Standardized Computational Framework for Prototypical Building Energy Model Creation and Building Energy Analyses

by

Yunyang Ye

B.S., Tongji University, 2013

M.S., Tongji University, 2016

A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Department of Civil, Environmental, and Architectural Engineering

2019

This thesis entitled:
Standardized Computational Framework for Prototypical Building Energy Model Creation and Building Energy Analyses
written by Yunyang Ye
has been approved for the Department of Civil, Environmental, and Architectural Engineering

Dr. Wangda Zuo

Dr. John Z. Zhai

Dr. Moncef Krarti

Dr. Jian Zhang

Dr. Gang Wang

Date

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

Ye, Yunyang (Ph.D., Architectural Engineering)

Standardized Computational Framework for Prototypical Building Energy Model Creation and Building Energy Analyses

Thesis directed by Dr. Wangda Zuo

Past research has demonstrated that high-efficiency building technologies have great potential to reduce the energy consumption of commercial buildings. However, different technologies may have different impacts on various types of commercial buildings depending on the climates. Thus, it is necessary to conduct building energy analyses to identify areas where energy efficiency can be improved for different types of commercial buildings. Despite of the process, current research has three limitations: (1) Current research is often done in ad hoc fashion and requires lengthy computing time. A standardized computational framework to streamline and accelerate building energy analyses is needed. (2) Prototypical building energy models represent the standard or reference energy models for the most common commercial buildings. They are often used as the starting point in conducting building energy analyses. However, current prototypical building energy models only represent limited types of buildings in certain countries, which limits their applications. (3) To select energy efficiency measures (EEMs), researchers tend to apply static energy prices to estimate their return on investment (ROI). Recently, more and more commercial buildings are adopting dynamic electricity pricing programs and the ROI analyses based on static energy prices may not be valid anymore. However, the impacts of dynamic electricity pricing programs on the selection of EEMs has not been fully evaluated.

To address the above three limitations, this dissertation creates a standardized computational framework for U.S. commercial buildings, applies it to create new prototypical models, and analyzes the impact of dynamic electricity pricing using these models. First, this dissertation reviews existing energy-related data sources for U.S. commercial buildings. These sources include nine building energy databases in total, three from surveys and six from simulations. Their applications are detailed for building energy analyses. Based on the review, a standardized computational framework for U.S. commercial buildings is created, which can select the best data sources and methods to create prototypical building energy models and conduct building energy analyses.

Then, by using the framework, this dissertation proposes a new methodology for prototypical building energy model creation independent of building types and countries. By using this new methodology, this dissertation creates prototypical building energy models for four types of U.S. commercial buildings: (1) medium office buildings, (2) religious worship buildings, (3) college/university buildings, and (4) mechanical shops. The medium office buildings and religious worship buildings are used as two case studies.

Finally, this dissertation uses the framework to analyze the impacts of electricity pricing programs on the selection of EEMs. The DOE Commercial Prototype Building Energy Models for medium office buildings are the baseline models in these analyses. Furthermore, this research involves three global sensitivity analysis methods and five electricity pricing programs. The results by only considering building energy savings are similar to those of other studies. Moving on to the cost analysis, the results indicate that the ROIs of EEMs greatly change under different electricity pricing programs. If different electricity pricing programs were available to commercial buildings, building owners would be more likely to conduct energy retrofits to take advantage of these savings.

This dissertation address the three limitations: (1) create a standardized computational framework for U.S. commercial buildings regulates the analysis process and automizes the whole procedure, (2) develop a new methodology for prototypical building energy model creation, and (3) provide a new perspective about the selection of EEMs by considering the impact of dynamic pricing programs. The future research will extend the scope of the standardized computational framework, complement the sets of prototypical building energy models, and continue researching on the impact of dynamic electricity pricing programs.

Dedication

To my wife, Qingling Hu.

Acknowledgements

I would like to express my deep gratitude to Dr. Wangda Zuo, my advisor at the University of Colorado Boulder. He inspired and constantly supported me throughout this dissertation. His encouragement and guidance helped me complete my PhD study and my dissertation. I also thank him for training me writing papers, introducing me to the academic community, and teaching me how to be a researcher. He shared his experience with me, which helped me a lot for my research.

I am thankful to Dr. Gang Wang, a committee member for my dissertation. In the past three years, I received considerable his advices and comments from engineering perspectives, which are critical to my research.

I am grateful to Dr. John Zhai, one of my committee members. He provided critical comments on my dissertation. His input broadened my research scope.

I would like to acknowledge Dr. Moncef Krarti, who is also my committee member. His input was always critical for my research.

I express special thanks to Dr. Jian Zhang from the Pacific Northwest National Laboratory. He is my committee member. When I did the internship in the Pacific Northwest National Laboratory, he provided plenty of advice and guidance. Further, his hard work and dedication always inspire me. Further, I am thankful to him for providing critical comments on my research in these two years.

I would like to thank all of the former and current students in the Sustainable Buildings and Societies Laboratory. I usually spoke with them when I had questions. Among them are Dr. Sen Huang, Dr. Wei Tian, Dr. Thomas A. Sevilla, Yangyang Fu, Jing Wang, Xu Han, Katy

Hinkelman, Xing Lu, Danlin Hou, Yingli Lou, Cary Faulkner, Jes Stershic, Matthew Strong, Satish Upadhyaya, Shifang Huang, Guang Zhou, Qiujian Wang, Peilin Yang, Angelique Fathy, Saranya Anbarasu, Isabella Goltz Ver, Drake P. Peterson, Clay Wyda, Reymundo J. Miranda.

I deeply appreciate my parents, who supported me to come to U.S. for the Ph.D. study. Finally, I would like to thank my wife, Qingling Hu, who always encourages and supports me.

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Chapter 1

Introduction

1.1 Background

The Energy Information Agency's (EIA) *Annual Energy Outlook 2019* estimated that the commercial building sector was responsible for approximately 18.2% of primary U.S. energy use in 2018 [61]. It also projected that the primary energy consumption of U.S. commercial buildings would increase approximately 5% by 2050. The comparison of energy use intensities (EUIs) between existing buildings and high-efficiency buildings showed great potential to reduce the energy consumption in commercial buildings [74, 77, 103, 104, 109, 176]. For example, Griffith et al. [77] concluded that the site EUI with high-efficiency buildings, excluding photovoltaic (PV) panels, was 457.67 MJ/m^2-yr, which was only 45% of the average site EUI of existing commercial buildings at the time of the study. Glazer (2016) analyzed 272 building and climate combinations, and reported that high energy-efficient commercial buildings in the U.S. had the potential to consume only approximately 50% of the site energy compared to the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 90.1-2013 [11]. Therefore, it is necessary to conduct building energy analyses to identify areas where energy efficiency can be improved within commercial buildings.

Before conducting building energy analyses, energy-related data needs to be analyzed, which is useful to understand the broad picture of U.S. commercial building energy consumption. this dissertation classifies the data sets into two categories: survey data sets and simulation data sets [197]. Survey data sets collect the raw data mainly from surveys of building respondents and energy providers, on-site meters, utility bills, or other survey data sets. Then databases are created. For example, the *Commercial Buildings Energy Consumption Survey* (CBECS), the *California Commercial End-Use Survey* (CEUS), and the *Building Performance Database* (BPD) are the three popular survey data sets for the energy-related data of U.S. commercial buildings [22, 59, 107]. Simulation data is generated by building energy simulation programs [31]. Model developers collect the building model inputs from survey data, energy standards, and expert knowledge. Then building energy simulation programs produce the results based on the building model inputs. This dissertation defines both building model inputs and simulation results as simulation data. For instance, Huang and Franconi [88] and Griffith et al. [78] developed two simulation data sets for U.S. commercial buildings. The descriptions of the building models in the two data sources provide the values of main model inputs and the energy data, which was summarized in their reports. The simulation data consists of both model inputs and energy data. Further, Commercial Reference Building Models, Commercial Prototype Building Models, and OpenStudio-Standards gem are the three current popular simulation data sets created by the U.S. Department of Energy (DOE) [39, 45, 134]. Commercial Reference Building Models, Commercial Prototype Building Models, and OpenStudio-Standards gem all belong to prototypical building energy models. These models represent the standard or reference energy models for the most common commercial buildings and are important and treated as the starting point in conducting building energy analyses. Moreover, the National Renewable Energy Laboratory (NREL) developed DEnCity to store a rich set of existing OpenStudio building models for future research and makes it possible to conduct large-scale analyses [130, 131].

Based on these data sources, researchers conduct different types of building energy analyses in support of the energy saving and energy efficiency of U.S. commercial buildings. For example, based on the 1979 *Nonresidential Building Energy Consumption Survey* (NBECS) data, which is named CBECS now, the Gas Research Institute (GRI) conducted a project to develop a categorization of the office building sector by using clustering, and to characterize in detail the energy requirements of existing and new office building sectors [19, 20, 30]. Further, based on several databases, the Environmental Protection Agency (EPA) released a 1-100 ENERGY STAR score for U.S. buildings by using regression models [66]. Recently, existing research provided many varied methods to conduct uncertainty and sensitivity analyses to save energy and improve energy efficiency in U.S. commercial buildings [16, 34, 63, 89, 161]. Tian [174] reviewed the existing research for the sensitivity analysis applied in the building energy analyses and some researchers compared the advantages and disadvantages of the various sensitivity analysis methods [121, 123, 128]. Another example of an analysis is to select energy efficiency measures (EEMs) during building energy retrofit projects [97, 99, 106, 129]. Current studies usually select EEMs based on their return on investment (ROI), which aims to save both energy and cost. The researchers tend to apply static energy prices to estimate ROI, although more and more commercial buildings are adopting dynamic electricity pricing programs.

1.2 Problem Statement

A rich set of the existing research shows that building energy analyses are necessary and have been conducted for decades. However, there are still some problems and, if they can be solved, analysis results will become better. The three potential major problems for researchers are listed as following:

(1) **A standardized computational framework to conduct building energy analyses does not exist.** To generate accurate results with efficient methods, a comprehensive review of existing data sources and previous research is required before conducting building energy analyses. Further, it is more efficient to automatically conduct building energy simulations and analyses. To accomplish these, it is necessary to develop a standardized computational framework, which does not exist.

(2) **Current prototypical building energy models only represent limited types of buildings in certain countries.** As the starting point of the building energy analyses, it is necessary to prepare prototypical building energy models for all main building types in

different countries. However, in many countries, especially some developing countries, there is a lack of prototypical building energy models as the starting point to the building energy analyses. Further, although there is a rich set of existing prototypical building energy models in the U.S., there are still some building types missing, such as religious worship buildings, mechanic shops, and college or university buildings. These missing building types still account for over 20% of the total energy consumption in the U.S. commercial building sector and approximately 20% of the floor space [173, 36].

(3) **The impacts of dynamic electricity pricing programs on the selection of EEMs has not been fully established.** Building energy retrofits have great potential to save energy and cost. Current studies tend to apply static energy prices to estimate ROI. However, more and more commercial buildings are adopting dynamic electricity pricing programs, and the selection of EEMs based on static energy prices may not be valid anymore.

1.3 Objectives

There are three objectives for this dissertation, which are to solve the three problems mentioned in Section 1.2. These three objectives are shown as follows:

(1) **Develop a standardized computational framework.** This computational framework is able to systematically create prototypical building energy models and conduct various building energy analyses. The remaining objectives will be achieved by using this computational framework.

(2) **Develop a methodology to create prototypical building energy models for existing U.S. commercial buildings.** This methodology aims to create prototypical building energy models, which have representative model inputs and energy data. By using this methodology, this dissertation will create prototypical building energy models for missing types of U.S. commercial buildings. The energy results will be validated by using the empirical data.

