occupancy presence conditions into four typical patterns. The final goal of the research was to understand different occupancy patterns in buildings for better prediction of building performance.

Similarly, Alhamoud et al. (2015) utilized two sets of data to conduct three experiments for energy-related occupant behavior pattern detection in a residential building. The datasets comprised of power and environmental data that were obtained from sensors and a volunteer survey while nine activities were defined on the basis of regular motions. During the first task, they used the Random Forest Classifier algorithm to build a model that established a correlation between occupant’s current location and real-time power consumption. After that, they used Apriori Algorithm to extract the temporal relations between activities, trying to recognize the activity pattern for a certain occupant. They compared the distributions of daily power usage for two different days and found high similarity between them concluding that people has a regularly routine power consumption behavior. All the information was mainly mined from electricity consumption of home appliances.

In some studies, the data mining method was integrated with ABM to simulate occupant behavior. For instance, Baptista, Fang, Prendinger, Prada, & Yamaguchi (2014) presented a Nearest Neighbor occupant behavior model in multi-agent systems. The model was established as a set of coordinating agents to mimic occupants. Data
mining techniques was employed to classify database according to the resemblance of states, which would later be selected as the agent’s next behavior with equal probabilities. Their model outperformed Markov Chain Model by producing better results.

**Stochastic modeling**

Building occupants naturally behave in a random way, which make stochastic modeling an effective way to model and estimate occupancy status and related energy consumption.

Markov Chains is the fundamental starting point of this methodology. Erickson, Carreira-Perpiñán, & Cerpa (2011) contributed to temporal dynamics of occupancy detection by developing two advanced Markov Chain Models from ground truth data collected from a sensor network. Also, they proved that their previous two models namely, ABM and Multivariate Gaussian model both have limitations. Their study showed improved accuracy in occupancy estimation and by implementing the real-time occupancy data into HVAC operation schedule, 42% annual energy savings can be achieved.

Also, Dong & Andrews (2009) discovered occupant presence and behavior patterns based on semi-Markov models to optimize occupancy schedule for lighting and HVAC control. Then, Dong & Lam (2011) developed an improved model with environmental data and occupancy ground truth data. A Hidden Markov Model based on Gaussian Mixture Model was implemented to estimate occupant numbers in a room. A Semi-Markov Model was generated for occupancy duration estimation to represent a long-term pattern of behavior.
Chen, Xu, & Soh (2015) proposed an advanced occupancy modeling method using stochastic modeling. This study introduced the methodology with Markov chain in an optimized manner. Two novel inhomogeneous Markov Chain models were proposed under two scenarios of Multiple-Occupants-Single-Zone (MOSZ) and Multiple-Occupants-Multiple-Zone (MOMZ). The novelty of this research is that the researchers defined the state of Markov Chain (MC) as the increment (change) of occupant numbers instead of occupant numbers for MOSZ; and for MOMZ, the state of MC was a vector in which each component is the increment of occupancy in each zone. In this way, the calculation load was much simpler. When calculating the probability matrix, they adopted maximum likelihood estimation (MLE). The testing data came from the research of Liao, Lin, & Barooah (2012), in which a wireless camera was used near the entrance of a zone. To evaluate the performance of the proposed model, they defined five parameters and two evaluation criteria to compare the results obtained from 1) estimation from measurement, 2) prediction from ABM by (Liao et al., 2012), and 3) their own models. Although some assumptions were made, the results showed this model outperformed ABM model.

The methodology could also associate energy consumption with occupant behavior pattern, which is indicated through an occupant behavioral model in (Virote & Neves-Silva, 2012). The model was based on Hidden Markov Models (HMM) for predicting building energy consumption using practically measured data. The HMM consists of an observable layer that represents actions that occupant may take and hidden layers that represent the factors that influenced the observed behavior. The stochastic nature of Markov chains Model would strongly influence energy consumption
model, which is a cluster of Markov Chains according to the authors. By developing an algorithm named frame-scene analysis, the energy use could be predicted under the impact of occupant behaviors. The models provided valuable information for simulating the influences that occupants have on a building in terms of energy consumption as they showed that different occupancy patterns result in different patterns of energy usage.

For a similar purpose, Zaraket, Yannou, Leroy, Minel, & Chapotot (2014) delivered an activity-based approach for energy consumption forecast in residential buildings using the stochastic method, since recent energy simulation methods lack occupant behavior integration. This study provided a probabilistic mapping between household profiles and corresponding domestic energy consumption. According to the researchers, there is a reference person in each residential house, plus three other parameters exist to influence the probability of high-level environmental awareness. In the same manner, the probability of a household to have a certain appliance and further energy efficient appliance was generated. Based on the estimating activity quantities per household, the energy for one behavior could be estimated. The energy use simulation was based on the variables above and calculated stochastically as a function of the equipment unit. Later the researchers conducted a case study on the behavior of “washing laundry”, with relevant data from the web-based survey. The model was validated by opposing the results to measured data.

Comparison of Major Methodologies

Since building occupant presence and behavior has been demonstrated as one of the most crucial elements for energy optimization at the building level, various methodologies have been introduced to detect and model occupant behavior for
enabling more efficient building energy management. In this chapter, four modeling methodologies were identified, namely agent-based modeling, statistical analysis, stochastic model (Markov chain), and data mining from end-use energy use. However, this is not a complete list for modeling approaches of building occupant behaviors. Generally, it could not be concluded that one specific method is more effective than the other, yet it is necessary to realize the advantages and limitations of these methods as well as the applicability of them. A detailed specification is described as follows.

Agent-based modeling starts from the perspective of agent, and constructs a virtual model based on some certain rules. ABM is a relatively new approach as a trial in occupant behavior modeling and simulation with its particular advantages and strengths. For instance, ABM can describe uncertainties in real-world as compared to the static model and can model all behavioral aspects theoretically. Also, ABM outperforms a simple “if-then” rule as the agents in the system can interact and change behaviors in each simulation cycle (Y. S. Lee & Malkawi, 2014). However, limitations still exist as the use of ABM approach to simulate building occupant behaviors is still at its development age. The comprehensiveness and completeness of the model are needed to be developed in the future. Researchers using this method have their own concentration when modeling occupant behavior. As classified in this chapter, some of the researchers have addressed the interaction between occupants and building systems while others focused more on communication between occupants themselves. Besides, the integration of simulated behavior and current energy modeling software need to be studied as well due to the complexity of this model. Last but not the least,
appropriate verification and validation process is needed to boost the robustness of an ABM, which is often lacked in most of the literatures.

Statistical analysis is the most traditional and common method in modeling occupant presence and behavior. This methodology is often applied to study the relationship between the occupant behavior and other factors, environmental parameters. The idea of this method is to study the probabilities of behavior due to driving factors through regression or observation. A typical example is the work of (Fabi, Camisassi, Causone, Corognati, & Andersen, 2014; Fabi, Maggiora, Corognati, & Andersen, 2014), who integrated the methods to understand two different behaviors in office buildings: window opening, and light switch turning on/off. The researchers measured indoor and outdoor environment parameters, along with window state in a temporal manner, and conducted a multivariate logistic regression to obtain the probability of operating windows with other information. The statistical analysis is a comparatively direct and convincing way to model occupant behavior, as occupant behavior will mostly be driven by surrounding environment. However, this method needs to be improved because of two reasons. First, this method is only limited to one or two certain types of occupant behaviors, such as window opening or light switch status. Although this method is somewhat meaningful and straightforward, it is difficult to build a comprehensive model and further integrate with energy simulation software. Second, no matter how high the probability is predicted for the behavior, in the real world, people may still behave or act in another pattern owning to individual psychology or other conditions (Tabak & de Vries, 2010; Yan et al., 2015). Therefore, involving real-time
data in the statistical analysis may be a useful solution for detecting occupant behaviors in buildings.

Data mining is the process of knowledge discovery in large databases. The goal of the approach is to explore consistent patterns and/or systematic relationships between variables and then to validate the findings by applying the detected patterns to new sets of data. For studying building energy efficiency, data mining has been used as one of the most popular methods. In terms of occupant behavior modeling in buildings, data mining is often applied to study a long-term occupancy pattern from end-use energy consumption data within a specific time. The benefit of this method is that the data collection and data management is simple to implement, as in most research studies, only electricity consumption or occupancy data is logged. Based on the strong prediction capability of data mining, great accuracy could be obtained through this method with potential room for improvement. This method is confined to pre-defined occupant behaviors or merely occupancy, which limits the application of this method. Moreover, research using this method mostly used residential buildings as experiment object, probably because the energy monitoring procedure is more convenient, and the occupant behaviors are easier to define. The other issue of this method is that the pattern mined is hard to link to energy simulation program.

Stochastic modeling is employed by many researchers due to a “random” nature of occupant behavior. A Markov Chain is the fundamental method that is a stochastic process following Markov property whose future status depends only on current status and will not be influenced by the past state. Some studies developed the algorithms from different perspectives. For example, Dong & Lam (2011) correlated environmental
conditions and occupancy numbers using Hidden Markov Chain and found out valuable accuracy in estimating occupancy status. Lee, Tong, & Cheng (2014) tracked and modified occupancy level according to the time of day and presented a slight difference between deterministic and stochastic model. Chen et al. (2015) only focused on occupancy data through images captured by cameras, which they used to adjust the size of the matrix that represent Markov chain states so that computing burden will lower down without decreasing accuracy. According to (Gunay et al., 2013), current building performance simulation tools provide application integration with stochastic control models. Thus, this method can test the impact of occupant behaviors on building energy use. But the drawbacks of this method could not be ignored. Stochastic modeling is more suitable for long-term occupancy schedule prediction or classification while detailed occupant behaviors or numbers of occupancy are not being researched using this method. Similar to ABM method, this method also need development for the completeness of occupancy model, and there is still no common views on how to build a perfect stochastic model for occupant behavior detection.

There are plenty of studies on tracking building occupant behavior using other methodologies apart from the categories mentioned in this paper which were all proved to have their advantages and acceptable accuracy of realistic conditions. In summary, the data sources that were analyzed for each method are usually similar, which are ambient factors, electricity consumptions, and direct occupant behavior status measurement. Although methods could be as simple as observation only, or as complicated as a novel algorithm for machine learning. The information is needed because surrounding environment is the main reason that may cause a change in
occupant behavior, and the electricity consumptions are the result of the adaptive behavior. This causal relationship provides technical support for building occupant behavior detection, thus cannot be ignored. However, improvement of existing methodologies is necessary. Understanding the features of these methodologies could provide researchers a thorough point of views for future study. A comprehensive comparison (Table 2-1) is illustrated in the table below to offer more insights.

**Coupling Mechanisms**

A seamless integration of building occupant behavior model and energy simulation platform can be helpful to quantify the influence of occupant behavior on building performance, increase the accuracy of building energy prediction, and assist practical energy optimization strategies. Nevertheless, the coupling mechanism of occupant behavior model and energy simulation program is still at the early research stage. This section summarized recent research efforts that indicated how researchers have explored the impact of occupants on building energy use.

Some researchers directly monitored real-time electricity usage data and occupancy status to seek energy saving possibility. Masoso & Grobler (2010) measured electricity use of six buildings and broke down the usage data by equipment type and by working periods that were defined as working hours and non-working hours. By analyzing the data, the authors found that more electricity was used during non-working hours than during working hours, which indicated a large energy saving potential by changing occupant behavior patterns. Likewise, Kavulya & Becerik-Gerber (2012) linked the appliance electricity loads data with occupant behaviors extracted from visual observations of five people in a shared office.
<table>
<thead>
<tr>
<th>Methodology</th>
<th>Representative references</th>
<th>Building type(s) that is more suitable</th>
<th>Ability to integrate with simulation</th>
<th>Additional Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agent-based Modeling</td>
<td>(Y. S. Lee &amp; Malkawi, 2014)</td>
<td>Both residential and commercial buildings</td>
<td>High</td>
<td>For improving simulation accuracy. This method is used more in simulation the process, usually lack of actual data for support</td>
</tr>
<tr>
<td>Statistical Analysis</td>
<td>(Li et al., 2015)</td>
<td>Commercial (Office)</td>
<td>Medium</td>
<td>For recognizing driving factors of occupant behavior, Statistical comes from early ages</td>
</tr>
<tr>
<td>Data Mining</td>
<td>(Zhao et al., 2014)</td>
<td>Both residential and commercial buildings</td>
<td>Low</td>
<td>For understanding occupant behavior Data mining method is usually for “passive” occupant behavior schedule learning.</td>
</tr>
<tr>
<td>Stochastic Model</td>
<td>(Virote &amp; Neves-Silva, 2012)</td>
<td>More on commercial buildings</td>
<td>Medium</td>
<td>Stochastic model is always for MPC, and long-term occupant behavior pattern modeling, it is now used more for occupancy modeling</td>
</tr>
<tr>
<td>Others</td>
<td>(Cali, Matthes, Huchtemann, Streblow, &amp; Müller, 2015)</td>
<td>N/A</td>
<td>N/A</td>
<td>Data sources are generally the same. But the methodologies cannot be generalized since they studied from different views and purposes for occupant behaviors</td>
</tr>
</tbody>
</table>
They identified during the experiments that occupants were not usually aware of how much energy was wasted when appliances were actually in use. The authors also suggested that providing occupants with information on their energy consumption patterns could somehow modify their behavior to a more efficient way. In energy simulation tools, occupant behavior patterns were often sorted into several typical types, such as “energy saving users,” “normal users,” and “energy wasting users” to analyze their impact on energy respectively. Hong & Lin (2012) claimed that occupant behavior is the driving factor that causes discrepancies among similar buildings in same climate zone. They identified and categorized occupant behavior styles into three different groups that are “austerity,” “standard,” and “wasteful.” They, then, selected three adjacent offices and assumed each office has a person with the corresponding type. The selected behaviors for different types consisted of several aspects including heating and cooling set point, occupancy controls, daylighting controls, etc. By simulating the energy use and comparing the results, this study was able to show the behaviors that relate to operation and control of energy service systems of private offices. In the study of (Peng et al., 2012), three classifications of occupant behavior patterns were assumed, and the energy consumption was simulated by changing air conditioning operation schedule, indoor temperature preference, and household loads based on the division type. Obvious variations were found in building performances.

Yu, Fung, Haghight, Yoshino, & Morofsky (2011) developed a novel technique for examining the influences of user behavior on building energy use by excluding overlapped effect of other conditions. They organized similar buildings among all the test buildings into four groups based on 12 representative parameters that stand for four
factors unrelated to user behavior so that these external factors all have similar effects on buildings in the same cluster. Grey relational analysis and data normalization were applied to this cluster analysis. Then, in these four clusters, the effects of occupant behavior on energy consumption were examined at the end-use level, as the end-use variations are only induced by occupant behavior.

Clevenger & Haymaker (2006) used DOE-2 as a popular energy simulation software to discover sensitivity of occupancy related parameters on energy usage. They identified ten parameters to represent occupant in the simulation software and then set all the parameters to medium values to run the simulation. Then each of these parameters were set to either a high or low value to repeat the experiment. By comparing the energy results with the control group, they were able to know the most significant contributors to energy use variability. The researchers concluded that a more reliable occupant model is needed for accurate prediction.

Adjustments relying on assumptions are more inclined to affirm the fact that occupants do influence building performance, but it lacks the ability to quantify the practical possible impact. Therefore, realistic data is needed. The paper of (Daniel, Soebarto, & Williamson, 2015) contributed in three ways. First, although Australia’s house energy rating system has been developed, namely Nationwide House Energy Rating Scheme (NatHERS), the regulation has many limitations. According to the questionnaire results from that research, the NatHERS protocols failed to reflect actual occupant preference and operations. Second, they validated the capacity of an energy modeling software that is based on NatHERS named AccuRate by comparing its simulation result with EnergyPlus and EnerWin. In particular, the simulation showed that
AccuRate simulation engine could adequately predict internal conditions in simple unoccupied buildings. Third, by modifying occupancy preference settings based on the survey data, such as thermostat temperature set point and rooms being conditioned, the research obtained much closer predicted heating and cooling loads to actual loads. This study concluded an overestimation of energy loads in the regulatory mode of the software. The study took advantage of real life choices of occupants to predict energy use and found out that the results matched to the actual energy use. The research also demonstrated that incorporating occupant information into energy simulation tools can obtain better results than traditional simulation methods. However, in this research occupancy settings are simple and not real time, thus lacking the ability to predict in a more accurate way.

Duan & Dong (2014) applied PIR sensor for occupancy detection in four low-income residential buildings as test beds to validate the information from the American Time Use Survey data. They created two scenarios that applied measured schedule of occupancy probability distribution into EnergyPlus and DesignBuilder. The temperature settings were revised in the second scenario. The simulation study indicated large energy saving potential compared to the baseline. Though the occupant behavior model in this study was only represented by occupancy information, it was based on measured data, which showed strong evidence that occupants do influence building energy use significantly.

There are some research studies that specifically analyzed the effect of particular occupant behaviors on energy use. For example, D’Oca, Fabi, Corgnati, & Andersen (2014) focused on the effect of thermostat adjustment and window opening behavior on
energy consumption in residential buildings. Their previously developed probabilistic human activity models were applied in the energy simulation phase. In an earlier research work, Haldi & Robinson (2011) attempted to study the impact of occupant behavior in terms of the window opening and shading devices on buildings. They concluded that building performance simulation will be more realistic by integrating occupant behavior models. Meanwhile, the influence of energy-related behavior change based on individual variability exceeded that of the change from other building design variables.

Wang & Greenberg (2015) focused on the impact of different types of ventilation scenarios caused by window operation on building performance. Four scenarios were defined by the authors, namely open windows, natural ventilation, changer-over mixed-mode ventilation and concurrent mixed-mode ventilation. Then by changing parameters in EnergyPlus to represent the four situations, the researchers simulated and cross-compared the energy and thermal results with three different climate zones. The researchers stated that mixed-mode ventilation can provide HVAC energy savings. However, this paper did not mention how to model these behaviors.