(3) **Analyze the impacts of energy savings and dynamic electricity pricing programs on the selection of EEMs.** The prototypical building energy models for existing U.S. medium office buildings are used for this objective. Based on previous research, the sensitive EEMs will be identified for the analysis. To analyze the impacts of dynamic electricity pricing programs on the selection of EEMs, this dissertation will analyze the impacts by using the static and four dynamic electricity pricing programs. The ROI is used as the indicator to select EEMs in this research.

1.4 Scope

This dissertation consists of eight chapters and is able to achieve the three objectives mentioned in Section 1.3. Figure 1.1 shows the structure of the dissertation and the main topic for each chapter is shown below:

(1) **Chapter 1: Introduction.** This chapter provides a general introduction of the background, existing problems, objectives, and scope of the dissertation.

(2) **Chapter 2: Literature Review.** This chapter conducts a comprehensive literature review for existing energy-related data sources for U.S. commercial buildings and the existing research on building energy analyses. The data sources and existing building energy analyses are used to create the standardized computational framework introduced in Chapter 3.

(3) **Chapter 3: Standardized Computational Framework.** This chapter details the structure of the standardized computational framework. Furthermore, this chapter discusses about the potential applications by using this framework.

(4) **Chapter 4: Methodology to Create Prototypical Building Energy Models.** This chapter proposes a new methodology to create prototypical building energy models for existing buildings and this methodology can be implemented by using the standardized computational framework. This methodology standardizes the rules to identify the values

and uncertainties of the model inputs, and provides the rule-based links for the models in different climate zones. Moreover, the improved genetic algorithm (GA) is adopted to calibrate the models, which enables the selection of the best values among the uncertainties of model inputs under the limited reference energy data.

(5) **Chapter 5: Creation of Prototypical Building Energy Models.** By using the methodology introduced in Chapter 4 and the standardized computational framework introduced in Chapter 3, this chapter creates the prototypical building energy models for the four types of U.S. commercial buildings: (1) medium office buildings, (2) religious worship buildings, (3) college/university buildings, and (4) mechanical shops. The medium office buildings and religious worship buildings are used as two detailed case studies. In the first case, the prototypical building models for U.S. medium office buildings are compared to the existing models in the DOE Commercial Reference Building Energy Models [39]. In the second case, the prototypical building energy models for religious worship buildings complement the existing simulation datasets.

(6) **Chapter 6: Impacts of Energy Savings on EEM Selection.** This chapter introduces one of the applications for the standardized computational framework and conducts sensitivity analyses to identify EEMs. The DOE Commercial Prototype Building Models for U.S. medium office buildings are used as the starting point of this research [45]. Three global sensitivity analysis methods were used for selection of EEMs based on the building energy savings. Furthermore, the impacts of different baseline models on the selection of EEMs are also discussed.

(7) **Chapter 7: Impacts of Electricity Pricing Programs on EEM Selection.** This chapter introduces another application for the standardized computational framework and analyzes the impacts of electricity pricing programs on EEM selection. The DOE Commercial Prototype Building Models for U.S. medium office buildings are used as the starting point [45]. Five electricity pricing programs are involved in this research. In addition, this

chapter further discusses the impacts of different baseline models on the selection of EEMs.

(8) **Chapter 8: Conclusion and Future Research.** This chapter makes a conclusion about the research completed in this dissertation and proposes possible future research based on the results.

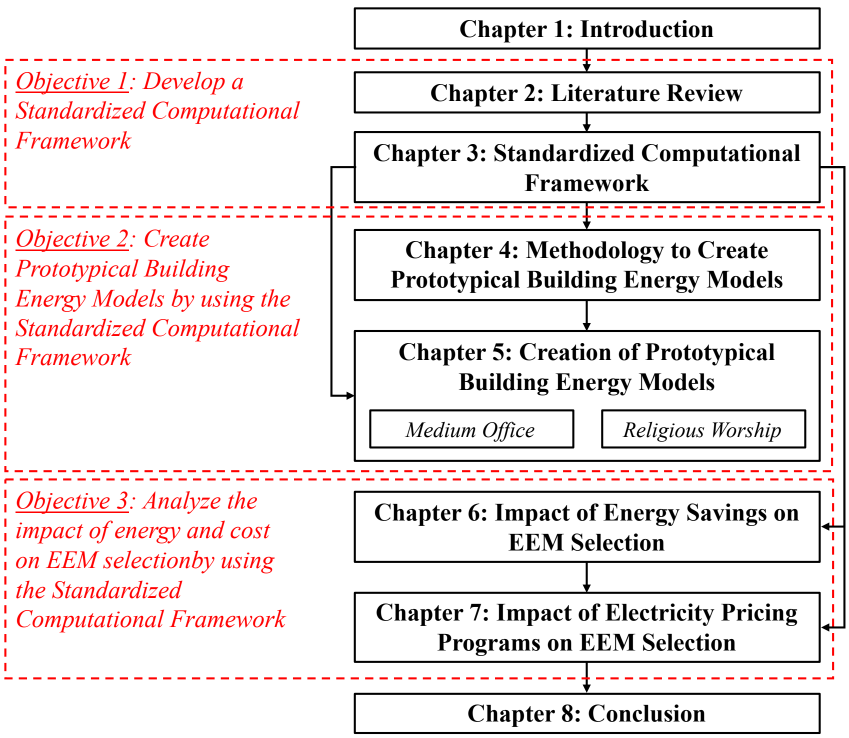


Figure 1.1: Structure of the dissertation

Chapter 2

Literature Review

2.1 Introduction

Before developing the standardized computational framework, it is essential to conduct a comprehensive review about the existing data sources related to building energy consumption. Based on the review, the rules can be designed to select right data sources for different applications related to prototypical building energy model creation and building energy analyses. This chapter summarizes the existing data sources for energy-related data of U.S. commercial buildings and provide a guideline to select right data sources for specific applications based on the existing research about building energy analyses. First, this chapter summarizes the main survey and simulation data sources for energy usage of U.S. commercial buildings, and compares the data sources in terms of their data collection methods, released information, and features. Then this review analyzes the applications for different survey and simulation data sources. Based on the different features, this chapter categorizes the applications of data sources into five categories, including energy performance benchmarks, energy usage forecasts and predictions, energy use contributions of building components, supports of energy policies and standards, and urban-scale energy use analysis, along with several cases to show how to use these data sources. Further, this chapter introduces the Key Performance Indicators (KPIs) and guide users to select the databases for specific applications. The summary of this chapter provides a reference to develop the standardized computational framework for prototypical building energy model creation and various building energy analyses, which will be introduced in Chapter 3.

2.2 Overview of Existing Data Sources

There are many varied data sources for energy-related data about U.S. commercial buildings. This section focuses on the data sets where the data is easy to obtain and can be used for new research, and classifies these data sets into two categories: survey data sets and simulation data sets. Survey data sets in this section collect the raw data mainly from surveys of building respondents and energy providers, on-site meters, utility bills, or other survey data sets. Then databases are created using the data. Simulation data is generated by building energy simulation programs [31]. Model developers collect the building model inputs from survey data, energy standards, and expert knowledge. Then building energy simulation programs produce the results based on the building model inputs. This section defines both building model inputs and simulation results as simulation data.

This section introduces the main data sources in the U.S., including three survey data sources and six simulation data sources. It compares the features of each data source. The introduction and comparison will provide a broad picture of the data sources and preferences to select the data sources for different objectives.

2.2.1 Survey Data

Based on the coverage area, survey data sources about energy consumption in commercial buildings can be classified into local and national sources. Based on the number of samples and information recorded from each sample, survey data sources can also be divided into in-depth and large-scale sources. The in-depth sources can provide detailed building characteristics and energy use data, such as building geometry, building schedules, and end-use energy consumption, for each building sample. The large-scale sources usually only provide several key building characteristics and energy data for each building samples, but consist of rich sets of building samples. This section introduces three typical survey data sources. The *California Commercial End-Use Survey* (CEUS) is one of the representative state's energy survey data sources for U.S. commercial buildings which can be considered as local and in-depth survey data sources [22]. The *Commercial Buildings Energy Consumption Survey* (CBECS) is a national comprehensive survey belonging to national and in-depth survey data sources [59]. The last one, the *Building Performance Database* (BPD), is one of the largest survey data sources for energy consumption in U.S. buildings, and it is a national and large-scale data source [107].

The three survey data sources were developed for different purposes. CEUS primarily aims to support the California Energy Commission's (CEC) energy demand forecasting activities. To gain the data for hourly end uses, CEUS utilized the building energy program to conduct the post-procession for the survey data [22, 116, 144]. CBECS data is a national-level sample survey of commercial buildings [59]. Its target is to display the distribution of the energy performance of the commercial building sector; thus, it provides a statistical design for sampling. The goal of BPD is not to achieve a representative national sample, such as CBECS. Instead, BPD is developed as a national-level decision-support platform. The BPD's purpose is to generate plenty of building samples, which makes it valid to use to conduct research at the local level [117]. BPD can be used to assess building energy efficiency, forecast building energy performance, and quantify the uncertainty of building energy consumption. Due to different purposes, the three survey data sources provide different procedures to collect, process, and generate data. Figure 2.1 summarizes the procedures for developing the three survey data sources.

CEUS conducted a comprehensive on-site survey and collected the information about the energy usage of samples from five utility companies [22]. Then DrCEUS (a simulation program developed based on SitePro and eQUEST) cleaned the data and generated hourly end-use energy data [41, 96, 119]. Finally, the CEUS data set was formed and developed based on the survey data and simulation end-use energy data.

As a national commercial building energy survey, the scope of CBECS is significantly larger than CEUS, which is focused on California. To reflect the change of building energy performance over time, The Energy Information Agency (EIA) updated the CBECS data continuously since 1979. The analysis of this chapter focuses on the two latest and most used versions: the 2003 and

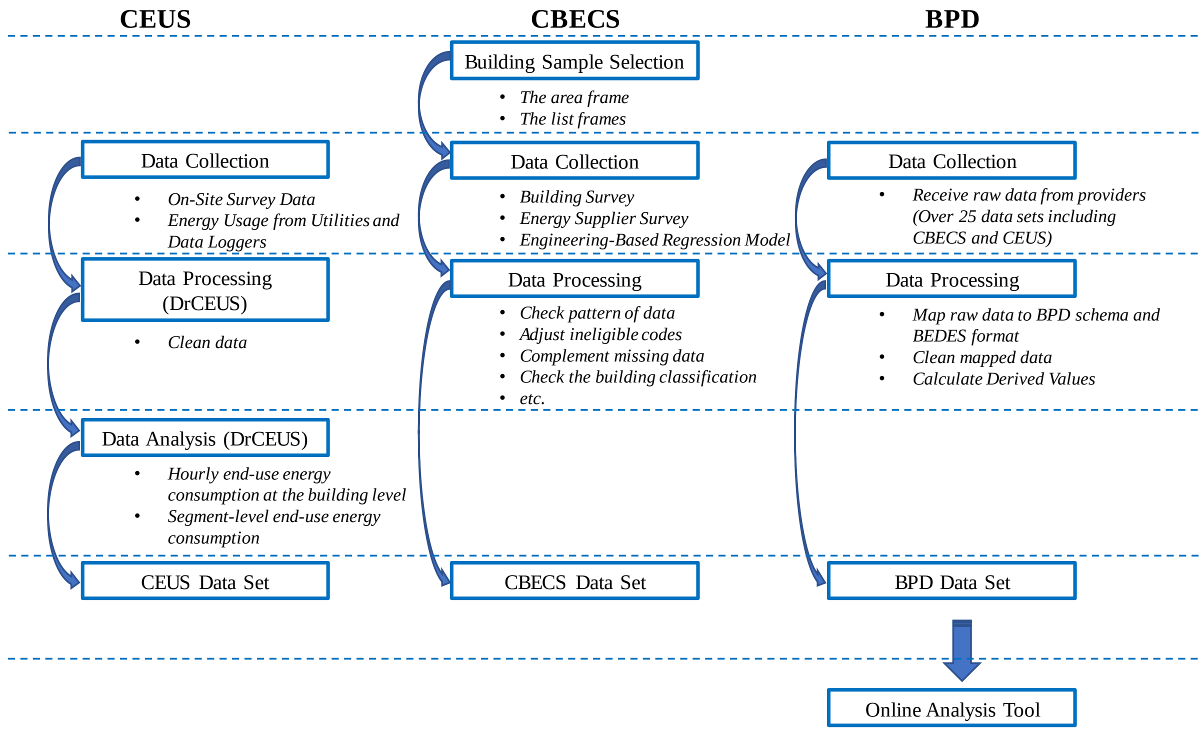


Figure 2.1: Procedures of developing the data sets

the 2012 CBECS [51, 57]. The 2003 and 2012 CBECS used an area frame portion and a list frames portion to select building samples [53]. The area frame portion ensures that the distribution of building samples is representative of all U.S. commercial buildings. The list frames portion optimizes the combination of large and small buildings to reflect their weighted impacts on the nation's energy consumption. Next, CBECS collected data about selected building samples from respondents and energy suppliers. In addition, regression models were used if the data could not be obtained [50, 54, 55]. After that, CBECS processed data to fix errors and fill in missing data.

Another national survey data source, BPD, shows a different way to collect data. Instead of collecting data through on-site surveys and from energy suppliers, BPD mapped over 25 source data sets, including CBECS and CEUS, and collected data from these data sets. Then BPD adjusted the data formats in different data sets into the format following the criteria of the Building Energy

Data Exchange Specification (BEDES). After that, BPD cleaned the data to fix errors. Finally, BPD derived its own data and formed the database [40]. Moreover, based on the data set, BPD created an online analysis tool which includes peer group analyses and performance comparison [21]. The online analysis tool makes it convenient for users to analyze the data and make decisions.

Besides the various data collection and procession methods adopted by the three survey data sources, they also published different information about building energy consumption. Table 2.1 summarizes the available information provided by the three survey data sources. The data of individual building samples in CEUS is not available to the public. Instead, CEUS provides the analysis results for end-use energy consumption for the entire commercial building sector in California. Meanwhile, DrCEUS supports a variety of commercial end-use energy analyses [22]. On the contrary, CBECS provides the building characteristics and energy data for individual building samples. Users can estimate locations of building samples based on the climate zones and census divisions [59]. Although BPD does not provide the details of each building sample either, users can easily analyze and compare the distribution of building energy-related features, such as energy use intensities (EUIs) and total floor areas at the local levels via BPD's user interface [21].

Since survey data sources are created for specific purposes, they have their own features and are suitable for different applications. To help readers select the right data source which suits their application needs, this paragraph discusses and compares the features of the three typical survey data sources. Table 2.2 lists the comparisons of the three survey data sources' features. First, CEUS uses building energy simulations to complement the data collected by surveys. Thus, it is able to characterize the changes of energy end uses caused by occupants. It can also provide hourly data via DrCEUS. However, it is a state-level data source and lacks publicly available data, which limits the usefulness of the study [78]. Second, CBECS is a comprehensive energy related data source for U.S. commercial buildings that provides the details of building characteristics and energy data for each sample. Thanks to the adoption of the area frame and list frames portions to select building samples, CBECS is considered to be the best data source to reflect the distribution of the energy performance of the U.S. commercial building sector. However, CBECS cannot provide the hourly

Table 2.1: Information provided by the three survey data sources

	CEUS	**CBECS**	**BPD**
Year Published	2006	1979, 1983, 1986, 1989, 1992, 1995, 1999, 2003, 2012	Started from 2014
Number of Building Types	12	Principal Building Activity: 20 More Specific Building Activity: 51[1]	Commercial Building Classification: 26 More Detailed Commercial Building Classification: 83
Location	California (Divided by climate zone)	U.S. (Divided by the CBECS climate zone and census division)[1]	U.S. (Divided by the ASHRAE climate zone, state, city, and zip code)
Number of Samples	2,800	Over 5,200 (2003 CBECS) Over 6,700 (2012 CBECS)	Over 75,000
Available Information	End-use energy consumption	Each sample building's characteristics, yearly expenditures, and end-use energy usages[1]	Distribution and comparison of yearly energy usages, building types, and ratings

[1] The information is only for the 2003 and 2012 CBECS.

data. Due to the high cost of data collection, CBECS has a relatively small sample size and the data updates infrequently [29]. The sample set maybe insufficient when the analysis only focuses on a specific building type at a specific location. At the last, BPD is the largest energy related data source for U.S. commercial buildings. Its online analysis tool is a decision-support platform which provides probabilistic risk analysis [21]. However, it does not provide detailed information of each building sample [117]. Moreover, building samples' energy-related data is collected in different periods and one building in different periods could be recorded as different building samples.

2.2.2 Simulation Data

Thanks to the fast computing speed, low cost, and easy modification, building energy simulations become more and more popular and provide rich energy-related data sets for broad applications. There are various building energy simulation programs, such as DOE-2 and EnergyPlus, with different features for model inputs, calculation methods, and model outputs [33, 42, 189]. Several literatures summarized and compared the major building energy simulation programs

Table 2.2: Comparisons of the three survey data sources' features

Feature	CEUS	CBECS	BPD
Use the building energy programs to post-process the survey data	Yes	No	No
Provide the hourly end-use energy consumption	Yes	No	No
Reflect the distribution of the energy consumption of commercial building sector	Only California	U.S.	U.S.
Collect energy consumption of given periods	Yes	Yes	No
Provide the characteristics for each building sample	Limited	Detailed	Limited
Provide enough data to conduct large-scale analyses or analyze energy performance at the local levels	Only California	Limited locations	Many locations
Provide probabilistic risk analysis and decision-support platforms	No	No	Yes

[4, 15, 31, 32, 152]. This section introduces six commonly used simulation data sources generated by building energy simulation programs as shown in Figure 2.2.

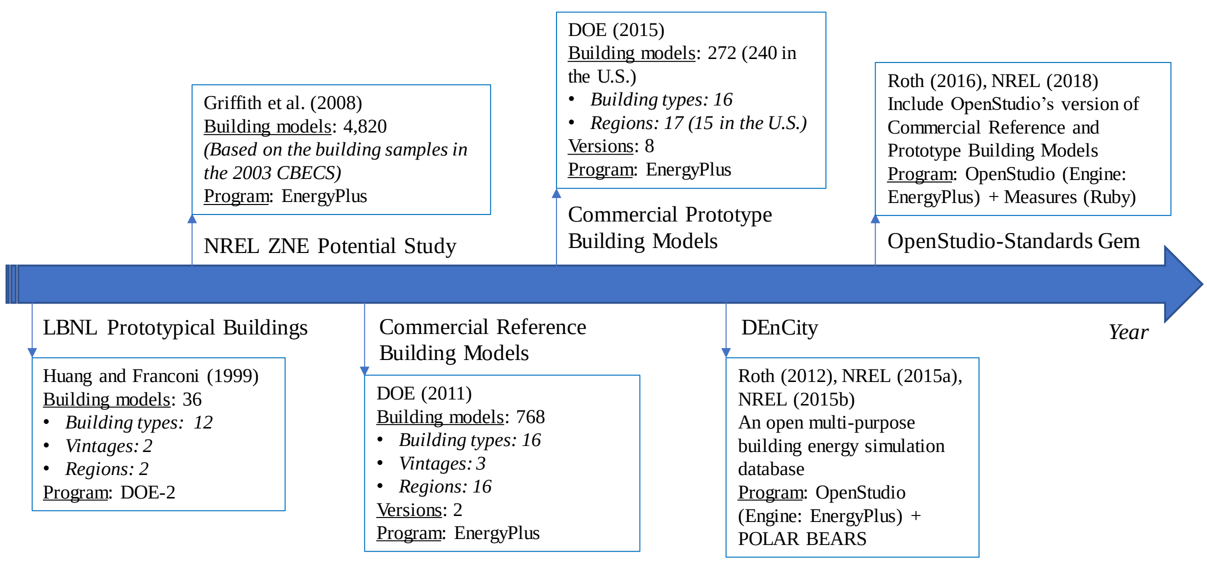


Figure 2.2: Summary of the six simulation data sources

First, Huang and Franconi [88] developed 36 commercial building models by using DOE-2 based on the previous researches [33, 87, 157, 178, 189]. Derived from the 1992 CBECS [49], the U.S. commercial building population was estimated by 36 building models which cover 12 main building types, two vintages, and two regions (six building types was only studied for one region). The building models were used to analyze the contributions of building components to heating and cooling loads in U.S. commercial building stocks and calculate the efficiencies of typical commercial heating and cooling systems to meet the loads.

Second, Griffith et al. [78] created a set of building energy models to simulate the existing commercial building sector. Based on the building samples in the 2003 CBECS, 4,820 building models were developed by using EnergyPlus [42]. The authors also introduced the procedure for creating the building models based on the limited survey data. By changing the model inputs of these building models, over 100,000 simulations were performed to analyze different scenarios of energy consumption in U.S. commercial buildings. For example, Griffith et al. [77] used the simulation results to analyze the net-zero energy (NZE) potential of the U.S. commercial building sector. Benne et al. [14] assessed the energy impacts of outside air in the commercial building sector.

In order to represent the U.S. commercial building stock with a small number of typical buildings, DOE created the Commercial Reference Building Models by using EnergyPlus [36, 39]. The inputs for the Commercial Reference Building Models came from several sources, such as the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 90.1, ASHARE Standard 62.1, and CBECS data. There were 768 building models consisting of 16 building types, 3 vintages, and 16 locations, which represented nearly 70% of the U.S. commercial building floor area. The technical report also discussed the methodology to create those building models and description of each model [36]. The building models are open-source available at `https://www.energy.gov/eere/buildings/commercial-reference-buildings`.

Based on the Commercial Reference Building Models, the Commercial Prototype Building Models were developed by using EnergyPlus, which represented around 80% of the U.S. commercial building floor area and over 70% of the energy consumed in U.S. commercial buildings [45, 173]. The building models consist of 16 building types and 17 ASHRAE climate zones. The building models aimed to simulate the commercial buildings that meet the requirements of ASHRAE Standard

90.1 and the International Energy Conservation Code (IECC). So far, the Commercial Prototype Building Models have nine versions to match the different versions of the ASHRAE Standard 90.1 and IECC. The building models are open-source available at https://www.energycodes.gov/development/commercial/prototype_models.

With the increased number of users for OpenStudio, which is a collection of software tools to support building energy modeling with EnergyPlus [79], there is an increasing need to enable the Commercial Reference Building Models and the Commercial Prototype Building Models in OpenStudio. However, the input file of EnergyPlus (.idf) cannot be directly transferred into the input file of OpenStudio (.osm), which limits users to use the Commercial Reference Building Models or the Commercial Prototype Building Models. Thus, the National Renewable Energy Laboratory (NREL) developed OpenStudio-Standards gem, a library created using the Ruby programming language [133, 150, 27]. By using the OpenStudio-Standards gem, users can automatically generate the OpenStudio versions of the Commercial Reference Building Models and the Commercial Prototype Building Models. In addition, NREL created many varied measures by using Ruby to enable the easy modification of model inputs [132]. The OpenStudio-Standards gem library is open-source available at https://github.com/NREL/openstudio-standards and measures are available at https://bcl.nrel.gov/.

Recently, DOE created an open-source multi-purpose building energy simulation database named as DEnCity [130, 131, 151]. The DEnCity database collects OpenStudio simulation inputs and results uploaded by users. Then using the large-scale simulation data stored in the database, DEnCity can provide users a quick analysis of building energy consumption for their simulation inputs without running the building energy simulation. The scripts of DEnCity are open source available at https://github.com/NREL/dencity-webandhttps://github.com/NREL/dencity-gem.