In a related research study, Santin, Itard, & Visscher (2009) showed that both occupant behavior and building characteristics can save energy. But sometimes occupant behavior is determined by the type of dwelling or HVAC systems and, therefore, the effect of occupant characteristics such as income or household size might be larger than expected since these determine the type of dwelling. In Table 2-2, a summary of research criteria for integration of occupant behavior model and building performance simulation is illustrated.
<table>
<thead>
<tr>
<th>References</th>
<th>Basis of Data</th>
<th>Behavior types: specific or overall evaluation</th>
<th>Optimized systems/parameters</th>
<th>Whether include actual occupant behavior model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Assumption</td>
<td>Overall</td>
<td>Specific</td>
<td></td>
</tr>
<tr>
<td>(Masoso &amp; Grobler, 2010)</td>
<td>√</td>
<td>√</td>
<td></td>
<td>HVAC, plug loads and lighting</td>
</tr>
<tr>
<td>(Kavulya &amp; Becerik-Gerber, 2012)</td>
<td>√</td>
<td>√</td>
<td></td>
<td>Plug loads</td>
</tr>
<tr>
<td>(Hong &amp; Lin, 2012)</td>
<td>√</td>
<td>√</td>
<td></td>
<td>HVAC(schedule, set point), lighting</td>
</tr>
<tr>
<td>(Peng et al., 2012)</td>
<td>√</td>
<td>√</td>
<td></td>
<td>HVAC(set point)</td>
</tr>
<tr>
<td>(Yu et al., 2011)</td>
<td>√</td>
<td>√</td>
<td></td>
<td>HVAC, water, kitchen equipment</td>
</tr>
<tr>
<td>(Clevenger &amp; Haymaker, 2006)</td>
<td>√</td>
<td>√</td>
<td></td>
<td>Ten parameters identified to represent occupant model</td>
</tr>
<tr>
<td>(Daniel et al., 2015)</td>
<td>√</td>
<td>occupancy</td>
<td></td>
<td>HVAC(schedule, set point), rooms</td>
</tr>
<tr>
<td>(Duan &amp; Dong, 2014)</td>
<td>√</td>
<td>occupancy</td>
<td></td>
<td>HVAC</td>
</tr>
<tr>
<td>(D'Oca et al., 2014)</td>
<td>√</td>
<td>Thermostat and window</td>
<td>Ambient data and Heating set point</td>
<td>Yes</td>
</tr>
<tr>
<td>(Haldi &amp; Robinson, 2011)</td>
<td>√</td>
<td>Window and shading</td>
<td>Temperature set point</td>
<td>Yes</td>
</tr>
<tr>
<td>(Wang &amp; Greenberg, 2015)</td>
<td>√</td>
<td>Window operation</td>
<td>Seven parameters related to window operation</td>
<td>No</td>
</tr>
</tbody>
</table>
Introduction of Agent-Based Modeling

Through literature review and analysis of different modeling methodologies, Agent-based Modeling is selected for this research. Agent-based modeling is a novel approach that provides a platform to modeling complex systems composed of interacting "agents" (Figure 2-4). Agents have their own characteristics and features including behaviors, and they have the capability of interacting with their located environment and other agents, which is often governed by user-defined rules. The rules are the foundation to model agents' relationships, interactions, and behaviors. According to (C. M. Macal & North, 2010), a typical agent-base model has three elements:

- Agents, along with their attributes and behavior options;
- Rules and topology, which defines how and with whom agents interact;
- Agents’ environment, agents who stay in the environment are supposed to interact with their environment, in addition to other agents if possible.

In contrast with other modeling approaches, agent-based modeling begins and ends with the agent’s perspective. The application of ABM is spread into many different domains which include areas of intelligent built environment and building energy efficiency. The system modeled by ABM is often referred as a Multi-Agent System (MAS), which could be any combinations of the built environment. In this research, ABM is used to model building occupants and their interactions with building components in the indoor environment. Though the application is in the early stages, Lee & Malkawi (2014) summarized several benefits of ABM implementation in occupant behavior research. For example, ABM is able to address uncertainties of the real world; an agent in ABM can simulate humans by perceiving surrounding environment and adapting to
changes in order to achieve a certain goal. Besides, even at the simplest level, there
could be valuable findings about the ABM system as a whole if proper agents and
relationships are invented (Jia, Srinivasan, Ries, & Bharathy, 2018).

It should be noted that Agent-based modeling is not mutually exclusive with other
modeling methodologies, in that an agent’s behavior can range from simplistic and
reactive rules to complex behaviors regulated by artificial intelligence techniques (Macal
& North, 2014). Specifically, if proved to be practical, ABM rules can be defined based
on statistical modeling or data mining results as part of the system that manage the
behaviors of autonomous agents.

Agent Interactions with Other Agents

Agent
Attributes:
Static: name, ...
Dynamic: memory, resources, neighbors, ...

Methods:
Behaviors
Behaviors that modify behaviors
Update rules for dynamic attributes
etc.

Agent Interactions with the Environment

Figure 2-4. Characteristics of agents in ABM (Adapted from Macal & North, 2014)

Common ABM Tools and PMFserv

Since ABM itself is not a new methodology, different commercial ABM software
exist for practical applications. In addition, some computing tools also provide
programming functions for developing ABM, such as MATLAB or R. For occupant
behavior modeling in built environment, the most common tools that have been successfully applied include Brahms (Kashif et al., 2013), AnyLogic (Azar & Menassa, 2012), NetLogo (Putra et al., 2017), Repast (Alfakara & Croxford, 2014), etc. Meanwhile, MATLAB is also a popular ABM tool (Langevin et al., 2015; Lee & Malkawi, 2014) due to its powerful computational ability. Moreover, Hong, Sun, et al. (2016) developed a particular occupant behavior modeling tool (obFMU) for integration with energy simulation engine. However, except the obFMU that is particularly developed for modeling occupant behaviors, the public available tools above are not specialized in tracking building occupant, thus lack of key modeling component and are challenging to expand the use or standardize due to unsophisticated theoretical framework.

This dissertation adopted a platform named PMFserv that has been well tested in the social science and system engineering fields and is particularly built for human behavior modeling. Silverman, Bharathy, Nye, & Eidelson (2007) have built the PMFserv framework and its derivatives centered on multi-resolution agent based approach. While some of these models are specialized in conflict scenario, the agents themselves are generic in representing human behavior under different context.

PMFserv modeling framework and the software were developed over the past ten years at the University of Pennsylvania as an architecture to synthesize many best-of-breed models and best practice theories of human behavior modeling. This environment also facilitates the codification of alternative theories of factional interaction and the evaluation of policy alternatives. More information on PMFserv can be found in (Bharathy & Silverman, 2013; Silverman, Bharathy, Nye, et al., 2007). In Table 2-3, a summary of the ABM tools observed from the literatures for occupant behavior modeling
in the built environment, as well as PMFserv which is used in this dissertation, is presented.

Table 2-3. Commonly used ABM tools for building occupant behavior modeling and PMFserv

<table>
<thead>
<tr>
<th>Platform</th>
<th>Application domains</th>
<th>Programming Language</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>AnyLogic</td>
<td>General purpose, also supports discrete event and system dynamics simulations</td>
<td>Java; UML-RT</td>
<td>Azar &amp; Menassa, 2012</td>
</tr>
<tr>
<td>Brahms</td>
<td>General purpose modeling, usually models humans as social and collaborative agents</td>
<td>Brahms language (Java-based)</td>
<td>Kashif et al., 2013</td>
</tr>
<tr>
<td>MATLAB</td>
<td>Multi-paradigm computing environment, not specifically built for ABM</td>
<td>MATLAB</td>
<td>Langevin et al., 2015; Lee &amp; Malkawi, 2014</td>
</tr>
<tr>
<td>NetLogo</td>
<td>Social and natural sciences, such as economics, physics, biology, psychology, etc.</td>
<td>NetLogo (runs on Java Virtual Machine)</td>
<td>Andrews, Putra, &amp; Brennan, 2013</td>
</tr>
<tr>
<td>PMFserv</td>
<td>Specifically for human behavior modeling in system engineering and social sciences</td>
<td>Python, with PMFserv GUI</td>
<td>Jia, Srinivasan, Ries, et al., 2017</td>
</tr>
<tr>
<td>Repast</td>
<td>Social sciences</td>
<td>Java, Python, Visual Basic, C++, etc.</td>
<td>Alfakara &amp; Croxford, 2014</td>
</tr>
<tr>
<td>obFMU (customized with Functional mock-up unit)</td>
<td>Built for building occupant behavior modeling that complies with the Functional Mock-up Interface standard (FMI)</td>
<td>XML and C</td>
<td>Hong, Sun, et al. 2016</td>
</tr>
</tbody>
</table>
Overview

In this chapter, the proposed occupant behavior modeling methodology using Agent-based Modeling (ABM) as well as its performance and integration approach with building energy simulation engine are discussed. ABM is selected as the occupant behavior modeling method for this research owing to its high potential to integrate with energy simulation program directly. While many researchers have been using ABM for building occupant behavior modeling, there is no collective agreement on the specifications of modeling process and standard. In Chapter 2, a brief summary was provided that listed major properties of different models. In particular, the uniqueness of the entire modeling method that distinguishes this research with other studies are as follows:

1. The ABM platform used in this research, namely PMFserv, is particularly designed for human behavior modeling. This is the first time such a modeling paradigm is applied to the built environment area. The ABM model takes three major perception types of humans into consideration, in order to provide a more comprehensive view for behavior modeling;

2. Although the idea of co-simulation has been proposed by other researchers, this research uses BCVTB to integrate PMFserv and EnergyPlus™. More importantly, the behavior options reflect the realistic situations for each modeling agent, where other research usually assumed some behavior patterns or changes that are not always practical for building occupants, such as thermostats adjustment, as the thermal condition is normally controlled via central HVAC unit in most of today’s buildings.

3. The case study of the modeling method will be based on an actual building rather than a simulated one, along with actual environment data for validation purpose to enhance the reliability of the model instead of using synthetic data on a pure simulation basis;
The objectives (introduced in Chapter 1) of the research will be realized through the following steps:

First, a virtual occupant behavior model is developed based on the case study prototype building and the targeted occupants. To fulfill the goal, three complementary paradigms in the modeling platform are embodied and created according to the reality. Then, the input and output parameters are identified for the model. Input parameters include fixed-value ones and the ones being updated at each simulation time step. Output parameters are the behaviors taken by the occupant at each time step. With certain input parameters being modified, the behaviors are modeled dynamically, which can be used for building energy modeling in the later stage.

Second, a co-simulation platform, the BCVTB, is used to integrate PMFserv and EnregyPlus™. Table 3-1 describes the general input and output of the occupant behavior model and building energy model when conducting integration experiment.

<table>
<thead>
<tr>
<th>ABM</th>
<th>Building Energy Model</th>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environmental conditions; building system status; occupant characteristics</td>
<td>Behavior schedules for each modeled building component</td>
<td>Occupant behavior decisions made at each time-step</td>
<td>Energy usage; variations in environmental conditions; occupant comfort index</td>
</tr>
</tbody>
</table>

Third, custom-built embedded sensor boards and paper-based surveys are used to observe “ground truth” to test and validate the occupant behavior model. By collecting required input data for the occupant behavior model, the simulation model can be fed with actual data and then generates the simulated results. Afterwards, the observed status data collected at the same time period of input data are compared with the
simulation results, so that the performance of the model can be evaluated in a general view.

Fourth, a few pertinent scenarios are identified to study the energy impacts of the developed ABM to building performance simulation using real-world educational building as a case study. After testing and calibration, the occupant behavior model is integrated with a building simulation tool to exchange input and output to enable a dynamic simulation process.

Figure 3-1 shows the overall workflow of the research. In this figure, the simulated environment and the physical environment form a parallel relationship. In the simulated environment, virtual models are developed based on the reality. ABM for occupant behavior belongs to this part. First of all, rule-based modules are created and attached to the model, along with input (built environment) and output (behavior schedule) defined for the ABM. Then, relevant data from physical environment are collected, with one portion used for ABM input, and the other portion for comparison with ABM output. Finally, the ABM output can be further applied in BEM created in the building simulation engine (EnergyPlus™) to enable a simulation coupling, for improving simulation functioning and accuracy. For future studies, it is essential to acquire actual building performance data (e.g. energy use) for the simulation coupling effect analysis. In the following sections, the methodology for proposed workflow is presented in detail.
Figure 3-1. Research workflow overview
Modeling Principles of the Proposed ABM

According to the literature review, the core elements of an ABM consist of a set of agent(s), an environment, and certain topology and rules that direct how the system works. In correspondence to the modeling background and context in this research, the specific projection of ABM structure is shown in Figure 3-2. Although the modeling scenario in the case study is based on an educational building, the modeling principles and theories can be extended to any building or occupant types. However, in this research, the focus is placed on commercial (educational) buildings rather than residential buildings. Details of the ABM development with the selected platform PMFserv are discussed in the following sections.

Figure 3-2. Projection of ABM structure to the context of built environment

Occupant Behaviors in Commercial Buildings

From the overview of a standard ABM structure as discussed above, the proposed ABM is characterized with three major parts. First, the agents in the model are humans, more specifically representing the building occupants. Humans are rather complex agents in terms of their attributes and characteristics. It is impossible and, sometimes, unnecessary and/or overly difficult to capture all of the characteristics. In this research, the model considers physical perceptions and mental cognitions of
individuals as the main features for agents. Meanwhile, emotion, stress, and physiology status are also included as subtle but useful factors for modeling process.

Second, the environment which agents interact with in the model is aptly identified. The location where agent stays is within the inside of a building (individual rooms), which is at the thermal zone- or room- level. The ambient environment is the direct stimulus or driver that influences the agent’s behavioral decisions. Under the current model development, other building properties such as room size, location, orientation, etc., are excluded in the ABM as these do not affect the occupant behavior for the purposes of this research. Researchers have demonstrated the feasibility and validity of the assumption (Hong, Sun, et al., 2016; Langevin et al., 2015). In addition, behavior options of agent in the modeled building is included for adapting to surrounding environmental conditions.

Lastly, as the built environment states and building component states are set, if the environment states are out of the acceptable range for the agent, it is expected that the agent will have the possibility to adjust the state of building components to reach their individual comfort level. This rule is an explanation of the organizational part “Plot/Play” according to a scenario frame proposed by (Silverman, Johns, Cornwell, & O'brien, 2006). However, it should be noted that ambient environment is not the only external factor that influences human’s behavior in real world. For example, usual time, economical concerns, and other agents’ impact can also affect the behavior patterns of building occupant (Azar & Menassa, 2012; Kashif et al., 2013), especially in residential buildings. Nevertheless, under the scope of this study, the ABM is considered to be
reasonable, since in commercial buildings, the dominant trigger of occupant behavior is one’s physical comfort level, rather than other issues such as energy expense, etc.

**Modeling Functions and Rules**

The conceptual idea of the ABM, along with its purpose is implemented in PMFserv. PMFserv is a server of many different Performance Moderator Functions (PMFs) that have been extracted from the literature. Refer to (Bharathy & Silverman, 2013) for more details on PMFserv. It is also an environment for adding new PMFs and testing them to see their effect on human behavior and performance. As the first trial of the tool in a built environment application, this research adopts the internal algorithms and modeling architecture within the platform. Although not a fully-developed model with the tool, the occupant behavior model complies with the rules as briefly described in the following. A more detailed introduction for the main functions is provided in Appendix A, which is extracted from the tutorial manuals of PMFserv (Silverman, Bharathy, & Nye, 2007a, 2007b; Silverman & Johns, 2007).

**Function 1: agent physiology, stress, and coping style**

This module stores and maintains the agent’s state of biological systems such as physical energy level in the format of tank flow, which eventually influence the agent stress status. The agent’s behavior is bounded by the stress status. This function is the native property of an agent, which can be used for behavior constraint that leads to behavior failure with some probabilities. However, in this research, it is considered that no such failures will happen under the modeling circumstances, according to the behavior characteristics in the context. Therefore, to emphasize the impact of external factors to behavior decisions of the modeling agent, the module is not fully expanded for this research. As a result, values of this function are set to medium to represent a
generic form during the simulation process. Some of the screenshot samples are available in Appendix B for visualization illustration. Users are allowed to scale the tank value as needed for different modeling objects.

**Function 2: agent emotions and value systems**

The emotion and value systems function is the major determinant of the agent’s cognitive appraisal of the environment, which can be measured by composite utility of the behavior options for the agent. The developers of PMFserv have chosen different emotion models that contains a number of theories for cognition modeling, while specific emotion is aroused by an individual’s value system. The value system is characterized by a Goal, Standard, and Preference (GSP) tree based on utility norm and Bayesian theorem that defines the agent’s short-term needs, behavior standard, and long-term preferences of the world. The GSP tree is in a hierarchical structure filled with node of particular cognition items, each attached with a weight that denotes to the importance of that item. A sample way PMFserv constructs the tree is provided in Appendix C as supported information. When building the ABM, it suffices to understand that the execution of a behavior activates selected leaf node items in the tree, and the values of these items will be used to calculate the utility of the behavior.

**Function 3: agent perception and object affordance**

The perception function in PMFserv defines how an agent perceives the objects and other agents surrounded in the virtual world and thus searches the environment for a potential action to take that affords the agent in terms of needs satisfaction. In the modeling environment, all the agents can share the perceptual types ruled by platform users. When certain objects’ status reaches the satisfactory condition of corresponding perception types, related actions become “visible” to the agent so that agent is able to
decide the “best” action to execute. In this research, the rules that govern the perceptual types are the focus of the occupant behavior model, as the application of PMFserv to the built environment area. Customized rules are described in the next chapter as case study examples to elaborate the specific implementation of this module.

Other optional functions

Besides the major functions above, PMFserv provides sociology module that is able to model socially-aware agents and groups. For example, this module characterizes relationships between different agents in the environment and how they influence each other’s emotions and decisions. However, since the case study scope is limited to single-occupied offices, this function is not applicable to the occupant behavior model at the current stage. But for a more comprehensive model for the entire building, for instance, classrooms and meeting rooms, the model could still be applied and expanded to a more complex level.

Decision Making Algorithm Based on the Model

The developed model executes the simulation process on a time-step basis (no particular time restrictions). At each time step, the model outputs the most dominant behavior that the agent gives priority to. The decision-making algorithm works as follows:

In general, agent behaviors are determined by two aspects. On one hand, the agents in this framework are cognitively deep and equipped with values (represented by the GSP tree). On the other hand, the surrounding environment (represented by P-types and object) provides the context, which makes physical perceptions available for consideration. Thus, the agent makes decisions based on a minimum of two sets of factors, (i.e. Decision Utility as a function of) namely,
• Values: the factors that an agent employs to evaluate the decision.
• Contexts: the factors that are associated with decision choices.

The values guide decision choices, and in this case, have been arranged hierarchically or as a network. The contexts sway the agent decisions by providing additional and context specific utility to the decisions evaluated. The contexts are broken up into micro-contexts. Each micro-context just deals with one dimension of the contexts (for example, relationship between the perceiver and target and so on). With a given set of values, an agent (or person) evaluates the perceived state of the environment and the choices it offers under a number of micro-contexts, and appraises which of its importance weighted values are satisfied or violated. This, in turn activates emotional arousals, which finally are summed up as utility for behavior decisions. At each step, the decision of the highest utility calculated is considered as the behavior that will be taken by the agent (occupant) (Bharathy & Silverman, 2013).

Figure 3-3. Decision making process of agent

The ABM platform adopts a decision making process which combines agent’s cognition (represented by Values) and perception of the environment (represented by Contexts) (Figure 3-3). Values and Contexts are instantiated by agent’s cognition and perception, respectively. In the simulation process, the latter part dominates the output via updating input environmental variables at each time step. Specifically, thermal,
visual, and air quality perceptions are associated with indoor (and indirectly, outdoor when the window is open) temperature and relative humidity, illumination, and indoor concentration of CO₂, respectively. Meanwhile, the status of the building component at this step is also automatically updated given the agent’s interactions.