Each simulation data source has its own features, which are suitable for specific applications. To guide users to select proper data sources for their applications, Table 3 compares three major features of six simulation data sources, including model availability, building status, and extendibility. In terms of model availability, Huang and Franconi [88] and Griffith et al. [78] do not provide their models for individual buildings. Thus, users can not repeat or extend their work. However, users can still utilize their conclusions on the contributors to building heating and cooling loads, and their methodology to create building models based on the insufficient information from the survey data. On the other side, users can obtain all the inputs and outputs of the individual building models in the Commercial Reference Building Models, Commercial Prototype Building Models, and OpenStudio-Standards gem [39, 45, 133]. Thus, users can change the model inputs and generate new building models based on their specific requirements.

2.2.3 Comparison between Survey Data and Simulation Data

There are discrepancies in energy data between survey and simulation data sources [110]. For example, Turner and Frankel [179] found that simulated energy use deviated from actual energy use by 25% or more in many buildings. Another example is the study of [78]. Although they provided great efforts to create the building energy models to simulate the energy consumption of building samples in the 2003 CBECS, the total site EUIs from the simulations and survey still have huge gaps in some building types. For instance, there is a nearly 40% average relative error for the site EUIs of food services between the simulation results and the 2003 CBECS data. There are four attributes to the differences between the survey data and simulation data: (1) difficulties to account for occupant behavior [153], (2) interactive effects between systems [25], (3) uncertainty in model inputs [63], and (4) inefficiencies in actual buildings [122, 135].

Despite their differences, the survey data and simulation data have their own advantages and disadvantages. On one hand, the survey data has shortages in aspects where the simulation data is excellent. First, the survey data does not contain details, such as system efficiency, insulation information, operating schedules, and hourly energy consumption, while the simulation data sources usually include the information [42, 88, 189]. Also, it is difficult to predict the broad impacts or energy saving potentials of individual components (e.g. a new HVAC equipment or window) by using survey data, which can be easily done by using simulation data [63, 74, 77, 88]. Moreover, it is time consuming and costly to conduct the building survey, and it is difficult to perform the

Table 2.3: Comparisons of the six simulation data sources' features

Feature	**Huang and Franconi [88]**	**Griffith et al. [78]**	**Commercial Reference Building Models**	**Commercial Prototype Building Models**	**OpenStudio-Standards Gem**	**DEnCity**
Model Availability	No	No	Yes	Yes	Yes	No
Building Status	Existing	Existing	Existing and New	New	Existing and New	Existing and New
Extendibility	No	No	Yes	Yes	Yes	Limited

survey and update the survey data frequently. However, users can easily generate sample data under different situations by running simulations.

On the other hand, the survey data has advantages over the simulation data and it has been used to improve the simulation data. The survey data provides the references to determine the model inputs, which ensures that the simulation data can reflect the actual building features [186, 188, 187]. Also, the energy data recorded in the surveys shows the actual energy consumption of existing buildings, and is widely used to calibrate and validate the simulation data [26, 64, 135].

2.3 Overview of Applications by Using the Data Sources

Based on the previous discussion and comparison of survey and simulation data, Section 2.3 summarizes the applications for the three survey data sources and six simulation data sources, and provides examples of the applications.

2.3.1 Applications of Survey Data

Energy-related survey data provides a rich set of useful information for different users [60]. This section classifies the applications into four categories: (1) energy performance benchmarks, (2) energy usage forecasts and predictions, (3) recognition of building energy contributors, and (4) developments of energy policies and standards. Table 2.4 summarizes the recommended data sources for different applications and provides some cases to demonstrate the usages of the data sources.

First, building *energy performance benchmark* is to evaluate the energy performance of a single building by comparing with other similar buildings [43]. The survey data sources provide the representative databases of building samples for building energy performance benchmarking. CEUS and CBECS have a large number of representative sample data. Thus, they are suitable to create energy performance benchmarks for U.S. commercial buildings. For example, based on CEUS, the Lawrence Berkeley National Laboratory (LBNL) developed Cal-Arch, which is a California-based distributional benchmarking model [101, 102]. Moreover, Mathew et al. [116] created a bench-

Table 2.4: Recommended survey data sources for various applications

	Energy Performance Benchmarks	**Energy Usage Forecasts and Predictions**	**Energy Use Contributions of Building Components**	**Supports of Energy Policies and Standards**
CEUS	✓	✓	✓	✓
CBECS	✓	✓		✓
BPD		✓		
Case	Kinney and Piette [101], Mathew et al. [116], EPA [66], Yalcintas and Aytun Ozturk [193], Sharp [158], Sharp [160], Matson and Piette [118]	Porras-Amores and Dutton [141], EIA [58], EIA [61], Kelso [100], Robinson et al. [149], Walter and Sohn [182]	Ma et al. [112], Stader et al. [162]	Sharp [159], ASHRAE [8]

marking tool that enabled users to perform the end-use and component-level benchmarking by using CEUS database. On the other hand, based on CBECS, the U.S. Environmental Protection Agency (EPA) developed Energy Star National Energy Performance Rating System, which is a national regression-based benchmarking model [66]. Also, Yalcintas and Aytun Ozturk [193] developed benchmarks by using Artificial Neural Network (ANN) method. Moreover, existing research developed benchmarks for energy uses in offices and schools [158, 160]. To evaluate the performance of benchmarks created by CEUS and CBECS, Matson and Piette [118] compared the results from the Energy Star National Energy Performance Rating System and Cal-Arch. The results from the two sources validated each other, and both benchmarking tools had the excellent performance. Brown et al. [21] pointed out that the objective of BPD is “not to achieve a representative national sample”. Thus, it is better to create the building energy performance benchmarks by using CBECS and CEUS.

Second, building *energy usage forecasts and predictions* display the future trend of building energy consumption. The survey data sources provide the building characteristics and energy use of existing commercial building samples. By using the regression models, the future building energy consumption can be estimated. All the three survey data sources can be used to forecast the trend of the commercial building sector and predict energy retrofit savings. With thousands of existing building samples in California, CEUS is a suitable source to predict the trend of energy consumption for the California's commercial building sector. For example, Porras-Amores and Dutton [141] assessed the energy and indoor air quality potentials in office buildings based on the CEUS data. By using the CBECS data, many analyses were conducted. EIA [58, 61] and Kelso [100] provided the prediction of energy consumption in the commercial building sectors in the next decades by using the data from CBECS. Also, based on the CBECS data, Robinson et al. [149] estimated commercial building energy consumption with machine learning. On the other hand, BPD can perform both national scale analysis and small-scale analysis for a giving type of building. For example, Walter and Sohn [182] predicted energy retrofit savings of commercial buildings based on the large-scale building energy data from BPD. Since BPD contains enough data to approximate the distribution for specific location and building type [21], it can be also used to predict energy retrofit savings for narrowly defined sets.

The third application category is *recognition of building energy contributors* to quantify their contributions to building energy consumption and energy saving potentials. To do so, the data sources should provide enough sampling data. It should also be able to adjust one or several building characteristics and keep the others as default values. Survey data usually have limited details of building characteristics and energy data. Therefore, it is difficult to decompose the contributions of components to energy consumption only based on the survey data. However, CEUS provides hourly end-use information based on the on-site survey and modeling. Thus, CEUS is the best choice among the three survey data sources to identify the contributions of components to energy consumption in commercial buildings. For instance, Ma et al. [112] and Stadler et al. [162] introduced the possibility to analyze the decomposition of components to end-uses serving for the demand response researches.

The fourth application category is *developments of energy policies and standards*. To make an informed decision on energy policies and standards, policymakers need to understand the building characteristics and energy performance of existing building stocks in a given period as well as predict the potential impact of the new policy and standards. Thus, the survey data serving for policies and standards needs to be representative and be recorded in given periods. For the California's commercial building energy-related policies and standards, CEUS is one of the best choices. For the national energy-related policies and standards, CBECS is one of the survey data sources that are usually selected. For instance, ASHRAE Standard 100 used the CBECS data as reference to create EUI targets [8, 159]. Usually, survey data is not used for urban-scale energy analyses directly because it is difficult to increase a large number of building samples in a short period. Thus, the urban-scale energy analyses are usually conducted based on simulation data, which is introduced in Section 2.3.2.

2.3.2 Applications of Simulation Data

This section introduces the five main applications of simulation data: (1) energy performance benchmarks, (2) energy usage forecasts and predictions, (3) recognition of building energy contributors, (4) developments of energy policies and standards, and (5) urban scale modeling. Table 2.5 summarizes the recommended data sources for different applications and provides some cases to demonstrate their usages.

First, simulation data can be used as building *energy performance benchmarks* [43]. The advantage of the simulation-based benchmarks is that the energy performance evaluation of target buildings will not be affected by the different operating assumptions. There are many successful examples to create building energy performance benchmarks by using the simulation data. For example, to estimate the potential cost saving of energy efficient commercial properties, Deru et al. [37] developed the prototypical building models based on the Commercial Reference Building Models. Similarly, Commercial Prototype Building Models and OpenStudio-Standards gem are also capable of quantifying the potential energy savings of different energy efficient measures. For larger scale analysis, DEnCity can perform the similar analysis with higher granularity as it can

Table 2.5: Recommended simulation data sources for various applications

	Energy Performance Benchmarks	**Energy Usage Forecasts and Predictions**	**Energy Use Contributions of Building Components**	**Supports of Energy Policies and Standards**	**Urban Scale Modeling**
Huang and Franconi [88]			✓		
Griffith et al. [78]		✓			
Commercial Reference Building Models	✓	✓	✓		✓
Commercial Prototype Building Models	✓	✓	✓	✓	✓
OpenStudio-Standards Gem	✓	✓	✓	✓	✓
DEnCity	✓	✓	✓	✓	
Case	Deru et al. [37], Roth et al. [151]	Griffith et al. [77], Griffith et al. [78], Benne et al. [14], Illinois [94], Glazer [74], Hooper et al. [85]	Huang and Franconi [88], Field et al. [71]	Thornton et al. [173]	Hong et al. [84], Macumber et al. [114], Reinhart and Davila [148]

contain simulation results under higher granularity of inputs. Roth et al. [151] provided a case study that illustrates the satisfying performance for energy performance benchmarks. Due to lack of available building energy models and the limited available simulation data in the studies of Huang and Franconi [88] and Griffith et al. [78], these two data sources are not recommended for building energy benchmarks. The operations and weather conditions are different between survey-based benchmarks and target buildings while the simulation-based benchmarks can use the same operations and weather conditions as the target buildings. Thus, by comparing with survey-based benchmarks, simulation-based benchmarks can conduct a pure evaluation of the building energy performance.

Second, simulation data sources can be used for *energy usage forecasts and predictions*. By changing prototypical model inputs based on new devices or improved technologies, users can predict their energy saving potentials. Griffith et al. [77], Griffith et al. [78], and Benne et al. [14] predicted the technical potentials for achieving NZE buildings in the commercial building sector and calculated the impact factors by simulating thousands of building models. Also, Glazer [74] researched on the maximum of technically achievable energy targets for commercial buildings based on the Commercial Prototype Building Models. Moreover, EnCompass (Energy Impact Illinois) identified retrofit opportunities in Chicago office buildings by running 278,000 EnergyPlus simulations based on the Commercial Reference Building [94]. For the U.S. commercial buildings, DEnCity can do the same work as EnCompare with the similar procedure [151]. Survey data is usually used to forecast the energy consumption trend of the whole commercial building sector while simulation data has the ability to predict the energy consumption trend and energy saving potential of a typical building or building type.