Data Collection and Validation Study of the ABM

Since ABM is a simulation-based modeling approach, verification and validation is a necessary step to enhance the reliability and robustness of the model. For this reason, it is significant to collect data in the aspects including indoor/outdoor environmental parameters, occupant behavior record, and actual building energy use. The information could be used by feeding real-world ambient conditions data into the ABM and compare the output to the actual behavior data. By conducting this process, the performance of the ABM can be assessed and the settings and rules of the ABM can be tuned accordingly. Moreover, actual data could be used to examine the building energy model output differences among scenarios such as default settings, simulated behaviors based settings, and actual behaviors based settings. Finally, it is possible to explore if the proposed method reduces the gap between modeled and measured energy use. It is also arguable that unlike data-driven modeling approaches, the data collection coverage in terms of volumes could be smaller for ABM, as the model is not developed on the basis of data.

Data Collection

Sensor devices, methods, and parameters for indoor environment monitoring

The data collection for this research includes two parts, namely environmental data sensing and occupant behavior data record (actual energy use data is not collected at this stage). The first part was measured by a customized embedded sensor
node. The sensor node consists of a smart single-board microcontroller computer with built-in Wi-Fi function, three separate sensors that record indoor temperature (°C), relative humidity (%), illumination (lux), and concentration of CO₂ (ppm) respectively, and some peripherals. The specifications of the sensors used are listed in Table 3-2. A programming script (Appendix D) is written and uploaded to the sensor board to configure the assembling device and log the environmental data along with time stamp information. The time stamp of data collection is set to 5 minutes, which could be modified as needed. All the data are stored in a Micro-SD card that is plugged into the smart sensor board. One of the advantages of the customized sensor node is its flexibility, which allows more sensors to be added to the sensor node if necessary, such as a particulate matter (e.g., PM2.5, PM10) sensor. In addition, online data transmission is available through Bluetooth or Internet thanks to the built-in communication functions. In this case, the data file is uploaded to a cloud drive every two hours via Wi-Fi connection for data extraction. Figure 3-4 shows a sample of the customized sensor node.

Figure 3-4. Customized smart sensor node
Table 3-2. Specifications of environmental sensors

<table>
<thead>
<tr>
<th>Sensing parameter</th>
<th>Model</th>
<th>Voltage</th>
<th>Range</th>
<th>Accuracy</th>
<th>Maximum sampling rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>DHT22</td>
<td>3 to 5 V</td>
<td>-40 to 80°C</td>
<td>±0.5°C</td>
<td>0.5 Hz (every 2 seconds)</td>
</tr>
<tr>
<td>Humidity</td>
<td>DHT22</td>
<td>Same as above</td>
<td>0 -100%</td>
<td>2-5%</td>
<td>Same as above</td>
</tr>
<tr>
<td>Carbon Dioxide</td>
<td>K-30</td>
<td>5.5-14 V</td>
<td>±30 ppm ±3 % of measured value</td>
<td>0-10,000 ppm</td>
<td>0.5 Hz</td>
</tr>
<tr>
<td>Illumination</td>
<td>TSL2591</td>
<td>3.3-5 V</td>
<td>0 - 88,000 Lux</td>
<td>188 uLux</td>
<td>400 kbit/s (Data rates)</td>
</tr>
</tbody>
</table>

Paper-based survey for recording occupant behavior

For behavioral data, a customized survey sheet with behavior options and corresponding time intervals on a daily basis was developed. The survey was submitted to and approved by the University’s Institutional Review Board (IRB) prior to conducting actual survey to collect data (Appendix E). To balance the data precision and to avoid disturbing occupants, the time interval was set to 15 minutes from 8:00 AM to 5:00 PM every day, and additional time intervals can be manually added according to actual schedule. The survey sheet is attached as Appendix F. The monitored occupants were asked to initialize the starting status of the targeted building components every day, and then manually make a check mark at the correct box when he/she conducts a behavior at a certain time, during a long duration stay in the office (more than 15 minutes).

Meanwhile, in one of the test rooms, a commercially available sensor system consisting of a hub and two magnetic sensors was installed on the door and window, to log their status with Ethernet connection. Although implemented, this sensor system was used only for the sole purpose of validating the survey sheet over a period of two days.

Outdoor environmental data

Since the ABM requires outdoor ambient temperature and relative humidity as model inputs as well, these data were acquired from a local weather report website.
(Weather Underground). The website provides historical weather data collected by different weather stations that are spread in the locations of interest. For this study, a weather station located in the University of Florida campus was used for data extraction. The temperature and relative humidity data with time information are available for selected date at the time interval of one hour for 24 hours. The data used for validation study are then extracted according to the survey time period for matching purpose.

**Data collection scale**

The coverage of data collection area and duration is determined based on the case study building, which will be described in detail in Chapter 4. For the purpose of this study, the scope of the data collection area is limited to one level of the building, with a corridor of offices located on the west side of the building. Five office rooms were selected as data collection sample spaces. The time period for relevant data collection is from two to four weeks in the season of spring. To improve the reliability of the validation result for the ABM, the data collection scale needs to be expanded with respect to both space and time period. However, the current setup is considered to be sufficient to evaluate the general performance of the model, and is also able to draw preliminary conclusions based on the observed results.

**Performance Test of the ABM**

**Explanation of data use**

Since the purpose of the ABM is to explore how occupants interact with building components under certain environmental conditions, collected ambient data are the input values for the ABM. Unlike data-driven modeling methodologies, instead of training a model based on environmental data and behavioral data, the occupant behavior model is developed from the agent's perspective. In other words, the model
will output the behavioral decisions based on the internal algorithm and user-defined rules with certain input, with some auxiliary parameters which are fixed values during the simulation process. The behavioral data is not involved for model development purpose, but only used for calibration and validation for the ABM. Hence, the use of the collected data can be summarized in two steps: First, as input parameters for the ABM, environmental data serves as virtual environment indicator that represents the same condition the occupant locates in the real world; second, after the ABM outputs the agent’s decision at each time step, the simulated results are logged to compare with the actual measured occupant behavior data within the same time period.

Another difference of the ABM from data-driven approach is the requirement on the accuracy of the environmental data. For data-driven methods, a higher accuracy of the measured value for each environmental variable is preferred as the data is the foundation of the model. However, some uncertainty is allowed for the input data of the ABM, since there will be little influence to the overall model performance by the uncertainty of the measured data, for the reason that occupants in buildings are not physically sensitive enough to the ambient environment that varies for a certain amount. For example, a range of temperature fluctuation will generate the same thermal comfort level for the occupant, so that the behavioral decision made by the occupant will stay unchanged.

In Figure 3-5, the dataflow for model testing and validation is shown. It should be noted that in this research, the validation study is performed at the first stage: behavioral validation. The second stage denote to energy use validation, which compares the output from building energy model to measured energy use with similar
means. This stage is out of the scope of the dissertation and will be discussed as future recommendations in Chapter 5.

Figure 3-5. Flow path of validation study

**Validation method**

The occupant behavior model is developed based on a simulation platform that uses a robust ABM. Although a few researchers used ABM for occupant behavior (Azar & Menassa, 2012; Kashif et al., 2013; Lee & Malkawi, 2014), none of these validated their models using data collected on-site. To prove the applicability of these models, testing and validating these models using actual data collected on-site is crucial. In other words, it is necessary to evaluate the performance of the simulation results of the ABM against actual behavior records. For this purpose, this research adopts a black-box validation method, i.e., the validation focuses on the final results as compared to white-box validation method that focuses on the internal mechanism and structure. The
reasons for using a black-box validation approach are two-fold: first, Bharathy & Silverman (2010) conducted white-box validation of the human behavior modeling platform - PMFserv. Besides, several documentation discussing the technical details of PMFserv is available and the modeling platform is widely applied to social sciences research, among others. Therefore, for the purposes of this research, it was deemed unnecessary to challenge the internal algorithms of how an occupant make decisions based on their characteristics and surrounding environment. Second, since the goal of this research is to enhance building energy modeling function by adding another crucial dimension to the current model, a black-box validation is sufficient to demonstrate its validity. Specifically, the research aims to incorporate a module providing occupant behavior information to a building energy model, therefore, the validation can only focus on whether the output of occupant behavior model reflects the reality, so that adding the module to a building energy model is reasonable to provide a potential improvement.

Based on the data type and property, four evaluation metrics are used to compare simulated and actual behavioral data for validation purpose, namely recall, precision, accuracy, and F1 score. The value span for the four metrics are from 0 to 1. The definitions of these metrics are easily interpreted using research data used in this study. It is assumed that the status of “open” for all targeted building components are positive samples, and “close” are negative samples. Thus, each simulation outcome of a building component is classified as: a True Positive sample (TP), a False Positive sample (FP), a True Negative sample (TN), or a False Negative sample (FN). Take window operation as an example, TP indicates the number of time steps when the ABM predicts the window is open while actually it is open at that time, and FN is the number
when ABM predicts window as close while it is open. Similarly, TN indicates the number of time steps when the ABM predicts the window is close while it is actually closed, and FP means when ABM predicts window as open while it is closed in reality. Based on this classification, detailed indication and formula for the evaluation metrics are as follows:

1. Recall (equivalent to “True Positive Rate”). It measures the proportion of positives that are correctly identified as such, regardless of how many spurious identifications were made. Recall is calculated as:

   \[
   \text{Recall} = \frac{TP}{TP + FN}
   \]  

2. Precision. It measures the proportion of correctly identified positives among all the predicted positives, regardless of whether it failed to retrieve correct items. Precision is calculated as:

   \[
   \text{Precision} = \frac{TP}{TP + FP}
   \]  

3. Accuracy. It measures the proportion of correctly identified results among the total number of samples. In other words, it indicates how well a binary classification test correctly identifies or excludes a condition. This is the most straightforward metric on the performance of simulation results. Accuracy is calculated as:

   \[
   \text{Accuracy} = \frac{(TP + TN)}{(TP + FP + FN + TN)}
   \]  

4. F1 score. It is referred as the harmonic average of the precision and recall, which balanced out the tradeoff between precision and recall. F1 score reaches its best value at 1 and worst at 0. F1 score is calculated as:

   \[
   \text{F1 score} = \frac{2TP}{2TP + FP + FN}
   \]  

To conduct the comparison for ABM testing, first, personal and environmental characteristics of real occupants are fed to the agent and surrounding environment variables in the ABM. These may include same behavior options, comfortable ranges, daily occupancy, local environment conditions, etc. Then, the ABM is executed under the same conditions as the actual world, to obtain the simulated behavior results. The process repeats at each time step to generate a list of targeted building components.
status. Meanwhile, the actual behavior data through the field survey is overlaid on the simulated results from the ABM for the same time period. Essentially, a direct mapping of simulated and actual data is obtained for analysis. Finally, for each behavior, the four standard metrics are calculated to measure the simulation performance of the ABM. This process could also be used to calibrate the ABM from the specific validation results. The case study results for the validation study are referred in Chapter 4.

Integration of Occupant Behavior Model with EnergyPlus™

Co-simulation Method Development

The development of the occupant behavior model aims to add another critical dimension to building energy simulation program and has the potential to improve its overall simulation performance. The goal of this research step is to integrate occupant behavior model and building energy simulation model in order to dynamically exchange information between the two simulators and to reflect a more realistic virtual environment for building energy estimation.

It is a broadly accepted fact that occupants in office buildings may adjust building components or devices such as windows, lighting switch, doors, and heaters to improve their working environment in a certain form to satisfy their perceptual comfort requirements. Thus, the building simulation engine should be able to capture these behavior changes to better estimate energy use. EnergyPlus™ is selected as the simulation engine due to its wide applicability and the capabilities of representing common behavior changes in its internal settings.

The concept of co-simulation meets the research goals above. The implementation of such a co-simulation framework not only enables an additional module for building energy simulation, but also accounts for influence brought by
building occupants (Langevin, Wen, & Gurian, 2016). The integration process works as follows. At the starting point of the co-simulation, the building energy model (created in EnergyPlus™) initializes all the necessary parameters and runs simulation on a time-step basis. At each time step, EnergyPlus™ calculates the zone-level environmental conditions and outputs these as well as occupancy information to the occupant behavior model (ABM created by PMFserv); with the updated information, the agent in the ABM will perceive the level of comfort and make a decision on what action to take that can satisfy his/her most urgent comfort needs. The decision outcome generated in the zone is then transmit back to EnergyPlus™ as the new input, where corresponding schedule settings are adjusted to reflect the particular behavior change (or stay still), for the calculation of next time step. This procedure repeats as the two simulators exchange data at each time step in a loop, until the ends of the simulation period. The entire process runs automatically through a bridging program, namely BCVTB, with the time step defined by users based on specific simulation scenarios. BCVTB is a software environment that allows users to couple different simulation programs for co-simulation, which is developed by Laurence Berkeley National Laboratory (Lawrence Berkeley National Laboratory, 2016). This software is developed based on Ptolemy II, particularly for simulation coupling with EnergyPlus™. Figure 3-6 depicts the inputs and outputs exchange mechanism in a general view.

As shown in the data exchange diagram, at the EnergyPlus™ interface port, typical behavioral adaptions must be represented in field settings. It should be noted that there are more than one parameters in the engine to reflect the common office behaviors. However, in this dissertation, the following parameters are selected to
represent the modeled behavior as listed in Table 3-3, each with a field for schedule update for the status of open/close or on/off.

Figure 3-6. Co-simulation method development

Table 3-3. Corresponding settings in EnergyPlus™ for modeling behaviors

<table>
<thead>
<tr>
<th>Objects</th>
<th>Status</th>
<th>Settings in EnergyPlus™</th>
</tr>
</thead>
<tbody>
<tr>
<td>Window</td>
<td>Open/Close</td>
<td>ZoneInfiltration: EffectiveLeakageArea</td>
</tr>
<tr>
<td>Door</td>
<td>Open/Close</td>
<td>ZoneRefrigerationDoorMixing</td>
</tr>
<tr>
<td>Blinds</td>
<td>On/Off</td>
<td>WindowProperty:ShadingControl</td>
</tr>
</tbody>
</table>

At the ABM interface port, the occupant behavior model takes seven input variables from EnergyPlus™, including temperature (both indoor/outdoor), relative humidity (both indoor/outdoor), CO₂ concentration, illumination, and occupancy at zone level and output the building components status under the current condition.

Finally, BCVTB connects the two simulation engines by establishing direct links to both ends. When executing the co-simulation function, BCVTB allows arguments for both ends, which increases the flexibility of the framework. Different models could be
loaded to the two simulation ends to enable co-simulation without developing a whole new structure in the bridging program. In Chapter 4, the case study describes the specific data exchange schema under this co-simulation setting.

**Simulation Scenarios Design**

With the function of co-simulation framework implemented, EnergyPlus™ is able to exchange information with the occupant behavior model at each time step, so that a dynamic behavioral schedule will be used for energy calculation. Ideally, with the additional module that accounts for occupant influences on building energy use, the simulated result by EnergyPlus™ will be closer to the measured energy use for the target building. However, there exists the possibility that the estimation deviate more than default settings. The reasons could be from various aspects, for example, there is another part that EnergyPlus™ does not consider or oversimplifies, or the internal algorithms of EnergyPlus™ needs modifications, while these are not the focus of this research. However, it is meaningful to compare the simulation results with different settings, to investigate the impact brought by occupant behaviors to building performance, so that extensive analysis can be conducted to improve simulation accuracy and design energy management solutions in reality.

To explore this idea, three scenarios are developed for building energy simulation, namely default setting (Scenario #1), actual behavior setting (Scenario #2), and co-simulation with ABM setting (Scenario #3) (Figure 3-7). For default setting, all the behavior-related parameters stay unchanged during the appropriate simulation period; for actual behavior setting, the original operation schedules of target building components are replaced with survey data when running simulation; for co-simulation with ABM, apparently the occupant behavior model will be executing simulation coupling
simultaneously with EnergyPlus™. One important setting is that the simulation period should be complying with the survey data collection time period. Besides, the result comparison will be mainly conducted at the room/zone level where the targeted occupants in the experiment locate, although the final results will be slightly different at the whole building level. Moreover, the simulation results of the scenarios above can be compared with actual building energy use in the future research, on a monthly basis or based on the availability of measured data. By analyzing the simulation results at both ends of the two simulators (ABM and BEM), we will gain more insight about how occupants will react under different environmental conditions and how they cause energy use variation with different behavioral patterns.

Figure 3-7. Simulation scenarios for building performance analysis
CHAPTER 4
CASE STUDY AND RESULTS

Development of ABM based on Actual Building

The ABM platform (PMFserv) provides generic functional modeling modules and relevant calculation algorithms for decision-making process. However, to develop an occupant behavior model specifically for built environment context, it requires the identification of necessary components to model, and the modeling rules design, etc. In addition, there is no definitive or general model for occupant behaviors in a building. The development of occupant behavior model must depend on the characteristics of target building (or rooms) and its occupants. For example, the schedule and activities of different types of rooms can be different due to their own functionalities; occupants may or may not have control access to certain building systems. In this research, an educational building is selected as the case study test bed. As a result, the development, testing, and application of the occupant behavior model are all based on the actual conditions of the building, which are introduced in this chapter.

Descriptions of Case Study Building

The case study building is an existing educational building situated in Gainesville, Florida, USA. This building has three stories with approximately 47,270 ft\(^2\) of total gross floor area, which is comprised of offices, classrooms, laboratories, and some student facilities. The designed occupancy for the building allows 38 full-time occupants such as faculties and staffs, and a maximum of 450 total occupants including students, visitors, etc. The building was built in 2003, and received a LEED Gold certification with diverse advanced technology building systems. Figure 4-1 shows the appearance of the building.
The building is supported with steel and the envelope is covered by composite wall panels of aluminum which enclose exterior insulation and finish systems. The exterior glazing (including windows, skylights, and external doors) adopts dual low-emissivity vertical glazing technology for an improved natural lights utilization.

The building has a central HVAC system that contains two air-handling units (AHU) to serve 54 thermal zones from separate variable air volume (VAV) boxes. AHU is used to mix outdoor air and returned indoor air and cool or heat the mixed air with chilled or hot water. VAV boxes then determine the volume of conditioned air according to different zone size and room temperature, and finally distributed the air via fans and ducts. A thermal zone usually covers several individual rooms residing to each other.

In this study, the research targets are focused on the third floor of the testbed building. More specifically, all the rooms on this level are office areas, with a corridor of 16 single-occupancy rooms that are used as university faculty’s offices. These offices are oriented to the west through their windows. Most of the rooms have a size of 139 or 141 square feet, and are served for full-time occupants. These occupants can control windows, doors, and window blinds in their private office, but do not have access to...
HVAC adjustment at room level. In addition, the lighting system is automatically turned on in each office if occupied through occupancy sensor and actuator, and can be turned off manually if preferred. A few occupants have personal devices such as heaters or desk lamps that are used for room condition control.

**Occupant Behavior Model Units**

Based on the modeling architecture within the ABM platform and the actual conditions of the testbed building, an occupant behavior model is developed to reflect how people working in the offices interact with building components. The development of the model follows the main modules of PMFserv, and is implemented in details with five parts.

First, the module of agent must be specified. In this case, the department faculty are the targeted occupants. A prototype of “Professor” is created in the library, which has native properties such as emotion, physiology, and stress level. The initial values of these properties are given in default numbers and could be modified to represent different types of occupants in terms of their internal status, probably due to personal properties such as age or gender. In this case, “Physiology” level is set to full tank, and the “Stress” level is set to 50 percent in the model, as an average state of the modeled agent. This setting is based on the assumption that the simulation process always starts from the beginning of each day.

Second, the module of objects that agent can directly perceive and interact with are identified, which can be modeled in hierarchy with multiple items in one object. As discussed in previous chapter, it is assumed that ambient environment is the major driver that affects individual’s comfort level and hence his/her behavior decisions. Therefore, “Built Environment” is created with its attached parameters in this module.
Basically, this object comprises of what the agent perceives, i.e., ambient conditions and what the agent interact with, i.e., building components and their status. Ambient conditions include environmental parameters such as indoor/outdoor temperature, relative humidity, level of CO\(_2\), illumination, etc. Building component status encompasses the open/close state of window, door, and window blinds, which will be associated with behavior decisions later. Other supporting parameters such as occupancy (room occupied status), comfortable ranges of environmental parameters are also created for ABM rules definition. A sample screen shot of object “Built Environment” is shown in Figure 4-2. The values of all the parameters are initialized in the model, among which occupancy, building component status and six environmental factors mentioned above are served as model inputs during simulation process, and the rest are fixed numbers. These fixed numbered parameters are also used as arguments for the rules definition, and the values of human comfort level are referred from (Engineering ToolBox, 2001), i.e. maximum comfort level of CO\(_2\) (Line 2 of Figure 4-2) is approximately 1000 ppm for most of the people. Table 4-1 listed the standard comfortable range of different environmental parameters used in the model.

### Table 4-1. Standard comfortable range of environmental parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Unit</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature (High)</td>
<td>Celsius Degree (°C)</td>
<td>26</td>
</tr>
<tr>
<td>Temperature (Low)</td>
<td>Celsius Degree (°C)</td>
<td>18</td>
</tr>
<tr>
<td>Relative Humidity (High)</td>
<td>Percentage (%)</td>
<td>60</td>
</tr>
<tr>
<td>Relative Humidity (Low)</td>
<td>Percentage (%)</td>
<td>25</td>
</tr>
<tr>
<td>Carbon Dioxide Concentration</td>
<td>Parts per million (ppm)</td>
<td>1000</td>
</tr>
<tr>
<td>Illumination (High)</td>
<td>Lux (lx)</td>
<td>600</td>
</tr>
<tr>
<td>Illumination (Low)</td>
<td>Lux (lx)</td>
<td>50</td>
</tr>
</tbody>
</table>

The third step is to define the module of “Goals, Standards, and Preferences” (GSP) Trees. As mentioned in Chapter 3, this module determines the mental awareness
and cognition of the agent. To elaborate, it describes the short-term and long-term goals and value systems of the agent. For example, safety, economic, and health concerns are some of the typical items in the tree structure. All the items are following a hierarchical architecture and are given a weight value to reflect the significance of that item. These items are selected to be activated when a behavior is conducted in the simulation process, so that the values of the related items will be used for “Utility” calculation for decision-making at next time step. In this model, a default structure of GSP Trees of generic human's mindset, as well as the weight values for each tree item, are used in the model after consulting with the platform developers, and the details could be referred to Appendix G.

![Table](image)  
**Figure 4-2.** Screenshot of “Built_Environment” object in PMFserv
Next module is the critical component of the ABM, namely Perceptual Types. This module indicates the agent’s perception towards the surrounding objects, and in this case, the office space. Previous studies (Yang & Wang, 2013) have shown that in the context of built environment, there are three primary types of physical perceptions, namely thermal, visual, and indoor air quality comfort. Therefore, different situations including a perception type and the state of related building components are created in this module. For example, the perceptual type of “FreshAirNeeded_Window_Close” refers to the scenario wherein the window is closed and the CO₂ level exceeds a fraction of the comfort level in the current step. Meanwhile, these perceptual types are bounded by self-defined perception rules that are programmed with parameters in object “Built Environment” as input arguments. Appendix H shows the code that define the custom perception rules for all seven perceptual types. Once the current situation (building component states and environmental factors) satisfies the threshold of certain rules, corresponding perceptual types are activated so that the agent will have the possibility to conduct relevant behaviors. Therefore, each perceptual type is correlated to at least one behavior, which is the last piece of the modeling units.

The final part of the model is the “Actions” module, which indicates the behavior options of agent. After a short interview and observation of the targeted rooms, the most common interactions between occupants and building components lie in operation of window, door, and window blinds. Therefore, to build a model that is close to the reality, the ABM incorporates six behavior options which consists of open and close for each building component. Moreover, as stated before, some occupants may have access to other miscellaneous devices for environment control. However, to represent a generic
behavior model for faculty members, and considering the number of such occupant only accounts for a small proportion of all the faculty members, behaviors related to these devices are excluded from the model. With the behavior options being modeled, each behavior causes a result and returns the outcome to update values in “Built Environment” object. Besides, a connection between each behavior and corresponding perceptual types is established, and how the behavior influences the items in GSP Trees must be defined. These are referred as affordances of the behavior. The significance of this property is to map environmental factors (model inputs) to behavior options (model outputs), while the decision-making algorithms calculate the Utility for each behavior during the simulation process of the ABM.

Discussion of the Model

In PMFserv, the occupant behavior model is saved as a library that comprises of the five major modules above. To execute the model, one more step is required, that is to create a simulation scenario in the platform based on the library. The first two modules, namely agents and objects, can be considered as class which is analogous to the concept in Object-oriented Programming (OOP). These two classes must be instantiated in the simulation scenario for modeling execution. Therefore, one or more instances could be added to the scenario, which increase the flexibility of the model. One of the benefits of this setting is that the model (library) can be extended to multi-occupancy rooms. Moreover, it allows combination of various agents and objects with only one library development. For example, if the ABM is expanded to the whole building scale, different occupants such as student, staff and building manager can be created; objects including time, room properties can also be added to the library. Hence,
the versatility of the model is improved, which can be applied to any actual sample rooms at building level.

For ABM execution, at the start of the simulation, all the values in the “Built Environment” object are initialized. Then, the model runs to output the behavior which the agent gives priority based on the Utility. If no perception is triggered, the agent will stay without making any physical status change to window, door, and window blind, i.e., with no output at this time step. If there is an output of behavior to a building component, the status of this component will be updated automatically in the corresponding parameter of the “Built Environment” object. Following this procedure, at the beginning of each time step, the values of environmental parameters are updated with measured data, and the model repeats the calculation process above until the simulation ends. A list of behavior outcomes can be exported in a Microsoft Excel™ file, which can be translated into any format that is used for simulation integration or validation study. Finally, a causal relationship between input data, perception types, and behavior options is depicted in Figure 4-3.

Figure 4-3. Causal relation between environmental parameters, perception types, and behavior options
Model Testing and Validation Study

With the virtual occupant behavior model being developed, a validation study is conducted to test the performance of the ABM, in order to extend the use of the model for application in the next step. The general idea of the testing step is to investigate how these targeted occupants will react to the changing environment in the offices, and compare the actual behavior data with simulation outcomes from the ABM under the same built environment. The setup of the testing approach is for the purpose of integrating the ABM with building energy simulation engine.

Data Collection Scope and Preprocessing

As mentioned in Chapter 3, the corridor of faculty offices that are oriented to the west on the third floor of the case study building are used as sample rooms. To avoid skewness of the sampling data, five faculty offices were further selected with occupants in different genders and age ranges. Five sets of smart sensor boards and survey sheets were distributed to the rooms, with overlapped data collection time period. Figure 4-4 shows the third floor plan of the test bed building and selected rooms for data collection.

Each survey sheet is used to record behavior data for one day. The targeted occupants were given multiple survey sheets and were requested to complete the survey sheet voluntarily, preferably on consecutive days. Embedded sensor board were placed near the occupants of this experiment, and were never powered off during the data collection period.

The data was collected in the spring season when the day/night temperature and humidity variations are obvious. The data collection process lasted for two to four weeks depending on the availability of occupants. Considering the average duration which the
occupants stayed in the offices, there are approximately 25 to 35 time steps of behavior records per person each day. For environmental data, the raw data file is in the format of CSV, with each line consisting of all variable values. A sample of the data is shown in Appendix I.

Figure 4-4. Selected sample rooms for validation study

Before the final use of the raw behavioral data from the survey, a preprocessing is conducted to translate the building component status of door, window, and blinds into numerical values of 0 or 1. Here, it is defined that the status of “close” of any component corresponds to “0” while “open” corresponds to “1”. Therefore, at each time interval (15 minutes in the survey sheet) when the occupant was in the office, a vector is generated indicating the current status of door, window, and blinds. For example, \([1, 0, 1]\) means at that interval, door is opened, window is closed and blinds is opened. This preprocessing step is completed for each occupant for all the days selected for validation purpose later. Also, at each time step, the inputs of the ABM were extracted from the sensor data, and with time information in the datasets, the environmental data
at the same time interval with survey results were used to generate the simulated output in order to have a one-to-one mapping for validation metric calculation.

**Results and Analysis of Individuals’ Behavior**

The occupants in the experiment are referred by index of A to E as five samples for results presentation. The actual behavioral data from surveys were compared with the ABM outputs, and plotted for analysis. Although the developed occupant behavior model aims to capture a generic behavior of faculty members, the behavioral differences between these individuals cannot be ignored. In this sub-section, two out of the five sample occupants who show an obvious discrepancy in behavior patterns are selected for results explanation.

For occupant A, the simulation result and actual record of behavior for window blinds operation of a random day are shown in Figure 4-5, as well as the sole influencing environmental factor fluctuation - indoor illumination. The results indicate that the initial status of blinds is open at the beginning of the day for the occupant, and during the most portion of the day, the lighting intensity is either satisfied with the occupant’s visual comfort level, or slightly lower than that. Therefore, the occupant kept the blinds open for the most time of the day. Towards the end of the day when the occupant resided in the office, the illumination level increased significantly, due to the outside sunlight from the west in the afternoon. The illumination level exceeded the normal comfortable range intensely, therefore, the occupant chose to close the blinds to block the direct exposure to the sunlight. It could be seen from the actual status, that the blinds closing behavior was slightly later than the maximum value state of illumination, while the simulation results assumed the behavior happened immediately in this situation. This delaying phenomenon is an interesting finding, and is observed and
studied by other researchers. There are many reasons that may cause this condition, however, the general trend of the simulation result is considered to agree with the actual record. Last, but not the least, it should be noted that there is a small period in the day that the occupant was out of the office. The gap in the simulation result reflected this vacancy since no environmental inputs were used for those particular time steps.

Figure 4-5. Simulation results and survey record for window blinds operation for occupant A in a selected day, with illumination level showing underneath

In Figure 4-6, the simulation result and actual record of behavior for door operation of a random day are shown. Unlike window blinds operation, there are three influencing environmental factors for door operation, namely indoor temperature, humidity, and CO$_2$ concentration. Figure 4-6 shows the temperature and CO$_2$ fluctuation only, as the relative humidity variation is relatively stable (with value of around 32%) and has a very similar trend with temperature change. The results indicate that the initial status of doors is closed at the beginning of the day for the occupant, and during the
daytime, the occupant opened and closed the door alternatively. However, door operation behavior may be related to many other non-environmental factors, for example, if the occupant needed to go to a class or meeting, or some visitors came to the office. For the simulation settings, it is difficult to capture these stochastic events. In the ABM, the door operation behavior is only influenced by indoor environment. However, the ABM considers the “goals” of agent, while one of the goals is privacy and security. This factor was modeled in the ABM and eventually affected the door simulation result. Therefore, it can be claimed that the ABM is more reliable if the occupant is in the room and no sudden events happen. Finally, in terms of comparison, simulated result agrees with actual record 70% of the time (Table 4-2), which is sufficient to make the ABM applicable for future use.

Figure 4-6. Simulation results and survey record for door operation for occupant A in a selected day, with indoor temperature and CO$_2$ concentration showing underneath
The window opening behavior is influenced by additional environmental variables, including outdoor temperature and relative humidity. For example, if it is cold and humid (i.e. rainy) in the daytime, even if the indoor environment is uncomfortable in some aspects, the occupant may not choose to open the window. In addition, if the CO$_2$ level is higher than the comfortable level, people may feel uncomfortable and would normally open the window for fresh air. However, in comparison with door operation behavior, window operation behavior is influenced more by the environmental factors. In fact, in the test building, window is the only building component for the occupant to adapt to the thermal conditions, with the HVAC control not accessible in the room.

Figure 4-7 shows the window operation behavior for occupant A in another typical day. It could be referred from the figure that CO$_2$ level is the major driver of the window opening behavior for this occupant. For thermal conditions, with the central HVAC, indoor temperature and humidity maintain on a stable level, while the outdoor environment has a rather significant change during the day. But since the outdoor temperature is low, the simulation model assumed that occupant will close the window for thermal comfort over air quality comfort for most of the time.

In contrast to occupant A, the simulated behavior patterns of occupant B differ more significantly from actual records. Figure 4-8 shows the window blinds operation results of a random day for occupant B. As the bottom of the figure shown, the overall lighting intensity in the room is much lower than the recommended light level (250 lux) for office work environment (Engineering ToolBox, 2001). However, according to the survey record, occupant B did not operate on the window blinds for the entire day.
Figure 4-7. Simulation results and survey record for window operation for occupant A in another selected day, with indoor/outdoor temperature and humidity, as well as CO₂ concentration showing underneath.

The reason could be due to a personal preference range difference of light intensity, or because of the occupant was using other sources of lighting for visual comfort adjustment, i.e. a desk lamp (with the sensor uncovered in the lamp area). On the other aspect, because of the initial illumination level is low, the occupant behavior model predict an open behavior for the blinds. An interesting phenomena is that around 2:00 pm in the day, although the light level dropped instantly to a very low level, the model did not output another open behavior. This is because at this time step, the model output another behavior, such as operation on door or window over blinds, according to
the Utility calculation results, which indicates that there are multiple uncomfortable perceptions felt by the agent at that time period.

For behavior to door, simulation results of occupant B can capture a similar trend as actual record (Figure 4-9), while miss some behaviors at certain time steps. The reason for this observation is given in the explanation of door behavior for occupant A. Nevertheless, the differences are that occupant B left the door open at most of the time, probably due to his personal habit. The door closing behavior periods are comparatively short, which caused some missing records for the simulation model. From the raw survey sheets, it is found that the missing data records are infrequent and sporadic and hence hardly affect the overall simulation results.
The actual record of window operation behavior for occupant B shows that the occupant never opens the window no matter how the ambient conditions change during the day (Figure 4-10). According to the in-situ observation and interview with the occupant, window operation is not a normal behavior for him, unless some extreme situations. However, since the ABM only focuses on the environmental impact on behavior decisions of occupant, the simulated results are fluctuated, mainly based on the level of CO$_2$ in this case. One of the reasons is that both the indoor and outdoor thermal conditions are within the comfortable range for most time of the day, which is a typical day in the spring season at the building located area.
Figure 4-10. Simulation results and survey record for window operation for occupant B in a selected day, with indoor/outdoor temperature and humidity, as well as CO₂ concentration showing underneath.

**Results and Analysis of Overall Performance**

Due to the complexity of occupant behaviors, the behavior pattern of each occupant may be independently different. There are even variations for the same occupant in different days according to the survey results. Therefore, the virtual model does not aim to track exactly how people in the built environment will react to certain ambient conditions. On the contrary, the model is considered to be applicable if the overall performance reaches an acceptable level, in terms of the evaluation parameters discussed in Chapter 3. In Table 4-2, a summary of the model performance is presented. It should be noted that the overall results are not simply the average of all five occupants, since the sample occupants generate various amounts of time steps.
due to schedule differences. Instead, the results are obtained by aggregating the data of all the occupants as a whole datasheet and then calculating the numbers for each building component. This measure reflects the general performance of the ABM, as the model aims to represent a generic “faculty” behavior pattern.

Table 4-2. Performance summary of the ABM for the sample occupants

<table>
<thead>
<tr>
<th>Occupant</th>
<th>Building system</th>
<th>Recall</th>
<th>Precision</th>
<th>F1 Score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Blinds</td>
<td>0.98</td>
<td>1.00</td>
<td>0.99</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>Door</td>
<td>0.88</td>
<td>0.53</td>
<td>0.66</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>Window</td>
<td>0.78</td>
<td>0.83</td>
<td>0.80</td>
<td>0.80</td>
</tr>
<tr>
<td>B</td>
<td>Blinds</td>
<td>N/A</td>
<td>0.00</td>
<td>0.00</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>Door</td>
<td>0.93</td>
<td>0.81</td>
<td>0.87</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>Window</td>
<td>N/A</td>
<td>0.00</td>
<td>0.00</td>
<td>0.67</td>
</tr>
<tr>
<td>C</td>
<td>Blinds</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Door</td>
<td>0.89</td>
<td>0.38</td>
<td>0.53</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>Window</td>
<td>N/A</td>
<td>0.00</td>
<td>0.00</td>
<td>0.73</td>
</tr>
<tr>
<td>D</td>
<td>Blinds</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Door</td>
<td>0.98</td>
<td>0.84</td>
<td>0.90</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>Window</td>
<td>N/A</td>
<td>0.00</td>
<td>0.00</td>
<td>0.84</td>
</tr>
<tr>
<td>E</td>
<td>Blinds</td>
<td>0.50</td>
<td>1.00</td>
<td>0.67</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>Door</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>Window</td>
<td>N/A</td>
<td>0.00</td>
<td>0.00</td>
<td>0.79</td>
</tr>
<tr>
<td>Overall</td>
<td>Blinds</td>
<td>0.82</td>
<td>0.84</td>
<td>0.83</td>
<td>0.74</td>
</tr>
<tr>
<td></td>
<td>Door</td>
<td>0.96</td>
<td>0.79</td>
<td>0.87</td>
<td>0.81</td>
</tr>
<tr>
<td></td>
<td>Window</td>
<td>0.78</td>
<td>0.35</td>
<td>0.49</td>
<td>0.77</td>
</tr>
</tbody>
</table>

From the table above, it can be seen that for each individual, the model simulation performance differs in behaviors on the three building components. For example, for occupant A, blinds operation has the highest accuracy, mostly because of the fact that the behavior is highly related to environment and not influenced by other external elements. However, door operation has a relatively low accuracy, while the reasons were partially explained before. Moreover, door is the most frequently operated building component that can even be open and closed repeatedly during a 15-minute time interval. This decreases the probability of door to be accurately tracked in an ABM model. For recall, or true positive rate, all the three components obtain satisfactory
values. In other words, in terms of opening behavior, the ABM can predict fairly well for this occupant. However, the ABM falsely predict the occupant’s behavior on opening the door while in reality it is closed for a portion of time steps. It is inferred that either the occupant has a wider comfortable range, or there are other factors that influence the behavior even though the indoor environment is out of the comfort level.