The third application is *recognition of building energy contributors*. Because most of the popular building energy simulation programs are able to change the building model inputs and generate the hourly energy end-uses, it is easy to decompose impacts of components to building loads and energy consumptions. Field et al. [71] mentioned the possibilities to analyze the impact of single building component on building energy consumption. Based on the decompositions of building energy models, the building components having great energy impacts can be identified [71, 88, 184, 183, 185]. For example, Huang and Franconi [88] provided a case to identify the building components that have great impacts on the heating and cooling loads in the U.S. commercial buildings. DEnCity can help users identify the building energy contributors quickly by alternating the model inputs and showing their impacts on energy consumption. Generally, the simulation data is a better option to recognize the building energy contributors by comparing to survey data.

The simulation data can be applied for the *developments of energy policies and standards*. For instance, Field et al. [71] introduced that NREL used Commercial Reference Building Models to estimate the aggregate savings of ASHRAE Standard 189.1 compared to 90.1-2004 and 90.1-2007. Recently, the Commercial Reference Building Models were not updated. Thus, it is recommended to develop energy policies and standards by referring to energy-related data from Commercial Prototype Building Models, which are updated to meet the different versions of ASHRAE Standard 90.1 and IECC. For instance, Thornton et al. [173] used the Commercial Prototype Building Models to validate whether the new ASHRAE Standard can achieve the energy and cost saving goals by comparing to the old standard. Moreover, Roth et al. [151] stated that policymakers can investigate the effects of proposed changes on building stocks by running thousands of simulations, which is an application of DEnCity. It is worth to mention that survey data is more appropriate to make policymakers understand the energy performance of existing building stocks while simulation data is more proper to evaluate the building energy saving potentials by using the new standards.

The fifth application is *urban scale modeling*, which is a popular topic recently. Based on the GIS, database, and urban-scale energy calculator, many researches were conducted [84, 114, 148]. The urban-scale energy calculators are usually developed based on EnergyPlus or OpenStudio. It is necessary to create some prototypical building energy models based on the survey data or building energy standards. For the U.S. commercial building sector, Commercial Reference Building Models, Commercial Prototype Building Models, and OpenStudio-Standards gem are the appropriate candidates.

2.3.3 KPIs of Survey and Simulation Data

To guide users to select survey or simulation databases, Table 2.6 lists the KPIs for the five applications. Each KPI has the same weight to evaluate whether the database is suitable for a specific application. Users will provide scores for individual KPIs. The high score means that the database meets the description of KPI. Then users are recommended to select the database with the highest aggregated score, which is the most suitable to be used for the specific application.

Figure 2.3 and 2.4 show the case to select the survey and simulation databases for the five applications. As the applications were analyzed in Section 2.3.1 and 2.3.2, it is necessary to determine the advantages and disadvantages for each candidate database based on the KPIs and then score the KPIs for each database. The left sub-figures of Figure 2.3 and 2.4 respectively show the scores for individual KPIs for each survey database and simulation database. The right sub-figures of Figure 2.3 and 2.4 respectively show the aggregated scores with the same weight. The vertical dot dash lines are the thresholds of the recommended databases. The databases with the higher score are recommended. For example, the CEUS and CBECS are recommended for the energy performance benchmarks. It is worth noting that this chapter adjusts the aggregated scores for Huang and Franconi [88] and Griffith et al. [78], and recommended these two databases because their reports respectively provide data for energy use contributions of building components, and energy usage forecasts and predictions. This section provides a general guideline. Based on the KPIs and guideline, users still need to provide their own judgments to select the suitable databases.

2.3.4 Combined Applications of Survey and Simulation Data

Due to the complement of two data types, combined applications of survey and simulation data make the results more robust and accurate for special purposes [22, 78, 105, 120]. The building energy simulation can generate more samples based on the survey data. On the other hand, the survey data can be used to validate and calibrate the building energy simulation, and then improve the quality of the simulation results.

Table 2.6: KPIs for the five applications

Application	**KPI**
Energy Performance Benchmarks	Be representative
	Not be affected by the operations
	Provide building characteristics and energy use
Energy Usage Forecasts and Predictions	Have large sample size/good extendibility
	Provide building characteristics and energy use
Energy Use Contributions of Building Components	Be able to control variables
	Provide building characteristics and energy use
Supports of Energy Policies and Standards	Be representative
	Record data in given periods
	Follow the energy policies and standards
	Keep updating
Urban Scale Modeling	Be representative
	Have large sample size/good extendibility
	Be able to control variables
	Provide building characteristics and energy use
	Provide the whole building energy models

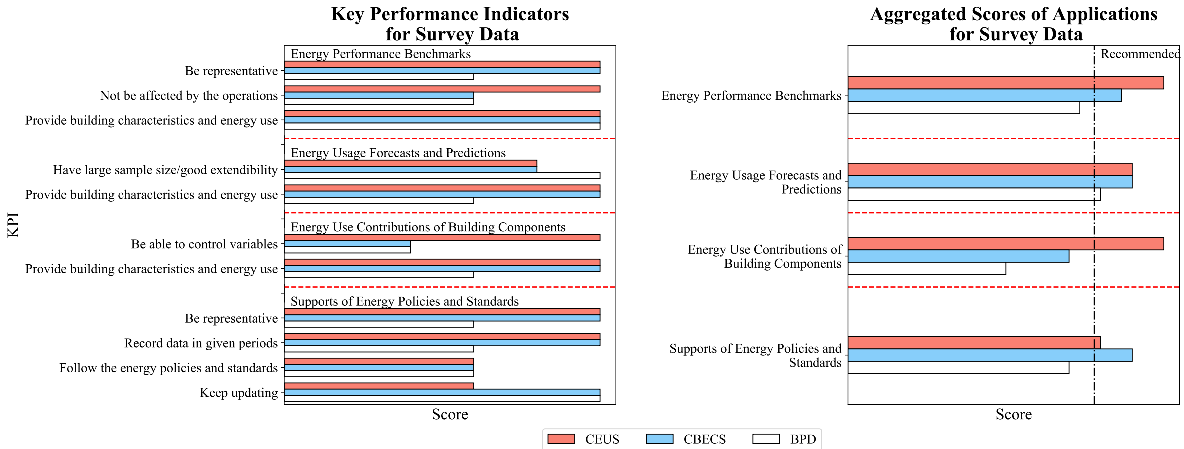


Figure 2.3: Key performance indicators and Aggregated scores for survey data

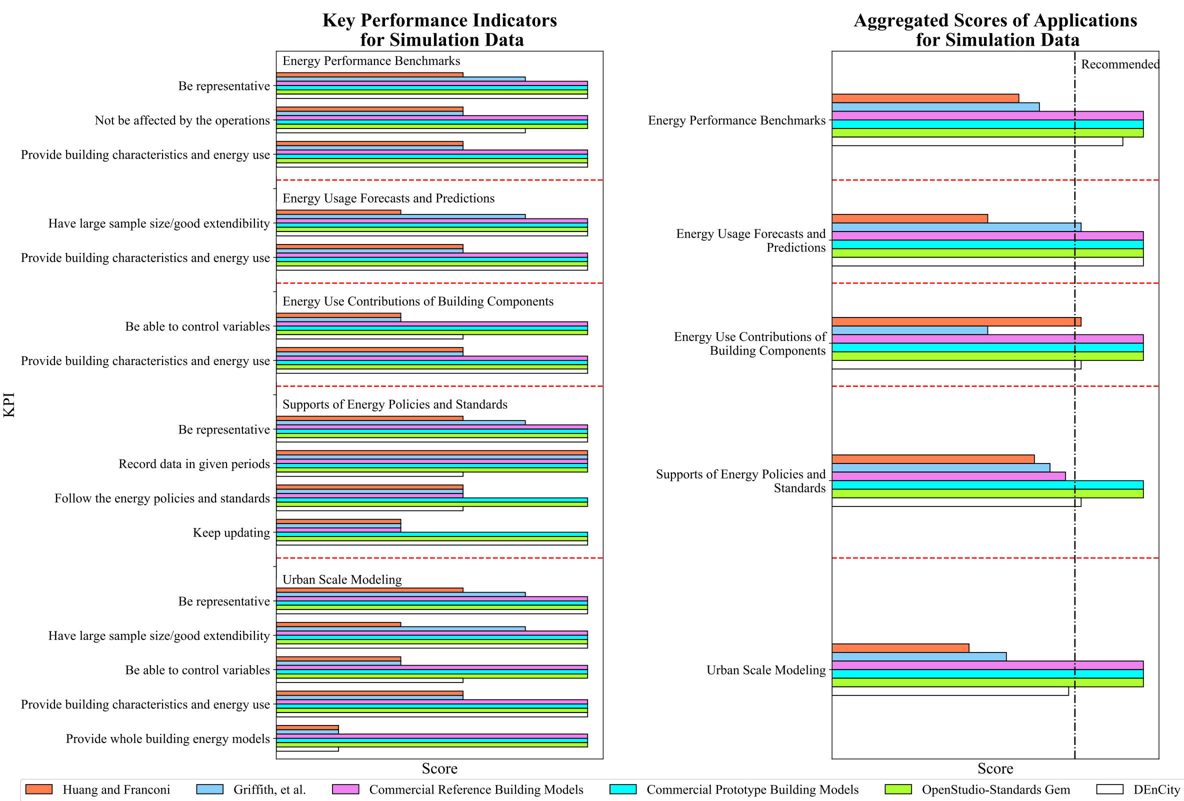


Figure 2.4: Key performance indicators and Aggregated scores for simulation data

On one hand, the simulation data, fast and inexpensively generated by building energy simulation programs, complements the shortages of the survey data. First, the simulation data can normalize the weather conditions and building characteristics in survey databases, which can avoid the errors to evaluate energy performance caused by different conditions. For example, DrCEUS adjusted the on-site survey data in CEUS from actual historical weather data to normalized weather data [22, 144]. Second, the simulation data can generate more details of energy uses. For example, the CBECS data can only provide yearly energy data for the whole building. The simulation data can provide the details, such as hourly energy data for major components. Since CEUS combines the survey and modeling methods, hourly end-use energy consumptions can be identified [22]. Furthermore, the simulation data can consider various possible situations and broaden the sample sizes in survey data sources. Griffith et al. [78] developed over 4,000 building energy models based on the 2003 CBECS. Then based on the models, Griffith et al. [77] and Benne et al. [14] changed the settings of the models to analyze the potential for achieving NZE buildings and assess the energy impacts of outside air. Finally, it is easy to conduct the uncertainty and sensitivity analyses by using simulation data [63, 155, 156, 174]. The energy data from surveys is affected by ambient conditions, building characteristics, and operating. Therefore, it is difficult for survey data to analyze the uncertainty of energy consumption due to the variances of some inputs and identify sensitive inputs to energy consumption. The simulation data can complement this shortage of the survey data. For instance, Eisenhower et al. [63] provided a successful case to conduct uncertainty and sensitivity analyses, and decomposition of building energy models.

On the other hand, the survey data can also help to improve the quality of the simulation data. First, survey data provide some important model input data, although not all, for developing building energy models. For instance, several studies provided a methodology how to use the 2003 CBECS to model envelopes and system [186, 188, 187]. Griffith et al. [78] provided a procedure to develop building energy models based on the 2003 CBECS data. Also, survey data can validate and calibrate the building models and improve the simulation results. As the discussion in Section 2, there are differences in energy data between survey and simulation data [78, 179]. Since survey data or measured data reflects the actual cases, they can be used to evaluate the quality of building energy models. Many researches provided methodologies to validate and calibrate the building energy models based on the survey data or measured data [82, 127, 135, 145, 146, 147, 167]. After validation and calibration, the simulation data is more persuasive.

2.4 Summary

This section conducts a critical review of energy-related data for U.S. commercial buildings along with their applications. Three typical survey data sources and six representative simulation data sources are summarized and compared.