Taking occupant B as another example, the simulation results deviate more from the survey records. Although the door operation behavior has an acceptable performance, both window and blinds are obtaining a lower accuracy. In the meantime, the recall is not applicable, and precision value is 0 for this occupant. The reason which caused the phenomena above is that this occupant reported that he never opens the window and blinds while in the office. Therefore, as it is assumed that “opening” behavior is defined as positive outcome, there is no actually positive samples for this occupant. As a result, true positive and false negative numbers are both 0, which makes the value of precision 0 and the calculation of recall not applicable. Similarly, the value of “N/A” and “0” appear in other occupants’ results as well, and they are all attributed to the same reason.

In the summary statistics, referred as “overall”, behaviors on all the three building systems achieve a relatively high accuracy (approximately 80%). From the perspective of black-box validation, it is considered that the ABM can be applied for further use, i.e. simulation coupling. However, there are still concealed facts to be noticed. Specifically, for blinds use, most of the occupants kept the component open for better vision from natural lighting. This increases the positive sample numbers that leads to higher recall and precision; for door use, although all the parameters show a satisfactory value, the
ABM performs much differently between individuals, with some of the reasons mentioned above; for window use, since most occupants did not open their windows, the positive outcomes are largely coming from occupant A. In short, the fact that the sample data of time steps for each individual are slightly different needs to be taken into consideration when applying the model for other research purposes.

To present the model testing results from a more comprehensive view, Figure 4-11 illustrates the measured behavior percentages of each occupant during their self-reported time period. Different behavior patterns can be observed clearly from the figure. Notice that window opening status is not common for the five occupants, and blinds operation is also a rare behavior. A clue to this phenomenon may be because of the data collection season, which is spring with occasional rain during daytimes. Also these occupants have rather distinguished visual comfort needs. Specifically for occupant C, a personal heater is presented in the office so that window is not the first option for indoor environment adjustment.

Figure 4-11. Percentage of five occupants on their actual interactions with building components during the survey period
Figure 4-12 shows the modeled behavior percentages as a comparison to Figure 4-11. Although the base model is applied to all occupants, the simulated behavior patterns still present an apparent difference, owning to different inputs (ambient conditions) for the five offices. In addition, the simulated results show a similar proportion of behaviors to the measured results, demonstrating a good performance of the occupant behavior model, for all five occupants in the experiment. However, the simulated results have a rather symmetrical distribution in behavior outputs, especially for the window opening behavior. The blinds operation behavior is also slightly over-estimated by the model, but the error rate is much lower. One explanation is that the ABM places thermal comfort and air quality comfort over visual comfort, which prioritizes the behavior options related to the first two perceptions.

![Figure 4-12. Percentage of five occupants on the simulated interactions with building components during the survey period](image)

**Summary and Discussion**

The testing results of the occupant behavior model demonstrate the performance of the ABM, and thus makes it feasible for simulation coupling application. Before
applying the model for further use, some conclusions can be drawn from the model test study.

To begin with, although the ABM achieved substantial results of comparison metrics (especially in terms of the overall circumstances), it is not yet a full validated model. Hence, it is claimed that the model has been tested and verified from the current sample data, whereas additional validation work is needed to improve the robustness of the model, both from the result corresponding and model architecture perspectives. Specifically, more sample data with respect to the data collection time period, occupants’ numbers and varieties, etc. as well as different validation methodologies are required for a full validation of the model.

The testing results of individual’s behavior selected two representative samples (occupant A and B) to evaluate the model performance. Obviously, people have distinct characteristics, such as perceptual comfortable range, which contribute to different behavior decisions under certain external conditions. This is also reflected in Table 4-2, where the ABM performs well for some occupants but achieves lower accuracy for others. Ideally, each individual should have an independent model, but it is not practical to create a model separately for each person. Nevertheless, from the other aspect, the model may perform better if tuned according to target population’s perception properties, through the methods of survey or quantification analysis, as the comfortable ranges of the current model are extracted from a general source.

The testing and verification process was conducted under the time periods when the occupants are present in their offices. In other words, the ABM is executed under the assumption that the room is occupied by the owner. Therefore, the parameter
“occupancy” is added in the “Built Environment” object to reflect the occupancy status in the modeling space. Currently, the perception rules are set that the agent can perceive the environment only when occupancy value is non-zero. When coupling with building energy simulation engine, the occupancy information is available from the default occupancy schedules and could be output for use in the ABM. More details will be explained in the simulation experiment section.

The survey records and interview for the occupants in this experiment also show some interesting facts about how occupant interact with building components in office. For example, some occupants have a rather stable pattern of behaviors in terms of the operation on the three building components, regardless of the variation of ambient environment. As mentioned above, the possible reasons are 1) they are always satisfied with the ambient environment (which means wider comfortable threshold); 2) other options exist such as desk lamp (for visual comfort), personal heater (for thermal comfort) which influence the use of the modeled building components indirectly. However, the major reason is that environment is not the only driver of occupant behaviors. Both external and internal factors (e.g. privacy) will affect the behaviors of occupant, even if the environment is the dominant element. More research should be conducted to discover the causality of driving factors and behavior decisions at both individual and group levels.

Finally, it is claimed that the validation work is not limited to demonstrating the accuracy of the ABM, but also to propose a possible method to associate a virtual occupant behavior model with the reality. It is argued that the validation approaches should comply with the future usage of the model. For example, in this research, the
ABM aims to integrate with a building energy modeling engine (EnergyPlus™) for improving simulation functions. Therefore, a stepwise testing was conducted since EnergyPlus™ is also executing on a time-step basis. In the next section, the simulation coupling framework is tested, along with the simulation results of the scenarios based on default schedules and survey-based schedules.

**Simulation Experiments**

Since one of the most significant aims of this research is to add the “human” dimension to the current building energy simulation programs, and improve simulation performance eventually, the last portion for the research is to investigate the integration capability of the occupant behavior model and existing building simulation engines. With the validation study of the ABM, the simulation experiments are conducted with the same test bed building and targeted occupants for results presentation. The building energy model (BEM) is created using EnergyPlus™. Compare to the other popular tools for building energy modeling, this program is considered to have broad applicability in industry and academia, and a variety of parameters settings in the model, which can reflect typical behavior changes within the program.

**Default and Survey-based Settings of Building Energy Model**

The virtual model of the test bed building is built with EnergyPlus™ routines. Basic settings are identical to the actual conditions of the building, and the simulation period is set to about four weeks in accordance with survey period. Particularly, instead of using a weather file from the official website of EnergyPlus™ that provides historical statistic weather information, the weather data used in the simulation experiments is acquired from (White Box Technologies), where the information contains the realistic weather information for the designated time duration. In this study, the data covers
duration of a full year that consists of two consecutive calendar years (from 2017.5 to 2018.4). The running time step is set in correspondence with the paper-based survey, namely 15 minutes (4 time steps per hour).

Besides the default settings, another scenario which is based on the survey results is created for simulation study. To elaborate, the raw results collected from the survey sheets from five experiment occupants are translated into the schedule format that is usable by EnergyPlus™. For each occupant, there are three separate schedule documents created for the targeted building components. In order to eliminate the warning message from EnergyPlus™ due to input schedule requirement that schedules must cover a full year, each single document is expanded to 8760 hours. However, the dates when actual survey results are available are the focus of the study, which will be taken for simulation results comparison later in the section. Following this manner, for each occupant, a separate IDF (EnergyPlus™ input file format) file is created with the building component operation schedules being filled with survey data.

After importing the schedule files in the IDF file, corresponding parameters information are updated to reflect behavior variations. In Chapter 3, the key variables in EnergyPlus™ is listed in Table 3-3, and in this case study, specific values for each field of the variable is shown in Figure 4-13 to 4-15, with a sample of one occupant showing only. For window opening behavior, new object is created in “ZoneInfiltration: EffectiveLeakageArea” with the field values (Figure 4-13); for door opening behavior, new object is created in “ZoneRefrigerationDoorMixing” with the field values (Figure 4-14); for blinds opening behavior, new object is created in “WindowProperty:ShadingControl” with the field values (Figure 4-15), and this object is
applied in the field of “Shading Control Name” in “FenestrationSurface:Detailed” at the corresponding room location.

<table>
<thead>
<tr>
<th>Field</th>
<th>Units</th>
<th>Obj1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name</td>
<td>Occupant_A_window</td>
<td></td>
</tr>
<tr>
<td>Zone Name</td>
<td>03ThirdFloor:03\AVX\53</td>
<td></td>
</tr>
<tr>
<td>Schedule Name</td>
<td>A_window_actual</td>
<td></td>
</tr>
<tr>
<td>Effective Air Leakage Area</td>
<td>cm²</td>
<td>5570</td>
</tr>
<tr>
<td>Stack Coefficient</td>
<td></td>
<td>0.000435</td>
</tr>
<tr>
<td>Wind Coefficient</td>
<td></td>
<td>0.000271</td>
</tr>
</tbody>
</table>

Figure 4-13. Window operation variable settings for one occupant

<table>
<thead>
<tr>
<th>Field</th>
<th>Units</th>
<th>Obj1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name</td>
<td>Occupant_A_door</td>
<td></td>
</tr>
<tr>
<td>Zone 1 Name</td>
<td>03ThirdFloor:03\AVX\53</td>
<td></td>
</tr>
<tr>
<td>Zone 2 Name</td>
<td>03ThirdFloor:03\AVX\49</td>
<td></td>
</tr>
<tr>
<td>Schedule Name</td>
<td>A_door_actual</td>
<td></td>
</tr>
<tr>
<td>Door Height</td>
<td>m</td>
<td>2</td>
</tr>
<tr>
<td>Door Area</td>
<td>m²</td>
<td>1.95</td>
</tr>
<tr>
<td>Door Protection Type</td>
<td>None</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4-14. Door operation variable settings for one occupant

<table>
<thead>
<tr>
<th>Field</th>
<th>Units</th>
<th>Obj1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name</td>
<td>Occupant_A_blinds</td>
<td></td>
</tr>
<tr>
<td>Shading Type</td>
<td>InteriorBlind</td>
<td></td>
</tr>
<tr>
<td>Construction with Shading Name</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shading Control Type</td>
<td>UntilScheduleAllows</td>
<td></td>
</tr>
<tr>
<td>Schedule Name</td>
<td>A_blinds_actual</td>
<td></td>
</tr>
<tr>
<td>Setpoint</td>
<td>W/m², W or deg C</td>
<td></td>
</tr>
<tr>
<td>Shading Control Is Scheduled</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Glare Control Is Active</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Shading Device Material Name</td>
<td>Blinds_faculty</td>
<td></td>
</tr>
<tr>
<td>Type of Slat Angle Control for Blinds</td>
<td>FixedSlatAngle</td>
<td></td>
</tr>
<tr>
<td>Slat Angle Schedule Name</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Setpoint 2</td>
<td>W/m² or deg C</td>
<td></td>
</tr>
</tbody>
</table>

Figure 4-15. Window blinds operation variable settings for one occupant

The schedule update process is carried out for all occupants to represent more comprehensive and detailed models for the test bed building. Since the influencing areas are limited to five rooms/zones only, the simulation results difference is not expected to be significant on the whole building scale. However, the focus will be placed on the targeted zones to explore and compare the energy use difference as well as other related factors to the thermal zones.
Co-simulation Data Exchange Schema

With the concept of co-simulation introduced in the previous chapter, this section describes the implementation steps of the proposed simulation integration method.

First, the variables to be exchanged between two simulation tools are identified. For the ABM (PMFserv), seven input variables are needed that are output from EnergyPlus™ at each simulation time step, namely indoor temperature, indoor humidity, outdoor temperature, outdoor humidity, indoor CO₂ level, indoor illumination, and occupancy. For EnergyPlus™, three variables including status (open/close) of window, door, and blinds are updated at each time step from ABM.

Second, EnergyPlus™ configuration is done. According to the manual of BCVTB (Wetter, 2016), to activate the external interface of EnergyPlus™ and enter schedules to which the external interface writes, particular objects must be created and initiated with name and values. Details of this configuration is shown in Appendix J. Similar to the simulation scenario in survey-based case, these schedules coming from the external interface are used in the same parameter objects that are related to corresponding building components. In addition, output variables that are exported from EnergyPlus™ to ABM are declared in the object of "Output: Variable".

Third, an XML file is created that maps the data to be exchanged between EnergyPlus™ and PMFserv, and specifies the order of the input/output signal vector. In Appendix K, a sample code is shown for the XML file that describes the data exchange mechanism for one occupant. Then, a graphical model (Ptolemy II) must be created in the BCVTB graphical interface to establish a logical connection for the two simulators. Some auxiliary modules are also created and connected for input/output format.
manipulation and real-time results showing during the simulation process, as shown in Appendix K also.

Finally, PMFserv must be configured to be called by BCVTB. With this being said, an exe application is developed based on the prototype model and simulation scenario created in the graphical interface of PMFserv. To comply with the input/output format with EnergyPlus™, the application is configured to receive the environment and occupancy data from EnergyPlus™, and feed the values to corresponding parameters in “Built_Environment” object of PMFserv (Figure 4-2). After the internal calculation for decision utility of each behavior option, the application will update the status of the three building components according to the behavior decision at each time step and output a vector consisting of the current status that returns to EnergyPlus™ for simulation in the next time step.

After all the configurations are completed, BCVTB can start the co-simulation process as the manager. The simulation results are assessed from the EnergyPlus™ outputs, and are discussed in the following sub-section.

**Application and Results**

The simulation experiments not only aims to test the integration function of the ABM and EnergyPlus™, but also to seek the impact of involving detailed occupant behaviors in building energy model. Three simulation scenarios are studied in the experiment, with the implementation approaches introduced above. In short, the scenarios are referred as default, survey-based, and ABM-based for results comparison:

- Default: no occupant-building interaction schedule is involved.
• Survey-based: survey results for all occupants are applied to the operation schedules on window, door, and blinds at their situated zones.

• ABM-based: co-simulation running with EnergyPlus™ exchanging information with occupant behavior model at each time step.

In particular, there are five IDF files for survey-based and ABM-based scenarios, with each file representing the behavior update for one occupant. The simulation period is set from the end of February to end of March in 2018 (28 days). Results are presented in the following.

Energy use and cooling/heating demand differences

Occupant behaviors influence building performance in various aspects. The involvement of behavior information directly causes variation on the building side such as energy use and building system loads. Although the analysis focuses on the zone level, differences at the building level for some factors can be observed.

Figure 4-16 shows the site energy use (EUI) comparison for the simulation period, among five occupants’ behavior input, respectively. It can be seen that with the occupant behavior information involved, even individual’s behaviors cause whole building energy use variation, in different magnitude and direction. It is noticeable that simulation period is restricted to approximately a month, therefore the absolute discrepancy for an annual energy consumption can be larger. Moreover, even though the adjustment of window, door, and blinds are not direct energy-consuming behaviors, their impact to total energy use are still considerable according to the simulation results. Specifically, for survey-based scenario, all the occupants caused a slight increase for the total energy use, except for occupant A; for ABM-based scenario, the energy use shows a descending trend. Intuitively, the decreased energy use results can be partially explained by the window opening behavior, as natural ventilation would lower the
overall energy use with the mitigated use of mechanically conditioned air. However, it is also possible that the outdoor air will increase the HVAC load for maintaining at the set point, which may compensate the ventilation effect. Hence, more case studies should be conducted to explore the causality of the energy use and specific occupant behaviors. In addition, the descending trend of ABM-based scenario indicates that more energy saving could be achieved if proper energy-efficient occupant behavior is encouraged, without compromising the occupant comfort level.

Figure 4-16. Energy use intensity comparison at building level

Besides the total energy use variation, the end use distribution also changed in terms of fuels. In Table 4-3, the end uses differences at building level among three simulation scenarios are shown. In this table, it can be seen that the ABM-based scenario shows a larger use of electricity comparing to the other two scenarios. Similar to the explanation above, as the major contributor of electricity use is the HVAC fans, and the opening of windows and doors potentially affects the infiltration rate/load, so that increase occurs in the electricity use. Meanwhile, district cooling and heating uses decreased in certain amount for ABM-base scenario, probably due to the window
operations that have the aid of outside air for a natural temperature adjustment, and the blinds closing behavior that block the external heat. On the contrary, survey-based scenario generally deviate less for the three end uses, except for occupant A, who recorded more window and blinds operation behaviors than others.

Table 4-3. End uses of case study building

<table>
<thead>
<tr>
<th>End Uses</th>
<th>Occupant</th>
<th>Default</th>
<th>Survey-based</th>
<th>ABM-based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity (kWh)</td>
<td>A</td>
<td>30956</td>
<td>31628</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>30431</td>
<td>31624</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>30430</td>
<td>31556</td>
<td></td>
</tr>
<tr>
<td>District Cooling</td>
<td>D</td>
<td>30435</td>
<td>31618</td>
<td></td>
</tr>
<tr>
<td>(kWh)</td>
<td>E</td>
<td>30430</td>
<td>31562</td>
<td></td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>23353</td>
<td>22350</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>23440</td>
<td>22334</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>23447</td>
<td>22356</td>
<td></td>
</tr>
<tr>
<td>District Heating</td>
<td>D</td>
<td>23447</td>
<td>22334</td>
<td></td>
</tr>
<tr>
<td>(kWh)</td>
<td>E</td>
<td>23447</td>
<td>22335</td>
<td></td>
</tr>
<tr>
<td></td>
<td>A</td>
<td>19029</td>
<td>19653</td>
<td></td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>21015</td>
<td>19782</td>
<td></td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>21026</td>
<td>19605</td>
<td></td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>21027</td>
<td>19809</td>
<td></td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>21033</td>
<td>19783</td>
<td></td>
</tr>
</tbody>
</table>

Apart from the comparison at building level, selected parameters at zone level also show discrepancies. Table 4-4 presents the results of zone level energy-related parameters. Among these, zone air system sensible heating and cooling energy report the heating or cooling delivered by the HVAC system to a zone. This does not always indicate the operation of heating or cooling coils, as outside air can also be supplied for cooling or heating even if the coils are off (EnergyPlus Documentation, 2015). Results show that survey-based scenario generate similar trend for cooling energy while different on the heating energy. This is because most of the time the outside air is warmer during the simulation period that can contribute to zone heating. For total internal latent gain energy, although slight deviation is observed, the percentage of
difference is subtle in this case. This can be explained by the fact that the behavior adaptation is not directly consuming energy use and therefore will not influence the internal gain from people and building equipment in a significant amount.

Table 4-4. Zone level energy-related data

<table>
<thead>
<tr>
<th>End Uses</th>
<th>Occupant</th>
<th>Default</th>
<th>Survey-based</th>
<th>ABM-based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone Air System</td>
<td>A</td>
<td>24.46</td>
<td>294.00</td>
<td>136.28</td>
</tr>
<tr>
<td>Sensible Heating</td>
<td>B</td>
<td>12.10</td>
<td>12.02</td>
<td>109.86</td>
</tr>
<tr>
<td>Energy (kWh)</td>
<td>C</td>
<td>12.10</td>
<td>14.85</td>
<td>149.44</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>10.98</td>
<td>13.38</td>
<td>111.63</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>10.98</td>
<td>13.32</td>
<td>147.94</td>
</tr>
<tr>
<td>Zone Air System</td>
<td>A</td>
<td>601.48</td>
<td>521.61</td>
<td>519.86</td>
</tr>
<tr>
<td>Sensible Cooling</td>
<td>B</td>
<td>352.06</td>
<td>353.99</td>
<td>326.32</td>
</tr>
<tr>
<td>Energy (kWh)</td>
<td>C</td>
<td>352.06</td>
<td>355.25</td>
<td>324.83</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>349.98</td>
<td>354.76</td>
<td>332.39</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>349.98</td>
<td>357.34</td>
<td>327.3</td>
</tr>
<tr>
<td>Zone Total</td>
<td>A</td>
<td>91.98</td>
<td>84.51</td>
<td>85.39</td>
</tr>
<tr>
<td>Internal Latent</td>
<td>B</td>
<td>40.51</td>
<td>40.52</td>
<td>38.93</td>
</tr>
<tr>
<td>Gain Energy (kWh)</td>
<td>C</td>
<td>40.51</td>
<td>40.86</td>
<td>39.75</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>36.02</td>
<td>36.37</td>
<td>35.27</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>36.02</td>
<td>36.41</td>
<td>35.95</td>
</tr>
</tbody>
</table>

Figure 4-17 is the user design load per area based on zone sensible heating for the HVAC system. The results illustrates that with the behavior information imported, the calculated design load generally raises, while only the survey-based scenario for occupant A shows different outcome. Because design load is based on heat balance for each zone, the behavior on doors apparently influenced the calculated results. According to the survey records, occupant A shows a more frequent door use in the survey period, which complies with the results.

Table 4-5 lists some heat gain factors information for the targeted spaces. Due to the seasonal effect, both survey and ABM-based scenarios shows ascending trend for HVAC sensible air heating, and descending trend for air cooling. Unexpected results appear in the window heat addition and infiltration heat addition rows. For window heat
addition, the occasionally closed window blinds could be a cause for blocking the heat energy from the sun outside. For infiltration heat gain, survey-based scenario is showing a slight decrease for occupant C, D and E. The possibilities may include no opening window records for the occupants, and infiltration through zones kept stable and balanced under the same HVAC set point. However, despite how the values of these factors change, it is clear that the heat gain factors will eventually influence the working conditions of the entire facility, thus leads to building energy use and built environment variation under different behavior patterns.

Figure 4-17. HVAC sizing: design load per area

Table 4-5. Building sensible heat gain factors

<table>
<thead>
<tr>
<th>Heat Gain</th>
<th>Scenario</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>HVAC Terminal</td>
<td>Default</td>
<td>0.088</td>
<td>0.044</td>
<td>0.044</td>
<td>0.040</td>
<td>0.040</td>
</tr>
<tr>
<td>Unit Sensible Air</td>
<td>Survey</td>
<td>1.058</td>
<td>0.043</td>
<td>0.053</td>
<td>0.048</td>
<td>0.048</td>
</tr>
<tr>
<td>Heating [GJ]</td>
<td>ABM</td>
<td>0.492</td>
<td>0.395</td>
<td>0.316</td>
<td>0.402</td>
<td>0.531</td>
</tr>
<tr>
<td>HVAC Terminal</td>
<td>Default</td>
<td>-2.165</td>
<td>-1.267</td>
<td>-1.267</td>
<td>-1.260</td>
<td>-1.260</td>
</tr>
<tr>
<td>Unit Sensible Air</td>
<td>Survey</td>
<td>-1.878</td>
<td>-1.274</td>
<td>-1.279</td>
<td>-1.277</td>
<td>-1.286</td>
</tr>
<tr>
<td>Cooling [GJ]</td>
<td>ABM</td>
<td>-1.870</td>
<td>-1.175</td>
<td>-1.206</td>
<td>-1.197</td>
<td>-1.180</td>
</tr>
<tr>
<td>Window Heat Addition [GJ]</td>
<td>Default</td>
<td>0.511</td>
<td>0.533</td>
<td>0.533</td>
<td>0.538</td>
<td>0.538</td>
</tr>
<tr>
<td></td>
<td>Survey</td>
<td>0.377</td>
<td>0.533</td>
<td>0.436</td>
<td>0.441</td>
<td>0.441</td>
</tr>
<tr>
<td></td>
<td>ABM</td>
<td>0.418</td>
<td>0.481</td>
<td>0.488</td>
<td>0.483</td>
<td>0.488</td>
</tr>
<tr>
<td>Infiltration Heat</td>
<td>Default</td>
<td>0.090</td>
<td>0.059</td>
<td>0.059</td>
<td>0.058</td>
<td>0.058</td>
</tr>
<tr>
<td>Addition [GJ]</td>
<td>Survey</td>
<td>0.249</td>
<td>0.059</td>
<td>0.057</td>
<td>0.056</td>
<td>0.056</td>
</tr>
<tr>
<td></td>
<td>ABM</td>
<td>0.305</td>
<td>0.312</td>
<td>0.171</td>
<td>0.326</td>
<td>0.241</td>
</tr>
</tbody>
</table>
Occupant comfort level differences

The interactions between occupants and building components also have an impact on the building occupant side. In Table 4-6, a detailed occupant-related factor is presented at zone level. From the table, it could be inferred that window opening behavior dominates the people sensible heat addition in the case study building. For survey-based scenario, the values remain almost the same for all occupants except occupant A, who recorded more frequent window opening behavior as stated before. Furthermore, although the value differences seem subtle, the unit for the factor namely gigajoule still indicates a considerable volume of heat addition. But from the perspective of human, whether such amount of heat addition will arouse thermal perception reflections needs to be studied in the future research.

Table 4-6. People sensible heat addition

<table>
<thead>
<tr>
<th>People Sensible Heat Addition [GJ]</th>
<th>Default</th>
<th>Survey-based</th>
<th>ABM-based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupant A</td>
<td>0.995</td>
<td>1.022</td>
<td>1.019</td>
</tr>
<tr>
<td>Occupant B</td>
<td>0.496</td>
<td>0.496</td>
<td>0.499</td>
</tr>
<tr>
<td>Occupant C</td>
<td>0.496</td>
<td>0.494</td>
<td>0.493</td>
</tr>
<tr>
<td>Occupant D</td>
<td>0.459</td>
<td>0.458</td>
<td>0.462</td>
</tr>
<tr>
<td>Occupant E</td>
<td>0.459</td>
<td>0.458</td>
<td>0.461</td>
</tr>
</tbody>
</table>

Another way to understand occupant comfort level is to examine the Predicted Mean Vote Index (PMV) values within designated time period. PMV stands among one of the most recognized thermal comfort models that was developed by P.O. Fanger (Fanger, 1972). Fanger’s equations are used to calculate the mean response of a large group of people for a combination of thermal and metabolic conditions, according to the ASHRAE thermal sensation scale, which is a seven-point scale from -3 (cold) to +3 (hot). With the value of “0” being the neutral sense or the most ideal value, ASHRAE defined a recommended limits for PMV from -0.5 to +0.5 as the comfortable range. In
EnergyPlus™, the PMV information is available to extract after declaring the output variable in the engine, at the user-defined time stamps. In this study, hourly PMV values are declared for the targeted thermal zones of the building and aggregated for the simulation period. Table 4-7 summarizes the average PMV values for each experiment zone where the occupant is situated respectively, for the three simulation scenarios.

Table 4-7. PMV statistics for experiment occupants

<table>
<thead>
<tr>
<th>Average PMV values</th>
<th>Default</th>
<th>Survey-based</th>
<th>ABM-based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupant A</td>
<td>-0.879</td>
<td>-0.954</td>
<td>-1.086</td>
</tr>
<tr>
<td>Occupant B</td>
<td>-0.983</td>
<td>-0.982</td>
<td>-1.182</td>
</tr>
<tr>
<td>Occupant C</td>
<td>-0.983</td>
<td>-0.979</td>
<td>-1.135</td>
</tr>
<tr>
<td>Occupant D</td>
<td>-1.013</td>
<td>-1.009</td>
<td>-1.194</td>
</tr>
<tr>
<td>Occupant E</td>
<td>-1.013</td>
<td>-1.008</td>
<td>-1.179</td>
</tr>
</tbody>
</table>

From the table, all the PMV values are below zero, and are out of the comfortable range defined by ASHRAE. This complies with the reality that most permanent occupants on the third floor of the case study building stated a cold indoor environment in general. However, from the survey-based results, nearly all the PMV values were slightly closer to the neutral value, which indicates occupant behaviors tend to adapt to a more comfortable environment. The only exception is occupant A, who obtained a higher absolute value representing “cold” with the actual behavior inputs. One of the reasons can be that this occupant’s behavior is not only driven by thermal comfort, while air quality comfort is possibly the dominant stimuli. Besides, non-environmental factors can also lead to occupant behaviors on the building components. Similarly, for all ABM-based scenarios, the PMV values are moving away from the ideal value. This is mainly because the ABM considers three perceptual types of the agent, while not limited to the traditional models that only focused on thermal sensation. This also demonstrates and calls for the necessity to involve different perceptions using ABM
for occupant behavior modeling in order to have a thorough representation and understanding of how occupants interact with building. Aside from the analysis on the ABM side, other aspects can also be responsible for the results above, for example:

- The parameters settings and calculation algorithms for the criteria in EnergyPlus™ does not fully reflect the actual impact of targeted behaviors;
- Environment setpoint is out of the range of actual occupant preference, comfortable level based on ASHRAE does not conform to the actual needs of the case study building occupants;
- The environmental data simulated by EnergyPlus™ should also be considered as a factor, and must be fully validated for a more improved building performance simulation.

However, although the summary information do not completely meet the anticipated results, it implies other meaningful information. First, the hypothesis are demonstrated that occupants and indoor built environment of the space are mutually influenced. Additionally, the co-simulation functioning was able to accounting for the dynamic behavioral adaptations with the fluctuation of environmental inputs in the space.

To provide a more comprehensive view of PMV, Figure 4-18 to 4-20 display the PMV trends for one of the occupants (occupant A) during the simulation period (672 hours). In fact, for the rest of occupants, the default and survey-based graphs show a parallel fluctuation with only magnitude differences. While for occupant A, although the general trend is similar, obvious discrepancy can be observed from certain time intervals. For example, the extreme value for default scenario almost reach the number of -3.5, while survey-based scenario tend to have a rather moderate value. The reason that dragged down the average of PMV in the survey-based scenario is because the positive numbers have a generally descending tendency. However, a lower positive
number indicates a more comfortable “warm” environment, which is the pursuing goal of built environment. Therefore, it is claimed that the increase of average absolute value of PMV does not necessarily mean a worse built environment. According to the variation calculation for occupant A, the default and survey-based scenario achieve the value of 0.763 and 0.642, respectively. This reveals a more stable indoor environment in terms of thermal conditions.

As for the ABM-based scenario, the variation is more significant comparing to the other two cases. The result is partly due to the explanation before. However, it also implies the room for improvement in the future for the occupant behavior model. Further research needs to be conducted to ascertain the results and analysis of PMV trends in a meaningful way, based on the preliminary study.

![Figure 4-18. PMV fluctuation for occupant A in default simulation scenario](image-url)
Summary

The simulation experiment in the section accomplished two research goals. First, it implemented the simulation coupling idea by enabling a co-simulation framework with EnergyPlus™ and PMFserv. In other words, the applicability of the novel occupant behavior model is demonstrated. Second, through the comparison study for different simulation scenarios, mutual influences of building and occupants are quantified and
analyzed. The presented results can help building designers and engineers optimize building’s mechanical or electrical systems, resulting in energy savings and more comfortable indoor environment.

Future studies may include simulation running period extension, i.e., a whole calendar year, and probe the seasonal differences among different behavior scenarios. Sensitivity studies can be performed to delve the relations between pertinent environment factors, occupant behavior options, and building energy use. The parameters in EnergyPlus™ that reflect behavioral changes should be revised by researchers and tool developers to completely capture the actual impact of the behaviors.

At this stage, the simulation experiment focuses on the functioning improvement rather than estimation accuracy for building energy simulation. Therefore, the experiment approaches are not limited to the studied spaces, while can be expanded to multiple zones or other buildings. The simulation results also suggest a lower energy use with occupant behavior information inputs for ABM scenario, which promotes feasible energy conservation solutions through human-in-the-loop building operation. The capability of accounting for the human side to building performance in a dynamic manner will benefit all the stakeholders of a building for informed decision-making.
CHAPTER 5
DISCUSSION AND CONCLUSIONS

Summary and Conclusions

Occupant behaviors are identified as one of the most influential factors of building energy use. A deeper understanding of the way occupants interact with building components not only can optimize system design and energy use during the life cycle of the building, but also improve occupants’ indoor comfort level. In the design phase of a building, a solid occupant behavior model that provides information to the building energy model can improve the simulation performance and potentially reduce the gap between simulated and actual energy use; in the operation phase, occupant behavior model can be used for building systems and equipment schedule control for better services. As an innovative study, this research proposed a framework that combines the development, testing, and application stages of an occupant behavior model, for the purpose of gaining insights of how building and its occupants influence each other. A case study that implemented the framework to a realistic commercial building was conducted to illustrate the validity and feasibility of the research.

First of all, an agent-based model was developed in the context of built environment that virtually predicts building occupant’s behavior. This model was built under the assumption that occupant may adapt to the surrounding environment through accessible building component for physical comfort adjustment. Three types of physical comfort (perceptions in the ABM) were considered including thermal, visual, and air quality comfort. Pertinent built environment parameters such as temperature, relative humidity, illumination, and CO$_2$ level were used as model inputs. Customized rules were defined to regulate the decision-making process of the modeling agent at each
simulation time step. Moreover, behavior options were provided according to the case study building while could be modified based on specific conditions if necessary. With a certain group of input numbers updated at each time step, the model outputs one behavior that is the first priority for comfort enhancement.

Subsequently, the occupant behavior model was tested with a black-box validation method, using the data collected by smart sensor nodes and paper-based survey sheets. In the test bed building, five single-occupied offices were selected to distribute the data collection combination. Real-time environment data were logged by sensors for each office and used as input of the occupant behavior model, and the simulation results were then compared to the survey records which represent the actual behaviors. The comparison results on both individual and group levels indicate an acceptable fit on a time-step basis, which verified the theoretical foundation of the model and showed the validity of using the model for further studies such as integrating with building energy models.

Finally, a simulation experiment was conducted to seek the mutual impact of the test bed building and its occupants. In addition, the experiment also served as an application trial of the occupant behavior model. This experiment adopted EnergyPlus™ – a powerful building performance simulation engine to create a model for the test bed building, with all the routines involved. Three simulation scenarios were then designed including the default setting, survey-based setting, and ABM-based setting to execute the experiment. For survey-based setting, behavior records from the survey sheets were applied as behavioral inputs for the scenario; for ABM-based setting, a co-simulation framework was established that exchanges data from the occupant behavior
model and building simulation model at each time step. The simulation results were analyzed in the aspects of energy use, occupant comfortable level, and behavior change patterns, which quantify the influence to building performance brought by occupant behaviors.

In summary, this research developed a novel occupant behavior model that was demonstrated to be practical for providing another crucial dimension to the existing building simulation models. Through these research initiatives, a new knowledge system has been supplemented to the domain, and the simulation accuracy and comprehensiveness of building energy models are generally improved. This research can be considered as a contribution to building energy efficiency from a life cycle perspective.

Limitations of the Research

Although this research accomplished the proposed aims in a holistic way, limitations still exist that should be addressed in the future.

Development Barriers of Occupant Behavior Model

The most significant barrier of this research is that the occupant behavior model was developed with the emphasis on ambient environment. In other words, it was assumed that environment is the only stimulant for occupant behaviors, which is considered as a valid idea by other researchers. However, it has been demonstrated that many other factors also affect people’s decision of their behaviors. For example, external factors such as occupant routine, usual time, and room size or locations etc., internal factors such as personal background (e.g. comfort range, age, gender), psychological state, privacy etc. are all contributing to people’s behaviors. Apparently, the completeness of the model can be advanced by incorporating more relevant factors.
as the behavior drivers. Nevertheless, from the perspective of engineering study, it may be unnecessary or redundant to consider every aspect that may influence human behaviors, since this research does not intend to capture what exactly an occupant will do, but focuses more on providing additional dimension for building energy modeling. In addition, as stated by Tabak & de Vries (2010), it is impossible to completely model occupant behavior, as individuals are too complex and random. With this being said, the model suffers another limitation that concerns with the randomness of people.

To elaborate, the model only investigated the deterministic relations between the behaviors and drivers. Stochastic influences should be studied and engaged in the future model, as people in reality will not act exactly like the programmable agent in most of the cases. Moreover, some subtle behaviors that are not directly energy-related were excluded from the model. These behaviors may lead to different heat gains to the indoor environment, which should not be intentionally ignored. However, these are out of the scope of the research and could be studied in the future as a follow-up to this research.

**Case Study Scale Limitations**

The case study is an instantiating process of the proposed research framework. It is natural to place limitations to this research. To begin with, the test bed building is a commercial building, more particularly, an educational building. Offices were the sample rooms for both validation and simulation studies. The model is not tested in a different types of building, such as residential buildings or more complex functional buildings. In fact, occupant behaviors varies significantly in different buildings due to the accessibility of building components and factors they concern about. Despite the fact that this
research is defined in the scope of office buildings, the generality of the model is limited under the current conditions.

Furthermore, the data collection period is two to four weeks in the season of spring, while did not cover different climate in a full year. This in turn limited the simulation experiment running period. However, people may have different preferences and habits during different seasons, thus leads to different behaviors under similar built environment. Meanwhile, only five occupants were selected as research samples, which can be expanded to a larger scale for a more convincing demonstration. Additionally, the offices are all single-occupied rooms, which means no interactions between multiple occupants were considered. This, however, has been studied by other researchers as separate research and can be modeled in the modeling platform in the future.

Last, but not the least, the paper-based survey may cause unexpected error in the data collection stage. Especially as the time interval was set to 15 minutes for the survey sheet, it is possible that the occupants conduct multiple behaviors during this time interval. This problem could be solved by installing smart sensors on the experiment objects, so that the status can be logged accurately with any time granularity as needed.