Due to different objectives, the three survey data sources have different collecting methods and features. CEUS is a state-level in-depth survey data source, CBECS is a national in-depth source, and BPD is a national large-scale source. Thus, CEUS and CBECS provide detailed energy-related data. Even, by using DrCEUS, the hourly end-use energy consumption can be obtained in CEUS. BPD has the largest sample size among the three survey data sources. Among simulation data sources, Huang and Franconi [88] and Griffith et al. [78] do not provide their models for individual buildings, which limits users to repeat or extend their work. Commercial Reference Building Models, Commercial Prototype Building Models, and OpenStudio-Standards gem are open sources for their building energy models. Users can change model inputs and conduct new simulations. DEnCity, a multi-purpose building simulation database, provides users a quick analysis of building energy consumption without running the building energy simulation.

Both survey data and simulation data can be used for energy performance benchmarks, energy usage forecasts and predictions, recognition of building energy contributors, and developments of energy policies and standards. In addition, simulation data can be used to conduct urban scale modeling. Further, this chapter provides the KPIs to guide users for selections of databases. Because of the advantages and disadvantages of the survey data and simulation data, the combined applications of both data types are also selected in some researches. By doing so, the two types of data can complement each other.

Various users can use the section for their own work. Building owners and managers can select data sources for benchmarking and use the existing cases for applications as references. Energy modelers can follow the research mentioned in this section to forecast the energy consumption in U.S. commercial buildings. Product developers can use this guideline to gauge the market potential. Policy makers can update and validate the building energy standards by using data sources and the related applications mentioned by the section as reference.

This chapter is the basis for the standardized computational framework. Based on the comprehensive literature review about existing data sources and applications for these data sources, Chapter 3 develops the framework, which is able to create prototypical building energy models and conduct building energy analyses.

Chapter 3

Standardized Computational Framework

3.1 Introduction

This chapter develops a standardized computational framework for prototypical building energy model creation and building energy analyses. By reviewing the existing research, both prototypical building energy model creation and building energy analyses consist of four steps: (1) provide requirements of specific applications, (2) select data sources for these applications, (3) process data from different data sources, such as data cleaning and building energy simulations, and (4) achieve objectives. Figure 3.1 shows the general workflow for existing research. By using this general workflow, a rich set of research has been conducted.

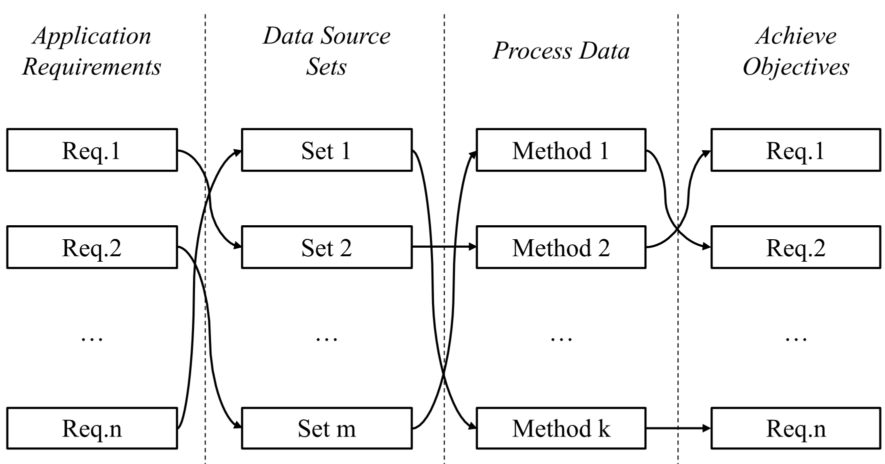


Figure 3.1: Current general workflow for prototypical building energy creation and building energy analyses

However, it is possible to select inefficient methods for data source selection, simulations, data analyses, and result generation by using this current workflow. Furthermore, the results may not meet the requirements or evenly are wrong. Generally, there are three main reasons to cause these potential problems:

(1) There is no time to conduct a comprehensive literature review before selecting methods for prototypical building energy model creation or building energy analyses. The limited references are insufficient to conduct deep analyses and generate high-quality results.

(2) It is complex to design the suitable workflow and write clear scripts to systematically and automatically create prototypical building energy models and conduct building energy analyses. Furthermore, the new research is sometimes conducted by using the workflow and scripts from previous research. However, it is possible that these workflow and scripts are not proper for new specific cases.

(3) It is difficult to consider all details to select data sources, process the data, conduct simulations, and analyze the results. If partial work is conducted manually, some mistakes are possible to be caused by carelessness. Furthermore, if some decisions are made based on arbitrary judgments, some biases may lead to the inaccurate or evenly wrong results.

Thus, it is meaningful to design a standardized computational framework based on a comprehensive review about existing related research. Based on the literature review summarized in Chapter 2, this chapter develops a new standardized computational framework. Figure 3.2 shows the general workflow to create prototypical building energy models and conduct building energy analyses by using this new framework.

This new workflow has three nodes (P1, P2, and P3), which are used to identify the best procedures to achieve objectives provided in the application requirements. First, the node, P1, is used to identify the most suitable data sources for specific application requirements. Second, the node, P2, is used to identify the best methods to process the data from the selected data

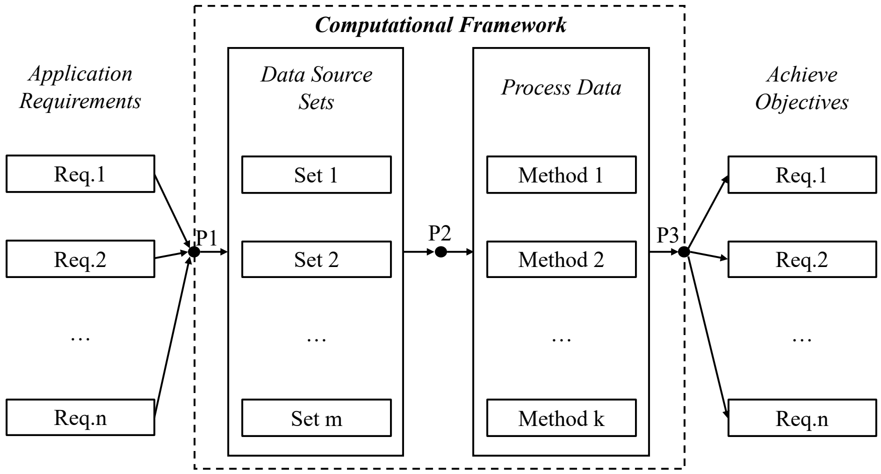


Figure 3.2: New general workflow for prototypical building energy creation and building energy analyses by using the standardized computational framework

sources. Third, the node, P3, is used to generate and validate the results, which are required in the application requirements. To develop this standardized computational framework, six questions need to be answered:

(1) What information need users provide in the forms of application requirements?

(2) Are there sufficient data sources for various building energy analyses?

(3) What are the rules for a standardized computational framework to identify the best data sources from the sets of the data sources?

(4) How does a standardized computational framework convert data from different data sources into the required format?

(5) What factors should a standardized computational framework consider when selecting methods to process data?

(6) What modules should a standardized computational framework include for building energy analyses based on the simulation results?

The following sections answer these six questions and detail this standardized computational framework. Section 3.2 shows the structure of this framework. Section 3.3 makes a discussion about the potential applications of this framework. Section 3.4 makes a conclusion and briefly introduces the following research by using this framework.

3.2 Structure of the Standardized Computational Framework

This section introduces the structure of the standardized computation framework for prototypical building energy model creation and building energy analyses. This framework is developed by using a programming language, Python, which automatizes the whole process and is used to identify the best procedures to generate results. This framework consists of six steps, which are shown in Figure 3.3 with red numbers and dash outlines. They are (1) requirements for applications, (2) data source selection, (3) data pre-processing, (4) simulations, (5) data post-processing, and (6) result generation.

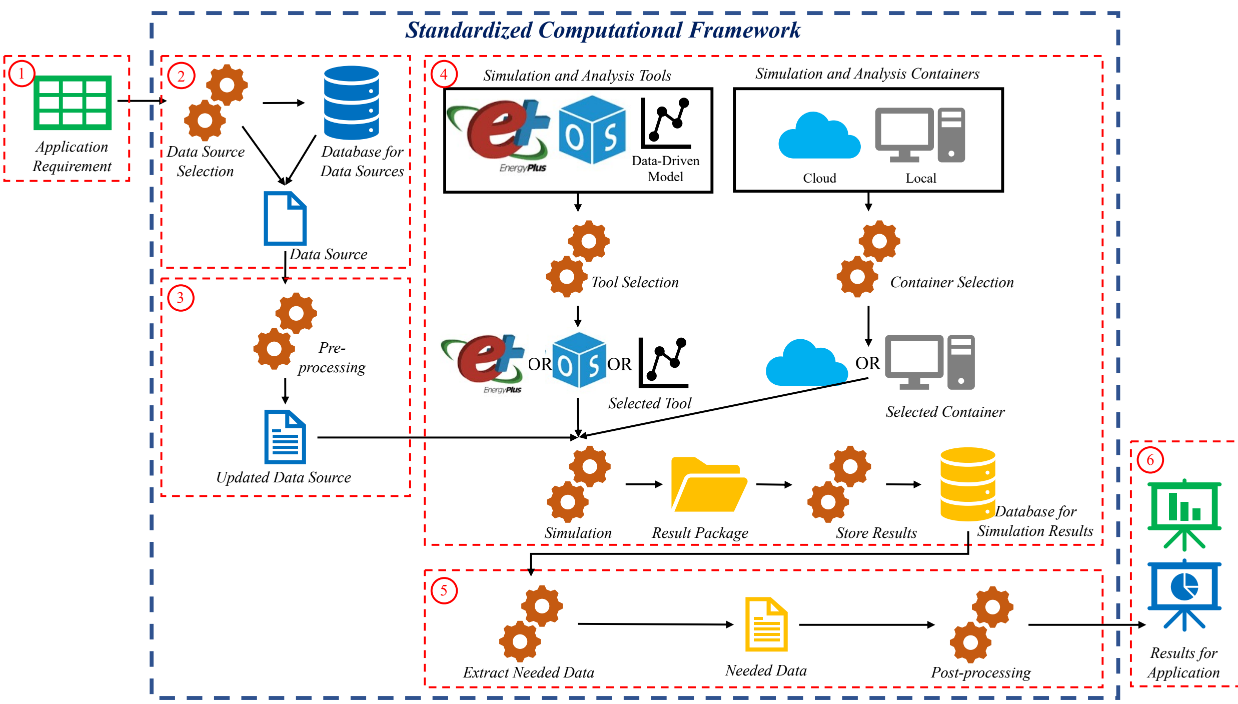


Figure 3.3: Structure of the standardized computational framework

In Step 1, users provide application requirement forms with all necessary information. For example, the forms have to include the specific types of applications: prototypical building energy model creation or building energy analyses. In Step 2, based on the requirements of applications, the framework selects data sources from the database, which is the work for the P1 node shown in Figure 3.2. In Step 3, the framework pre-processes the data from the data sources and prepares the required data for simulations. In Step 4, the tools and containers for building energy simulations are selected. The simulations are conducted by using the selected tools and containers. All key parameters and simulation results are stored into another database, which is used to avoid loss of the data. Furthermore, the data in this database can be used for future related research. In Step 5, the key parameters and simulation results are extracted. By using these parameters and results, the standardized computational framework completes to create prototypical building energy models or conduct building energy analyses. The method for these steps are the work for the P2 node shown in Figure 3.2. In Step 6, the results are processed and sent back to the users, which is the work for the P3 node shown in Figure 3.2. Figure 3.4 shows the six highlights in the standardized computational framework. Based on these six highlights, the following sections will answer the six questions asked in Section 3.1.

3.2.1 Application Requirement Form

The application requirement form requests users to provide a table with all requirements for their specific applications. Table 3.1 lists the necessary information for different requirements. The items 1 to 7 show the basic information that needs to be provided. If the users have specific needs, they should put details into the eighth item. Then the standardized computational framework will transfer the information from the table into the inputs of the framework, which are readable for Python.

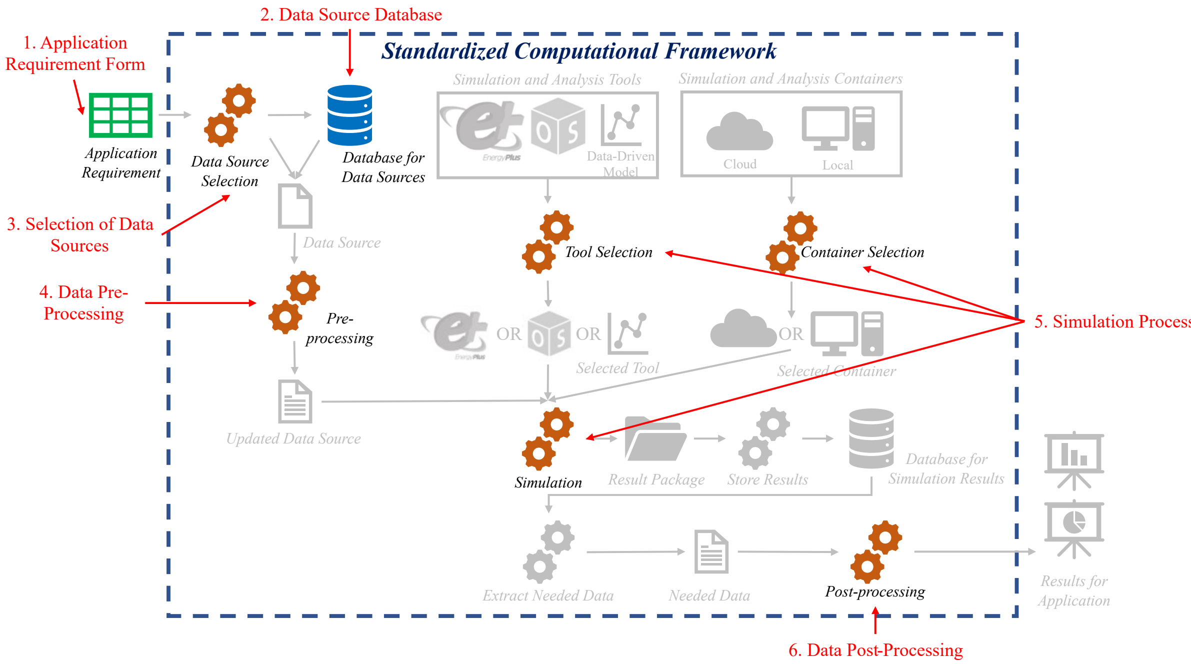


Figure 3.4: Highlights in the standardized computational framework

3.2.2 Data Source Database

This database stores main survey and simulation energy-related data sources for U.S. commercial buildings, such as the 2003 Commercial Buildings Energy Consumption Survey (CBECS), 2012 CBECS, DOE Commercial Reference Building Models, and DOE Commercial Prototypical Building Models [51, 57, 39, 45]. Since current prototypical building energy models only represent limited types of buildings in certain countries, the standardized computational framework is creating new models for the missing types, such as college/university buildings [195], auto service and repair shops [196], and religious worship buildings [194]. To implement the database, these models are stored as the starting point for future research. The methodology to create prototypical building energy models will be introduced in Chapter 4. By using this methodology, Chapter 5 creates the prototypical building energy models for the missing types.

Table 3.1: Necessary information for the application requirement form

No.	Item	Description
1	Type of Applications	It consists of five options: 1) Energy Performance Benchmarks; 2) Energy Usage Forecasts and Predictions; 3) Energy Use Contributions of Building Components; 4) Supports of Energy Policies and Standards; 5) Urban Scale Modeling.
2	Building Type	The types of the researched commercial buildings need to be provided.
3	Location/Climate	The typical cities or ASHRAE climate zones need to be provided.
4	Type of Data Sources Preferred	It consists of four options: 1) Survey data sources; 2) Simulation data sources; 3) Combined both survey and simulation data sources; 4) No preference.
5	Tools Preferred	It consists of four options: 1) EnergyPlus; 2) OpenStudio; 3) Data-driven model; 4) No preference.
6	Container Preferred	It consists of three options: 1) Local; 2) Cloud; 3) No preference.
7	Researched Variables/ Model Inputs	For survey data, users need to provide the researched variables; for simulation data, users need to provide the researched model inputs.
8	Specific Requirements	The users also need to provide specific requirements, such as sampling method, uncertainties of variables or model inputs, and number of the samples.

3.2.3 Selection of Data Sources

This highlight is objective to select the most suitable data sources for specific applications. If a table for the application requirements provides the preference of the data sources, the standardized computational framework will select data sources based on this preference. Otherwise, the framework will select data sources based on the key performance indicators (KPIs) and aggregated scores of different data sources. Figure 2.3 have already showed the KPIs and aggregated scores for the three main survey data sources; Figure 2.4 have already showed the KPIs and aggregated scores for the six main simulation data sources. The data source, which has the highest score, tends to be selected. For example, if the research is support of the energy policies and standards by using the survey data, the standardized computational framework will select the CBECS, which has the highest aggregated score.

3.2.4 Data Pre-Processing

Data pre-processing aims to collect and clean data from the selected data sources, and then convert the data from data sources into the required formats. Figure 3.5 shows the workflow to pre-process the data. The standardized computational framework firstly identifies whether the selected data sources include survey data.

If there is no survey data included, based on the information in the application requirement forms, the framework will decide whether it needs to modify the model inputs. If model inputs do not need to be modified, the framework will use the models as baselines; otherwise, the model inputs will be modified by following the requirements and then use the new models as baselines.

If the selected data sources include survey data, the framework will collected related data and clean data firstly. Then the data will convert the data formats. If the data is used to create EnergyPlus or OpenStudio models, the data will be converted into model inputs; otherwise, the data will be converted into the formats required by regression models.

The building energy simulations also needs the uncertainties or values of the researched variables or model inputs. Thus, the outputs of the data pre-processing consist of two parts: (1) training data for regression models or baseline models, and (2) uncertainties or key values for the researched variables or model inputs. The key values usually include median, average, and 25% and 75% percentile values.

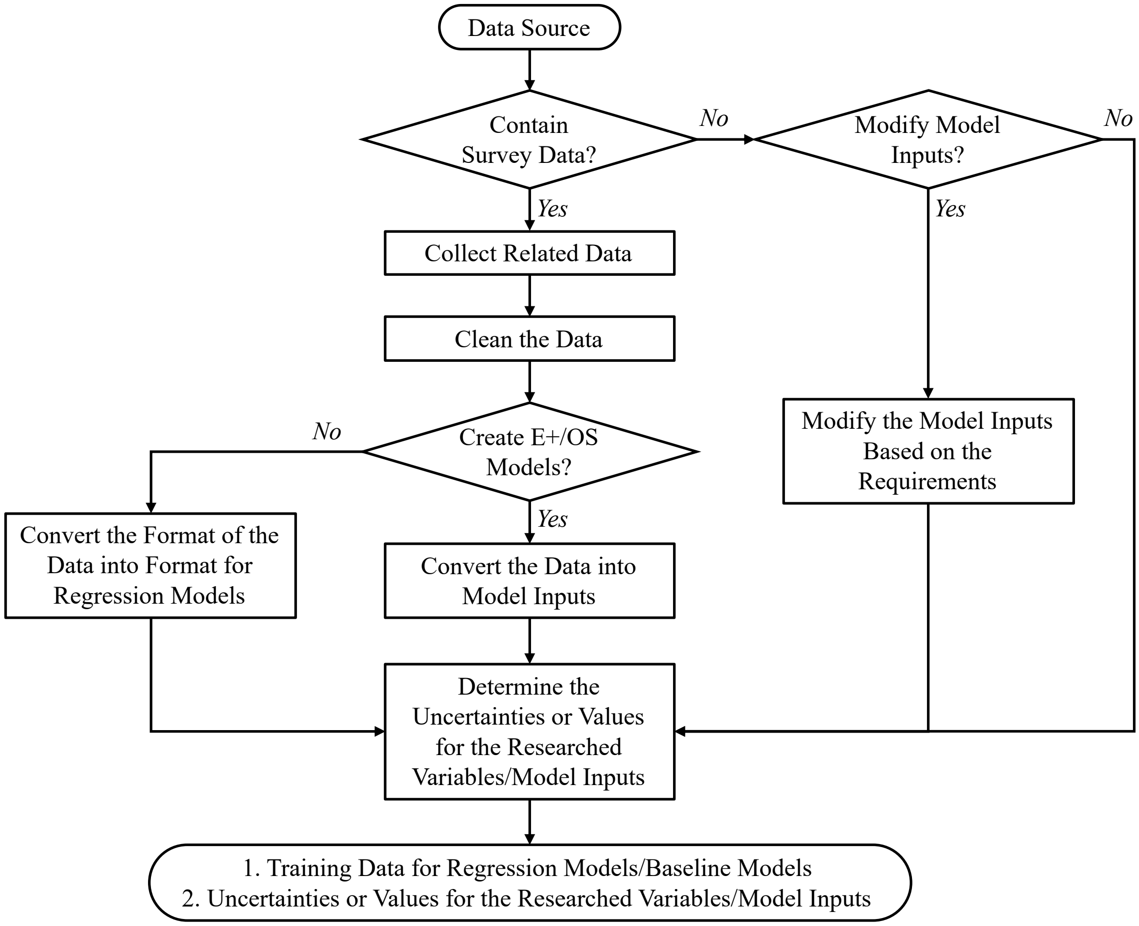


Figure 3.5: Workflow for the data pre-processing

3.2.5 Simulation Process

Simulation process consists of tool selection, container selection, and simulation. In this highlight, three questions needs to be answered for specific applications: (1) Which tool does the standardized computational framework select for simulation? (2) Are simulations run locally or on the cloud? (3) Are simulations run in parallel or in succession? Figure 3.6 shows the flow chart, which answers these three questions. The framework firstly identifies whether there are EnergyPlus or OpenStudio models in the outputs of the data pre-processing.

If there is no EnergyPlus or OpenStudio model, the framework will develop regression models by using the training data. Since the development of regression models usually needs short computational time and limited computing sources, the simulations will be conducted locally. The framework includes a rich set of Python packages to develop regression models, such as scikit-learn and XGBoost [138, 23]. If application requirement forms do not specify the methods to develop regression models, the framework will try all methods in the set. Then the methods that have simple structure and can generate accurate results are selected to create regression models. After that, the framework will randomly select some data to test the performance of the regression models. If more than one regression methods are selected, the simulations will be run in parallel.

If the EnergyPlus or OpenStudio models are used, the framework then identifies whether uncertainties of model inputs are provided. If only the values of the selected model inputs are provided, the number of building samples is small, which usually costs the short computational time and limited required computational sources. Thus, the simulations will be run in succession locally.

If the uncertainties of model inputs are provided, the first step is to estimate the sample size. If the sample size is small (sample size is no larger than m), the framework will select samples and run EnergyPlus or OpenStudio simulations in succession locally. If the sample size is large (sample size is larger than m and no larger than n, which n is larger than m), the framework will select samples and run EnergyPlus or OpenStudio simulations in parallel on the cloud. If the sample size is super large (sample size is larger than n), the framework will select a small building sample sets in the spare grid firstly and run EnergyPlus or OpenStudio simulations in parallel on the cloud. Based on the simulation results, the framework conducts sensitivity analysis to identify the sensitive model inputs. Then the framework only focuses on these sensitive inputs. After this process, the dimensions of the problems are reduced. For example, assuming that there are 20 model inputs at first and only 10 inputs are sensitive, if three values are select for each values and all possible combinations are considered, the new sample size is only $\frac{1}{3^{10}}$ times by comparing with the former one. To continue reducing the computational time, the framework uses the results of the small sample size to train meta-model and use the meta-model to run large-scale building energy simulations. Table 3.2 provides an example about the comparison of the computational time by using EnergyPlus and meta-model. In the example, the computational time of meta-model is only 3×10^{-5} times of the EnergyPlus models.