**Co-simulation Function**

At the current research stage, the co-simulation function was implemented with the assistance of BCVTB. However, due to the technical constraint, the data exchange schema was defined at the zone level. Since the ABM is a prototype class, multiple instances can be created based on the model. Therefore, a hierarchical structure is needed for a larger scale of simulation that enables a simultaneous running at multi-zone level.
Recommendations for Future Study

This research systematically established a framework from developing and testing an occupant behavior model in the area of built environment, to the application of the model. The simulation experiment is a pilot study that lays the foundation to future studies. It can be concluded that the framework could be used by different stakeholders including building designers, building owners, and building management staff to evaluate behavioral changing patterns or plan energy use policies based on potential building users. Ultimately, the presented framework is aiming to help promote functions and accuracy of building simulation programs, design behavior interventions, and develop energy management solutions, etc. However, further studies are required to realize the future goals. Some of the possible future research directions are suggested as follows.

The ABM is developed on a rule based platform, which is a simulation approach of modeling occupant behaviors. As stated in Chapter 2, there is another category of approaches that are based on behavior-related historical data. It is worthwhile to compare those typical data-driven methods to the ABM in terms of prediction results accuracy. Since one of the advantages of data-driven approaches is that it is not necessary to explore the causality of human and his/her behaviors, one can also combine these approaches with the ABM which potentially utilizes the benefits of both methods. A feasible way is to modify the rules that manipulate the agent according to the statistical inference obtained by collected data. In this way, the need to delve the causal relationship between behaviors and influencing factors is reduced, and the randomness of occupant behaviors can be involved by adding probability variables to the management rules.
Since the occupant behavior model was defined in single-occupied offices, further research could be extended to multi-occupied rooms. Under this circumstance, the behavior mechanism becomes more complicated as communications between different occupants influences how they operate building components. Fortunately, the ABM platform allows the modeling of multiple agents as well as their mutual effects. It is worthwhile to understand behaviors from individual level to group level as a whole. Meanwhile, more behavior options such as the ones pertaining to plug loads can be added and studied as other typical behaviors in office buildings.

With occupant behavior information supplemented to building energy model, theoretically the simulated energy use result will be closer to reality. Therefore, one can collect actual energy use data on daily or monthly basis, and compare and contrast the measured data to simulated result. Especially when the behavioral impact is expanded from zone level to the whole building level, a comparison on the annual fluctuation for energy use can assess building performance in a more systematic way.

Finally, the framework can be fed with real-time data to manage building operation and renovation for an existing building. As behaviors are mostly resulted from uncomfortable indoor environment, the building systems can start to adjust on/off schedule in advance to achieve a better balance between building energy efficiency and occupant comfort enhancement.
APPENDIX A
DETAILED INTRODUCTION OF PMFserv MAIN FUNCTIONS

Agent Physiology, Stress, and Coping Style

In PMFserv, the physiology module monitors the flows of energy and other components of the biological systems for PMFserv agents. The results of this system have an impact on effective-fatigue used in the stress model, which in turn impacts overall agent stress (Integrated Stress). The Integrated Stress determines the agent’s coping style, which in turn alters the cognitive and motive capabilities of the agent. If the agent is sick, hungry (for simplicity sake) or hurt, its cognitive abilities (i.e. perception and decision making) might be affected. If the agent is dead, unconscious, or in shock, this will clearly have an effect on its cognitive as well as motive ability. For this research, it suffices just to know that physiology acts as a constraint on cognitive and motive abilities and therefore requires modeling.

The agent’s physiology is based around an energy reservoir, or tank. As the agent’s desired arousal and magnitude of physical exertion change, the agent opens and closes a valve at the bottom of the tank that releases the energy to be used for those tanks. The agent is bound by the flow of energy out of the tank. For example, if the supply of energy in the tank is quite low, the flow out of the tank may not be sufficient to support a particular energy intensive task.

Event stress comes from the emotion module, and time pressure is derived from the simulated world. Effective fatigue is driven out of the physiology module that described before. These all are combined into Integrated Stress. The stress level values can be moved up and down on the three tanks and finally impacts Integrated Stress, as defined by user.
Agent Emotions and Value Systems

PMFserv has an extensible value system module, the purpose of which is to primarily output a number of measures of the condition of the agent, including:

- How the agent feels about the state of the environment: this is calculated as 11 pairs of oppositely-valenced emotions, with negative emotions summarized into event stress and sent to the Physiology Module. All emotions are summarized into a composite utility (U) measure, or more precisely, Subjective Utility.

- Utility to the agent of each of the candidate actions available for the next tick. Or more precisely, the Decision Module makes use of the Emotion Module as a ‘calculator’ to assess the utility of possible actions it might choose to do.

- Other Emotion calculator services – various other modules also make use of the Emotion Module to be a calculator for various measures they require (e.g., the Social Module uses it as part of the assessment of how the agent feels about various groups, persons, etc.)

Cognitive appraisal is deciding what the agent feels after interpreting or explaining what has just happened. In primary appraisal, people consider how the situation affects the personal well-being (1st bullet above). In secondary appraisal, people consider how they might cope with the situation (2nd bullet above). In other words, two things are important for modeling the cognition of agent: whether the event is interpreted as good or bad, and what the agent believes is the cause of the event.

To implement cognitive appraisal, one needs several ingredients including:

- A perception system (covered in the following sub-section)
- A value system (represented by GSP Trees) that is used to interpret events
- An emotion model that processes the activation and decay of positive and negative ‘arousals’ about how the values have been affected.
- A coping or decision module that consults the value-driven emotion model.

The field of cognitive appraisal contains a number of theories and viewpoints. As a result, there are a number of ways to model it. PMFserv’s implementation relies on
best-of-breed models and PMFs based on their pedigree and internal validity. More of
different emotion models' discussion are available in (Johns & Silverman, 2001;
Silverman et al., 2006) as well as the reasons for choosing to implement the so-called
the Ortony, Clore and Collins emotion model.

PMFserv’s implementation of an agent’s value system (GSP Trees) is based on
multi-attribute utility theory and Bayesian probability mathematics. Utility is the term
from welfare economics that refers to a non-monetary measure of satisfaction one
derives from various goods or situations. Multi-attribute utility simply means that people
have several attributes, or a tree of values, that they care about in any given situation.
Basing the value system trees on Bayesian mathematics means that in practice, one
could derive the value system as a frequency distribution of choices as defined by past
action decisions of a given agent. Thus each branch of the value system tree would
show the importance or prior odds of that value to the individual.

Once the value system of an individual is known, it can drive the emotion model’s
arousals. Thus a universal emotion model is feasible and computationally reasonable if
it is assumed the individual differences arise from the value system and its activations.
One added benefit of the value tree approach is that it is central to an agent’s
personality differences as well. That is, it is quite easy to express any of a number of
best-of-breed motivation theories, personality instruments, and cultural trait models
within a value tree based form. These are not the only source of individual differences,
but they are a vital set to be able to represent and reason with.
To produce emotions from values and combine multiple emotions into a utility estimate, a Goal, Standard, and Preference (GSP) Tree is defined as the structure to represent the value system of the agents (humans or other beings) where:

- **Goals**: short term needs
- **Standards**: Constraints or standards of behavior (what a person will or won’t do to reach for their long term preferences and short term goals)
- **Preferences**: Long term preferred states of the world -- Likes and Dislikes

Any such agent would have richly filled in GSP tree structures and the stopping rule on filling in GSP trees for any agent is the limit of what behavior is needed from them in the simulation scenario. Further, GSP trees hold an agent’s previously learned values or importance weights. Each link of a GSP tree is labeled with a weight, \( w \), and the sum of child weights always sums to 1.0 for the sake of convenience. These weights may be thought of as Bayesian prior odds, or the frequency with which the agent favors that branch of the tree, other things being equal. Finally, each child node can have no more than one parent.

**Agent Perception and Object Affordance**

In PMFserv, the perception module permits an agent to monitor the objects and other agents within the environment and to find out what actions it can do to those artifacts. The perception is based on “affordances” which is a form of distributing perceptions so that an agent’s knowledge of the environment is formed onto the objects in the environment rather than into the head of the agent. These knowledge holds ways to see an object or other agent (Perceptual Types or P-Types), actions that can be performed upon that object under a given P-Type, and what those actions afford the agent in terms of filling its needs (i.e., activations for its GSP trees, contributions to its tanks, and so on). The agent only needs to be aware of its needs, and when it scans the
environment for objects it can then pick the one with an action that best satisfies its
need structure (highest utility action choice).

Through this approach, it is no longer required to maintain a “world model” in the
mind of the synthetic agent, which used to mean a constant mapping and updating of
every object/event in the environment to what is in the agent's mind. Through an
affordance-based approach, one can independently markup any environment or third
party videogame world (buildings, resources, other agents, mission/plan objects,
alliance objects, speech act objects, etc.) without having to alter the internals of the
PMFserv agents themselves. The perceptual markups for a PMFserv agent make use
of Gibson’s situated cognition and affordance approach (Gibson, 1979). According to
Gibson (1979), people perceive objects in terms of the possibilities for action they offer,
or afford us.

As indicated earlier, each object’s markup includes its P-types, Actions Afforded,
and Activation levels and type. Unlike the properties such as GSP trees, and physiology
tanks, which are individually dependent, these markups are intended as universals. In
other words, all the agents in the virtual environment treat the object the same way and
get those affordances from taking one action. This setup reduces complexity of objects
and the frame problem. P-types have rules that can be defined by modeler. If the rules
are satisfied, corresponding P-types become visible to the agent so that the actions
associated with the P-types become available to execute.
This appendix shows the screenshot of the Stress and Physiology module of “Agent” in PMFserv. Values can be adjusted accordingly.

Figure B-1. Agent property: Stress module
Figure B-2. Agent property: Physiology module
This appendix shows the screenshot of how PMFserv uses tree items for utility calculation based on Emotion module.

Figure C-1. Activation of tree items for Utility calculation for decision making
#!/usr/bin/python
from __future__ import print_function
import RPi.GPIO as GPIO
import Adafruit_DHT as dht
import tsl2591
import timeit
import time
import datetime as dt
import os

GPIO.setmode(GPIO.BOARD)

air_quality = 40
temp_humid = 38
sound_on_off = 35
sound_data = 37
sound_clock = 36

GPIO.setup(temp_humid, GPIO.IN)
path = '/home/pi/Code/
csv_data_file = path+'Data.csv'
data_file = path+'Data.txt'

if not os.path.exists(csv_data_file):
    with open(csv_data_file,'w') as f:
        f.write("Temp (C), Relative Humidity (%), Illumination (Lux), Timestamp

if not os.path.exists(data_file):
    with open(data_file,'w') as f:
        f.write("Data Collected every 5 minutes.

while True:
    h,t = dht.read_retry(dht.DHT22, 20)
txt = 'Temp={0:0.1f}*C Humidity={1:0.1f}%, '.format(t,h)

tsl = tsl2591.Tsl2591() # initialize
full, ir = tsl.get_full_luminosity() # read raw values (full spectrum and ir spectrum)
lux = tsl.calculate_lux(full, ir) # convert raw values to lux
Time = dt.datetime.today()
txt += "Illumination = {} lux, Timestamp = {}\n
print(txt)
with open(data_file, 'a') as f:
    f.write(txt)
with open(csv_data_file,'a') as f:
f.write("{}, {}, {}, \n".format(t, h, lux, Time))
print("Sleeping for 5 minutes...")
sleep(300)

Data File Upload Code

###################################
The code is adapted from https://www.raspberrypi.org/forums/viewtopic.php?t=164166 and
https://github.com/andreafabrizi/Dropbox-Uploader
###################################
import os
import subprocess
from subprocess import Popen, PIPE
#The directory to sync
syncdir="/home/pi/ftp/cctv/
#Path to the Dropbox-uploaded shell script
uploader="/home/pi/Dropbox-Uploader/dropbox_uploader.sh"

#if 1 then files will be uploaded. Set to 0 for testing
upload = 0
#if 1 then don’t check to see if the file already exists just upload it, if 0 don’t upload if
already exists
overwrite = 0
#if 1 then crawl sub directories for files to upload
recursive = 0
#Delete local file on successful upload
deleteLocal = 0

#Prints indented output
def print_output(msg, level):
    print(" " * level * 2 + msg)

#Gets a list of files in a dropbox directory
def list_files(path):
    p = Popen([uploader, "list", path], stdin=PIPE, stdout=PIPE, stderr=PIPE)
    output = p.communicate()[0].decode("utf-8")
    fileList = list()
    lines = output.splitlines()
    for line in lines:
        if line.startswith(" [F]"):
line = line[5:]
line = line[line.index(' ') + 1:]
fileList.append(line)

return fileList

# Uploads a single file
def upload_file(localPath, remotePath):
    p = Popen([uploader, "upload", localPath, remotePath], stdin=PIPE, stdout=PIPE, stderr=PIPE)
    output = p.communicate()[0].decode(\"utf-8\")\.strip()
    if output.startswith("> Uploading") and output.endswith("DONE"):
        return 1
    else:
        return 0

# Uploads files in a directory
def upload_files(path, level):
    fullpath = os.path.join(syncdir, path)
    print_output("Syncing " + fullpath, level)
    if not os.path.exists(fullpath):
        print_output("Path not found: " + path, level)
    else:

        # Get a list of file/dir in the path
        filesAndDirs = os.listdir(fullpath)

        # Group files and directories
        files = list()
        dirs = list()

        for file in filesAndDirs:
            filepath = os.path.join(fullpath, file)
            if os.path.isfile(filepath):
                files.append(file)
            if os.path.isdir(filepath):
                dirs.append(file)

        print_output(str(len(files)) + " Files, " + str(len(dirs)) + " Directories", level)

        # If the path contains files and we don't want to override get a list of files in Dropbox
        if len(files) > 0 and overwrite == 0:
            dfiles = list_files(path)
#Loop through the files to check to upload
for f in files:
    print_output("Found File: " + f, level)
    if upload == 1 and (overwrite == 1 or not f in dfiles):
        fullFilePath = os.path.join(fullpath, f)
        relativeFilePath = os.path.join(path, f)
        print_output("Uploading File: " + f, level + 1)
        if upload_file(fullFilePath, relativeFilePath) == 1:
            print_output("Uploaded File: " + f, level + 1)
            if deleteLocal == 1:
                print_output("Deleting File: " + f, level + 1)
                os.remove(fullFilePath)
            else:
                print_output("Error Uploading File: " + f, level + 1)

#If recursive loop through the directories
if recursive == 1:
    for d in dirs:
        print_output("Found Directory: " + d, level)
        relativePath = os.path.join(path, d)
        upload_files(relativePath, level + 1)

#Start
#while True:
upload_files("", 1)
    #sleep(7200)
APPENDIX E
IRB APPROVAL LETTER

UF
Institutional Review Board
UNIVERSITY of FLORIDA

Behavioral/Non-Medical Institutional Review
Board
FWA0005790

DATE: 11/8/2017
TO: Mengda Jia

FROM: Ira Fischer, Ph.D., Professor Emeritus
Chair IRB-02

IRB#: IRB201702653
TITLE: Occupant behavior modeling for improving building energy use estimation

Approved as Exempt

You have received IRB approval to conduct the above-listed research project. Approval of this project was granted on 10/31/2017 by IRB-02. This study is approved as exempt because it poses minimal risk and is approved under the following exempt category/categories:

2. Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey or interview procedures, or the observation of public behavior, so long as confidentiality is maintained. If both of the following are true, exempt status can not be granted: (a) Information obtained is recorded in such a manner that the subject can be identified, directly or through identifiers linked to the subject, and (b) Subject’s responses, if known outside the research, could reasonably place the subject at risk of criminal or civil liability or be damaging to the subject’s financial standing or employability or reputation.

Special notes to Investigator (if applicable):

In the myIRB system, Exempt approved studies will not have an approval stamp on the consents, flyers, emails, etc. However, the documents reviewed are the ones that should be used. So, under ATTACHMENTS you should find the document that has been reviewed and approved. If you need to modify the document(s) in any manner, then you’d need to submit to our office for review and approval prior to implementation.

Principal Investigator Responsibilities:

The PI is responsible for the conduct of the study. Important
The responsibilities described at the above link include:

- Using currently approved consent form to enroll subjects (if applicable)
- Renewing your study before expiration
- Obtaining approval for revisions before implementation
- Reporting Adverse Events
- Retention of Research Records
- Obtaining approval to conduct research at the VA
- Notifying other parties about this project’s approval status

Should the nature of the study change or you need to revise the protocol in any manner please contact this office prior to implementation.

Study Team:

Ravi Srinivasan Co-Investigator

The Foundation for The Gator Nation
An Equal Opportunity Institution

Confidentiality Notice: This e-mail message, including any attachments, is for the sole use of the intended recipient(s), and may contain legally privileged or confidential information. Any other distribution, copying, or disclosure is strictly prohibited. If you are not the intended recipient, please notify the sender and destroy this message immediately. Unauthorized access to confidential information is subject to federal and state laws and could result in personal liability, fines, and imprisonment. Thank you.
APPENDIX F
BEHAVIORAL RECORD SURVEY SHEET

<table>
<thead>
<tr>
<th>Room Date</th>
<th>Door Open</th>
<th>Door Close</th>
<th>Window Open</th>
<th>Window Close</th>
<th>Blinds Open</th>
<th>Blinds Close</th>
</tr>
</thead>
<tbody>
<tr>
<td>8:00 - 8:15 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8:15 - 8:30 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8:30 - 8:45 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8:45 - 9:00 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9:00 - 9:15 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9:15 - 9:30 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9:30 - 9:45 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9:45 - 10:00 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10:00 - 10:15 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10:15 - 10:30 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10:30 - 10:45 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10:45 - 11:00 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11:00 - 11:15 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11:15 - 11:30 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11:30 - 11:45 AM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11:45 - 12:00 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12:00 - 12:15 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12:15 - 12:30 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12:30 - 12:45 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12:45 - 1:00 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1:00 - 1:15 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1:15 - 1:30 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1:30 - 1:45 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1:45 - 2:00 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2:00 - 2:15 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2:15 - 2:30 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2:30 - 2:45 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2:45 - 3:00 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3:00 - 3:15 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3:15 - 3:30 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3:30 - 3:45 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3:45 - 4:00 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4:00 - 4:15 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4:15 - 4:30 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4:30 - 4:45 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4:45 - 5:00 PM</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Please record the opening and closing of doors, windows, and blinds for thermal, air quality, and visual comfort. Purpose: we are trying to build a virtual model of occupant behavior in office.*

Figure F-1. Survey sheet for behavior record
Figure G-1. GSP Tree default architecture - part 1
Figure G-2. GSP Tree default architecture - part 2
APPENDIX H
CODE FOR PERCEPTUAL RULES DEFINITION

Figure H-1. Custom rules for blind open due to visual perception

```python
def perceptionRule(perceiver, perceived, scenario):
    windowStatusTgt = perceived.getProperty('Window_Status')
    doorStatusTgt = perceived.getProperty('Door_Status')
    acStatusTgt = perceived.getProperty('AC_Status')
    blindStatusTgt = perceived.getProperty('Blind_Status')

    illumination = perceived.getProperty('Illumination')
    illuminationMax = perceived.getProperty('Illumination_Comfort_Max')
    illuminationMin = perceived.getProperty('Illumination_Comfort_Min')
    humanComfortlux = perceived.getProperty('Illumination_Most_Comfort')

    humanLuxFraction = (humanComfortlux - illumination) / (humanComfortlux - illuminationMin)
    occupancyStatus = perceived.getProperty('Occupancy')

    if occupancyStatus > 0:
        if blindStatusTgt:
            blindsClosed = False
            return False
        else:
            blindsClosed = True
            if humanLuxFraction > 0:
                return min(1, humanLuxFraction)
            else:
                return False

    else:
        return False
```
Figure H-2. Custom rules for blind close due to visual perception

```python
def perceptionRule(perceiver, perceived, scenario):
    windowStatusTgt = perceived.getProperty('Window_Status')
    doorStatusTgt = perceived.getProperty('Door_Status')
    acStatusTgt = perceived.getProperty('AC_Status')
    blindStatusTgt = perceived.getProperty('Blind_Status')
    illumination = perceived.getProperty('Illumination')
    illuminationMax = perceived.getProperty('Illumination_Comfort_Max')
    illuminationMin = perceived.getProperty('Illumination_Comfort_Min')
    humanComfortlux = perceived.getProperty('Illumination_Most_Comfort')
    humanLuxFraction = (illumination - humanComfortlux) / (illuminationMax - humanComfortlux)
    occupancyStatus = perceived.getProperty('Occupancy')

    if occupancyStatus > 0:
        if blindStatusTgt:
            if humanLuxFraction >= 0:
                return min(1, humanLuxFraction)
            else:
                return False
        else:
            blindIsOpen = True
            return False
    else:
        blindIsOpen = False
        return False
```

Figure H-3. Custom rules for window or door close under comfortable air quality and thermal conditions

```python
def perceptionRule(perceiver, perceivable, scenario):
    indoorTempF = perceiver.getProperty('Temperature_Indoors_degF')
    outdoorTempF = perceiver.getProperty('Temperature_Outdoors_degF')
    indoorTempFMax = perceiver.getProperty('Temperature_Indoors_degF_Max')
    indoorTempFMin = perceiver.getProperty('Temperature_Indoors_degF_Min')
    outdoorTempFMax = perceiver.getProperty('Temperature_Outdoors_degF_Max')
    outdoorTempFMin = perceiver.getProperty('Temperature_Outdoors_degF_Min')
    humanComfortTempFMax = perceiver.getProperty('Temperature_HumanComfort_degF_Max')
    humanComfortTempFMin = perceiver.getProperty('Temperature_HumanComfort_degF_Min')
    isIndoorTempHigherThanComfortRange = indoorTempF > humanComfortTempFMax
    isIndoorTempLowerThanComfortRange = indoorTempF < humanComfortTempFMin
    isIndoorTempWithinComfortRange = (indoorTempF <= humanComfortTempFMax) and (indoorTempF >= humanComfortTempFMin)
    isOutdoorTempHigherThanComfortRange = outdoorTempF > humanComfortTempFMax
    isOutdoorTempLowerThanComfortRange = outdoorTempF < humanComfortTempFMin
    isOutdoorTempWithinComfortRange = (outdoorTempF <= humanComfortTempFMax) and (outdoorTempF >= humanComfortTempFMin)
    indoorHumidity = perceiver.getProperty('Humidity_Indoors_Func')
    outdoorHumidity = perceiver.getProperty('Humidity_Outdoors_Func')
    isIndoorHumWithinComfortRange = (indoorHumidity <= 60) and (indoorHumidity >= 25)
    indoorAir = perceiver.getProperty('CO2_Density')
    humanComfortAir = perceiver.getProperty('CO2_Comfort_Max')
    isIndoorCO2WithinComfortRange = (indoorAir <= humanComfortAir * 0.6)
    occupancyStatus = perceiver.getProperty('Occupancy')
    if occupancyStatus > 0:
        return (isIndoorTempWithinComfortRange) and (isIndoorCO2WithinComfortRange) and
    else:
        return False
```
Figure H-4. Custom rules for door open due to air quality perception

```python
def perceptionRule(perceiver, perceived, scenario):
    windowStatusTgt = perceived.getProperty('Window_Status')
    doorStatusTgt = perceived.getProperty('Door_Status')
    acStatusTgt = perceived.getProperty('AC_Status')
    indoorAir = perceived.getProperty('CO2_Density')
    humanComfortAir = perceived.getProperty('CO2_Comfort_Max')
    indoorCO2Fraction = indoorAir / humanComfortAir
    occupancyStatus = perceived.getProperty('Occupancy')

    if occupancyStatus == 0:
        if doorStatusTgt:
            doorIsClosed = False
            return False
        else:
            doorIsClosed = True
            return min(1.0, indoorCO2Fraction)
    else:
        return False
```
Figure H-5. Custom rules for window open due to visual perception

```python
def perceptionRule(perceiver, perceived, scenario):
    windowStatusTgt = perceived.getProperty('Window_Status')
    doorStatusTgt = perceived.getProperty('Door_Status')
    acStatusTgt = perceived.getProperty('AC_Status')
    indoorAir = perceived.getProperty('CO2_Density')
    humanComfortAir = perceived.getProperty('CO2_Comfort_Max')
    indoorCO2Fraction = indoorAir / humanComfortAir
    occupancyStatus = perceived.getProperty('Occupancy')

    if occupancyStatus > 0:
        if windowStatusTgt:
            windowIsClosed = False
            return False
        else:
            windowIsClosed = True
            return min(1.0, indoorCO2Fraction)
    else:
        return False
```
Figure H-6. Custom rules for window close due to thermal perception

```python
windowStatusInt = perceived.getProperty('Window_Status')

indoorTempF = perceived.getProperty('Temperature_Indoors_degF')
outdoorTempF = perceived.getProperty('Temperature_Outdoors_degF')

indoorTempMax = perceived.getProperty('Temperature_Indoors_degF_Max')
indoorTempMin = perceived.getProperty('Temperature_Indoors_degF_Min')

outdoorTempMax = perceived.getProperty('Temperature_Outdoors_degF_Max')
outdoorTempMin = perceived.getProperty('Temperature_Outdoors_degF_Min')

humanComfortTempMax = perceived.getProperty('Temperature_HumanComfort_degF_Max')
humanComfortTempMin = perceived.getProperty('Temperature_HumanComfort_degF_Min')

isIndoorTempHigherThanComfortRange = indoorTempF > humanComfortTempMax
isIndoorTempLowerThanComfortRange = indoorTempF < humanComfortTempMin

isOutdoorTempHigherThanComfortRange = outdoorTempF > humanComfortTempMax
isOutdoorTempLowerThanComfortRange = outdoorTempF < humanComfortTempMin

isIndoorTempWithinComfortRange = (indoorTempF <= humanComfortTempMax) \ and (indoorTempF >= humanComfortTempMin)

indoorHumidity = perceived.getProperty('Humidity_Indoors_Fcnt')
outdoorHumidity = perceived.getProperty('Humidity_Outdoors_Fcnt')

isIndoorHumHigherThanComfortRange = indoorHumidity > 60
isIndoorHumLowerThanComfortRange = indoorHumidity < 25

isOutdoorHumHigherThanComfortRange = outdoorHumidity > 60
isOutdoorHumLowerThanComfortRange = outdoorHumidity < 25

isOutdoorHumWithinComfortRange = (outdoorHumidity <= 60) and (outdoorHumidity >= 25)

if windowStatusInt:
    windowIsOpen = True
else:
    windowIsOpen = False

occupancyStatus = perceived.getProperty('Occupancy')

if occupancyStatus>0:
    return (isOutdoorTempHigherThanComfortRange and isIndoorTempWithinComfortRange) \ or (isOutdoorTempLowerThanComfortRange and isIndoorTempWithinComfortRange) \ and ((isOutdoorHumHigherThanComfortRange and isIndoorHumWithinComfortRange) \ or (isOutdoorHumLowerThanComfortRange and isIndoorHumWithinComfortRange)) \ and windowIsOpen
else:
    return False
```
Figure H-7. Custom rules for window open due to thermal perception

```python
def perceptionRule(perceiver, perceived, scenario):
    windowStatusInt = perceived.getPropert('Window_Status')
    indoorTempF = perceived.getPropert('Temperature_Indoors_degF')
    outdoorTempF = perceived.getPropert('Temperature_Outdoors_degF')
    indoorTempFMax = perceived.getPropert('Temperature_Indoors_degF_Max')
    indoorTempFMin = perceived.getPropert('Temperature_Indoors_degF_Min')
    outdoorTempFMax = perceived.getPropert('Temperature_Outdoors_degF_Max')
    outdoorTempFMin = perceived.getPropert('Temperature_Outdoors_degF_Min')
    humanComfortTempFMax = perceived.getPropert('Temperature_HumanComfort_degF_Max')
    humanComfortTempFMin = perceived.getPropert('Temperature_HumanComfort_degF_Min')
    isIndoorTempHigherThanComfortRange = indoorTempF > humanComfortTempFMax
    isIndoorTempLowerThanComfortRange = indoorTempF < humanComfortTempFMin
    isOutdoorTempHigherThanComfortRange = outdoorTempF > humanComfortTempFMax
    isOutdoorTempLowerThanComfortRange = outdoorTempF < humanComfortTempFMin
    isOutdoorTempWithinComfortRange = (outdoorTempF <= humanComfortTempFMax) and (outdoorTempF >
    indoorHumidity = perceived.getPropert('Humidity_Indoors_Fort')
    outdoorHumidity = perceived.getPropert('Humidity_Outdoors_Fort')
    isIndoorHumHigherThanComfortRange = indoorHumidity > 60
    isIndoorHumLowerThanComfortRange = indoorHumidity < 25
    isOutdoorHumWithinComfortRange = (outdoorHumidity <= 60) and (outdoorHumidity >= 25)

    if windowStatusInt:
        windowIsClosed = False
    else:
        windowIsClosed = True
    occupancyStatus = perceived.getPropert('Occupancy')

    if occupancyStatus:
        return ((isIndoorTempHigherThanComfortRange and isOutdoorTempWithinComfortRange) or
                ((isIndoorTempLowerThanComfortRange and isOutdoorTempWithinComfortRange))
        and ((isIndoorHumHigherThanComfortRange and isOutdoorHumWithinComfortRange) or
             (isIndoorHumLowerThanComfortRange and isOutdoorHumWithinComfortRange))
        and windowIsClosed
    else:
        return False
```
APPENDIX I
SAMPLE DATASHEET FROM SMART SENSOR

This appendix shows an example of the sensor collected data used in this dissertation.

Table I-1. Sample of sensor collected environmental data

<table>
<thead>
<tr>
<th>Temp (C)</th>
<th>Relative Humidity (%)</th>
<th>Illumination (Lux)</th>
<th>CO2 (ppm)</th>
<th>Timestamp</th>
</tr>
</thead>
<tbody>
<tr>
<td>21.79999924</td>
<td>32.59999847</td>
<td>42.5952</td>
<td>496</td>
<td>2/28/18 9:01</td>
</tr>
<tr>
<td>21.79999924</td>
<td>32.70000076</td>
<td>56.304</td>
<td>497</td>
<td>2/28/18 9:06</td>
</tr>
<tr>
<td>21.79999924</td>
<td>32.40000153</td>
<td>56.304</td>
<td>500</td>
<td>2/28/18 9:11</td>
</tr>
<tr>
<td>21.79999924</td>
<td>32.59999847</td>
<td>74.0928</td>
<td>535</td>
<td>2/28/18 9:16</td>
</tr>
<tr>
<td>21.89999962</td>
<td>33.20000076</td>
<td>79.6416</td>
<td>545</td>
<td>2/28/18 9:21</td>
</tr>
<tr>
<td>22</td>
<td>33.09999987</td>
<td>64.464</td>
<td>559</td>
<td>2/28/18 9:26</td>
</tr>
<tr>
<td>22.10000038</td>
<td>35.90000153</td>
<td>91.8816</td>
<td>578</td>
<td>2/28/18 9:31</td>
</tr>
<tr>
<td>22.10000038</td>
<td>33.79999924</td>
<td>91.8816</td>
<td>564</td>
<td>2/28/18 9:37</td>
</tr>
<tr>
<td>22</td>
<td>33.20000076</td>
<td>78.1728</td>
<td>557</td>
<td>2/28/18 9:42</td>
</tr>
<tr>
<td>22.10000038</td>
<td>33.29999924</td>
<td>79.6416</td>
<td>553</td>
<td>2/28/18 9:47</td>
</tr>
<tr>
<td>22</td>
<td>33.29999924</td>
<td>101.5104</td>
<td>552</td>
<td>2/28/18 9:52</td>
</tr>
<tr>
<td>21.89999962</td>
<td>33.29999924</td>
<td>111.1392</td>
<td>551</td>
<td>2/28/18 9:57</td>
</tr>
<tr>
<td>21.79999924</td>
<td>33.70000076</td>
<td>98.8992</td>
<td>570</td>
<td>2/28/18 10:02</td>
</tr>
<tr>
<td>21.89999962</td>
<td>33.79999924</td>
<td>91.8816</td>
<td>564</td>
<td>2/28/18 10:07</td>
</tr>
<tr>
<td>21.79999924</td>
<td>34</td>
<td>101.5104</td>
<td>560</td>
<td>2/28/18 10:12</td>
</tr>
<tr>
<td>21.79999924</td>
<td>34.20000076</td>
<td>116.688</td>
<td>559</td>
<td>2/28/18 10:17</td>
</tr>
<tr>
<td>21.70000076</td>
<td>34.29999924</td>
<td>107.0592</td>
<td>559</td>
<td>2/28/18 10:22</td>
</tr>
<tr>
<td>21.70000076</td>
<td>34.5</td>
<td>116.688</td>
<td>559</td>
<td>2/28/18 10:27</td>
</tr>
<tr>
<td>21.70000076</td>
<td>34.59999847</td>
<td>135.9456</td>
<td>558</td>
<td>2/28/18 10:32</td>
</tr>
<tr>
<td>21.70000076</td>
<td>34.79999924</td>
<td>112.608</td>
<td>561</td>
<td>2/28/18 10:37</td>
</tr>
<tr>
<td>21.70000076</td>
<td>34.90000153</td>
<td>101.5104</td>
<td>565</td>
<td>2/28/18 10:42</td>
</tr>
<tr>
<td>21.60000038</td>
<td>35.20000076</td>
<td>104.448</td>
<td>570</td>
<td>2/28/18 10:47</td>
</tr>
<tr>
<td>21.60000038</td>
<td>35.5</td>
<td>114.0768</td>
<td>580</td>
<td>2/28/18 10:52</td>
</tr>
<tr>
<td>21.5</td>
<td>35.59999847</td>
<td>122.2368</td>
<td>587</td>
<td>2/28/18 10:57</td>
</tr>
<tr>
<td>21.60000038</td>
<td>35.90000153</td>
<td>120.768</td>
<td>591</td>
<td>2/28/18 11:02</td>
</tr>
</tbody>
</table>
APPENDIX J
CONFIGURATION OF ENERGYPLUS EXTERNAL INTERFACE

External Interface

<table>
<thead>
<tr>
<th>Field</th>
<th>Units</th>
<th>Obj1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name of External Interface</td>
<td></td>
<td>PtolemyServer</td>
</tr>
</tbody>
</table>

Figure J-1. External Interface activation in EnergyPlus™

<table>
<thead>
<tr>
<th>Field</th>
<th>Units</th>
<th>Obj1</th>
<th>Obj2</th>
<th>Obj3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name</td>
<td></td>
<td>Window-PMF</td>
<td>Blinds-PMF</td>
<td>Door-PMF</td>
</tr>
<tr>
<td>Schedule Type Limits Name</td>
<td>Any Number</td>
<td>Any Number</td>
<td>Any Number</td>
<td></td>
</tr>
<tr>
<td>Initial Value</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

Figure J-2. Schedule defining in External Interface for behavior update
APPENDIX K
BCVTB CONFIGURATION FILE AND SCREENSHOT

Code of variable.cfg file

```xml
<?xml version="1.0" encoding="UTF-8"?>
<BCVTB-variables>
    <!-- The next three elements send the set points to E+ -->
    <variable source="Ptolemy">
        <EnergyPlus schedule="Blinds-PMB"/>
    </variable>
    <variable source="Ptolemy">
        <EnergyPlus schedule="Door-PMB"/>
    </variable>
    <variable source="Ptolemy">
        <EnergyPlus schedule="Window-PMB"/>
    </variable>
    <!-- The next two elements receive the outdoor and zone air temperature from E+ -->
    <variable source="EnergyPlus">
        <EnergyPlus name="03Thirdfloor:03AVX53" type="Zone Air CO2 Concentration"/>
    </variable>
    <variable source="EnergyPlus">
        <EnergyPlus name="03Thirdfloor:03AVX53" type="Zone Air Relative Humidity"/>
    </variable>
    <!-- The next two elements receive the schedule value as an output from E+ -->
    <variable source="EnergyPlus">
        <EnergyPlus name="03THEIDFLOOR:03AVX53_MALL_B_A_A_0_0_0_0_WIN" type="Surface Outside Face Incident Solar Radiation Rate per Area"/>
    </variable>
    <variable source="EnergyPlus">
        <EnergyPlus name="SDF_2100_Cal_Hall_OccupancySchedule" type="Schedule Value"/>
    </variable>
    <variable source="EnergyPlus">
        <EnergyPlus name="03Thirdfloor:03AVX53" type="Zone Mean Air Temperature"/>
    </variable>
    <variable source="EnergyPlus">
        <EnergyPlus name="03Thirdfloor:03AVX53" type="Zone Outdoor Air Drybulb Temperature"/>
    </variable>
</BCVTB-variables>
```

Figure K-1. XML code for variable settings for data exchange

Figure K-2. Logical connection for the two simulators in BCVTB graphical interface for co-simulation running
LIST OF REFERENCES


160


Mengda Jia received his Bachelor of Engineering degree in hydraulic and hydroelectric engineering at School of Civil Engineering in Tianjin University, China. Upon graduation in 2010, he came to the United States for his master's studies in civil engineering with a focus on construction engineering and management at University of Southern California in Los Angeles, California. After that, he started his Ph.D. career in the M.E. Rinker, Sr. School of Construction Management at University of Florida in Gainesville, Florida. During his doctoral studies, he earned his Master of Science degree in computer science concurrently at University of Florida in 2017. He completed his Ph.D. degree in design, construction, and planning in 2018, with specialization in construction management.