In this highlight, the framework usually consumes high computational time to conduct thousands of simulations by using full-scale building energy simulation tools, such as EnergyPlus and OpenStudio. To avoid duplicating the process, it is important to save all important data. Thus, after completing the large-scale building energy simulations, the framework stores the key variables, model inputs, and energy data into a database. The data in the database will be extracted in the next step. Furthermore, the data can also be used for future research.

Table 3.2: Comparison of computational time by using EnergyPlus and meta-model

Sample Size: 1,000,000 Number of Cores for the Computer: 4	
EnergyPlus	**Meta-Model**
1.9 years	30 min

3.2.6 Data Post-Processing

Data post-processing is used to process the results of simulations and generate the required data for different applications. The standardized computational framework consists of four modules for data post-processing, which are shown in Figure 3.7. The first module, named as "Data Analysis Module", can conduct four types of simple data analyses: (1) comparison of energy data; (2) classification/clustering/regression; (3) correlation analysis; and (4) sensitivity analysis. The results for comparison of energy data can be used to quantitatively evaluate the energy savings by conducting building energy retrofits or upgrading building energy standards. The results of classification, clustering, and regression can be respectively used to identify which building type a building belongs to, group similar buildings into sets, and predict the future energy consumption. The results of correlation analysis can be used to identify the relationship between different variables or model inputs. The results of sensitivity analysis can be used to identify the relationship

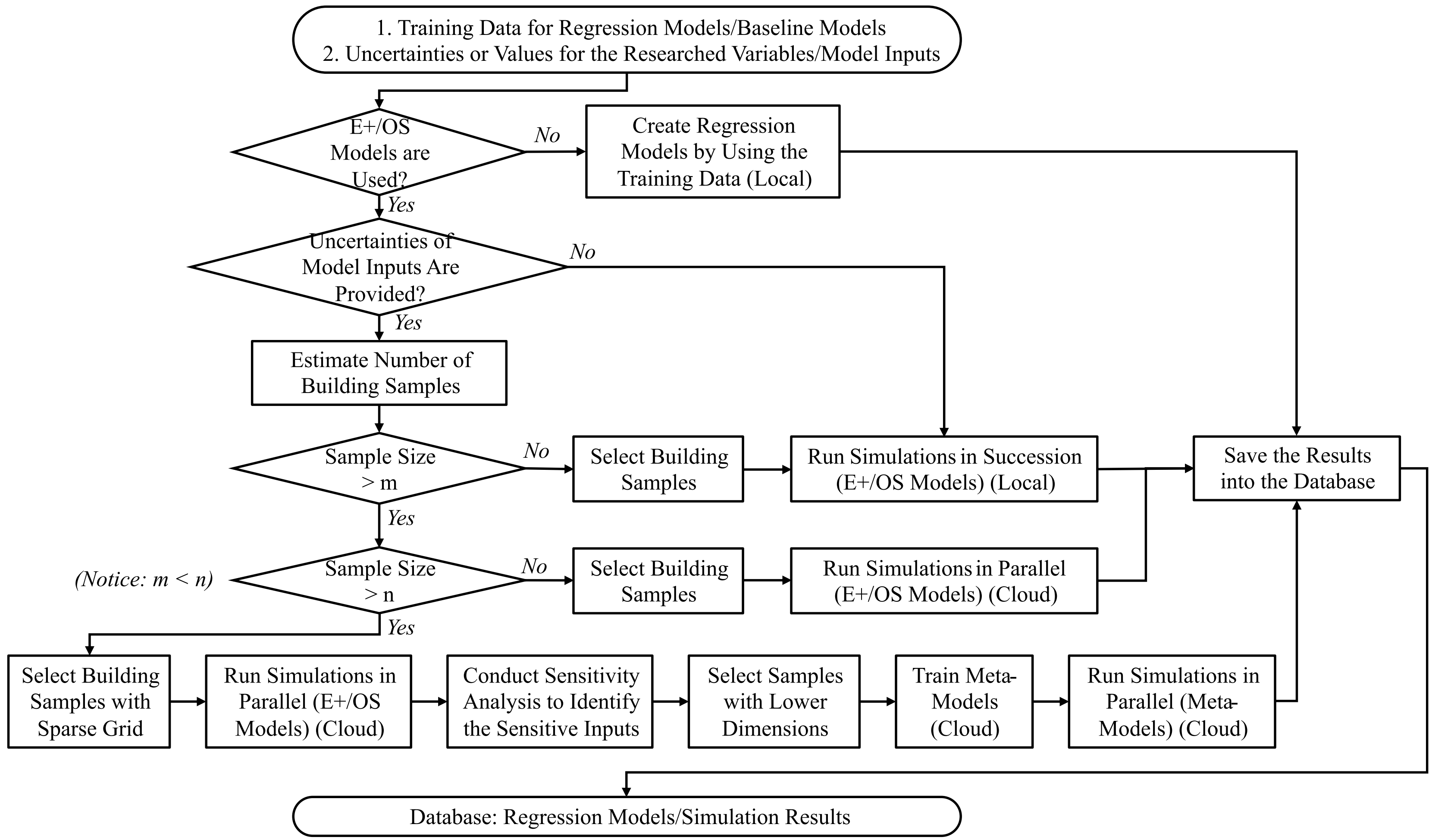


Figure 3.6: Flow chart to decide the simulation process

between building characteristics, building operations, and building energy consumption. A rich set of methods are included for these four types of analyses and this dissertation will provide several examples in the following chapters.

The second module, named as "Model Calibration Module", is used to calibrate EnergyPlus or OpenStudio models based on the empirical data and users' criteria. There are two calibration strategies. The first strategy is for the building models representing specific buildings. Users need to provide the monthly energy data from utility bills and hourly data from sensors. The workflow to calibrate these buildings is developed based on a rich set of existing research [82, 124, 143, 136]. The second strategy is for the prototypical building energy model. The data is mainly collected from survey data and existing research [39, 45, 51, 57, 78, 186, 188]. Usually, in this case, the data only provides the yearly end use energy data. A new methodology is needed and it will be detailed in Chapter 4.

The third module, named as "Validation Module", is used to validate the performance of results calculated by using the standardized computational framework. Users can provide either criteria based on calibrated data from on-site measurements and existing data sources, or rule-based criteria for model validation. The last module, named as "Visualization Module", is used to provide readable result summary. The standardized computational framework can provide the various types of chart, such as bar chart and boxplot. If users only need to output the raw data, they can skip this module.

3.3 Potential Applications by Using the Standardized Computational Framework

This section discusses the applications by using the standardized computational framework. Section 3.3.1 discusses the applications for prototypical building energy model creation by using this framework. Section 3.3.2 discusses the applications for building energy analyses by using this framework.

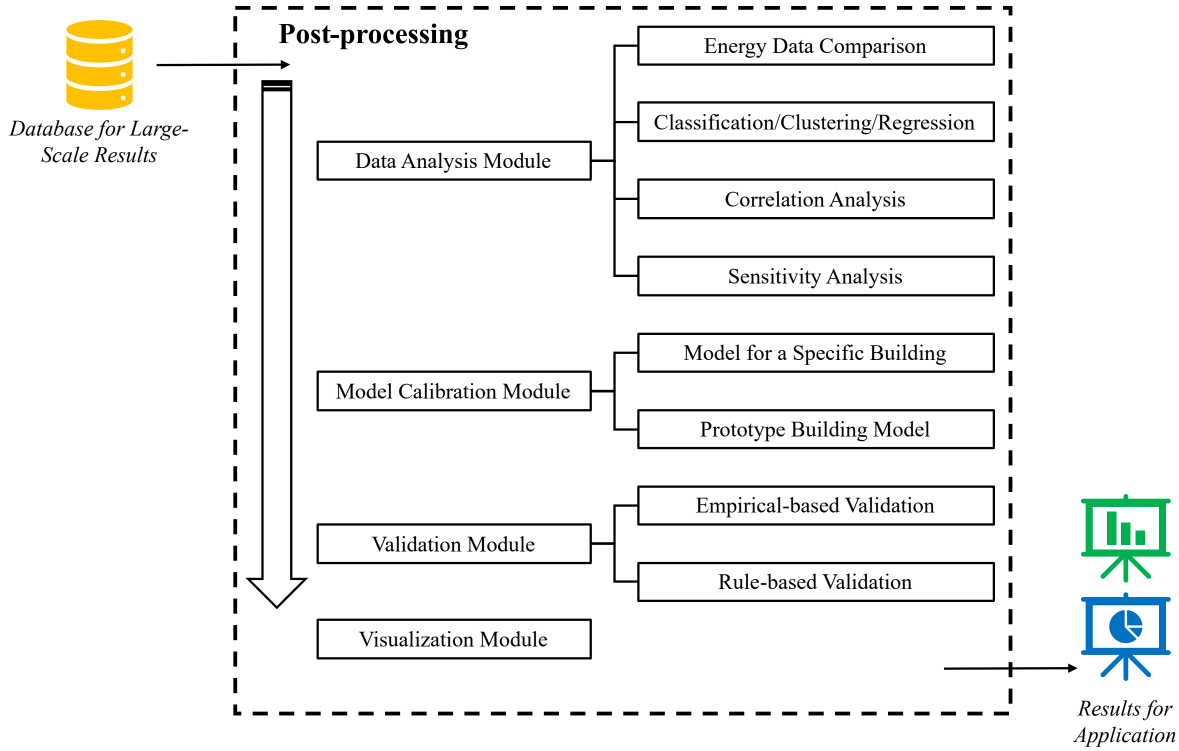


Figure 3.7: Four modules in the data post-processing

3.3.1 Application for Prototypical Building Energy Model Creation

The prototypical building energy models provide the starting point for research on building energy analyses [36]. These models represent realistic building characteristics, building assets, and building operations. Furthermore, these models have the representative energy performance. By reviewing the existing sets of prototypical building energy models, some building types in some counties are missing. However, these missing models are required for building energy analyses. This standardized computational framework can create prototypical building energy models for these missing building types, which implements the existing sets of prototypical building energy models.

Figure 3.8 shows the application for prototypical building energy creation. First, in the requirement for applications, the framework provides the related information for creating prototypical building energy models. Second, this framework selects survey data sources for the model creation. Third, the framework collects and cleans the data from the selected survey data sources. Then the data is converted into model inputs. It is noticeable that some required data is not provided by survey data sources and needs to be provided by users in the application requirement forms. The data is usually collected from the existing related research and building energy standards. Fourth, the framework identifies the possible building samples and conducts simulations for these samples. In Step 5, the framework calibrates the prototypical building models based on the simulation results and then validates the results by using the empirical data. Finally, the prototypical building energy models are generated and they are the outputs for this application. The new prototypical building energy models will be stored into the database for simulation data sources. These new models will be used for future research. Chapters 4 and 5 will detail this procedure and create prototypical building energy models for four U.S. commercial building types.

3.3.2 Application for Building Energy Analyses

Based on the data sources, various building energy analyses can be conducted. The existing research related to building energy analyses has already been reviewed in Section 2.3. The standardized computational framework can systematically conduct different types of building energy analyses.

Figure 3.9 shows the applications for building energy analyses by using the framework. First, in the requirement for applications, the framework provides the related information for specific building energy analyses. Based on literature review in Section 2.3, there are five main types of applications. Currently, this framework mainly focuses on the building-level analyses. Thus, the framework can conduct analyses for *energy performance benchmarks*, *energy usage forecasts and predictions*, *energy use contributions of building components*, and *supports of energy policies and standards*. However, for urban scale modeling, the framework is only able to do preparation and conduct building-level simulations. In the future, the framework will be updated and include the

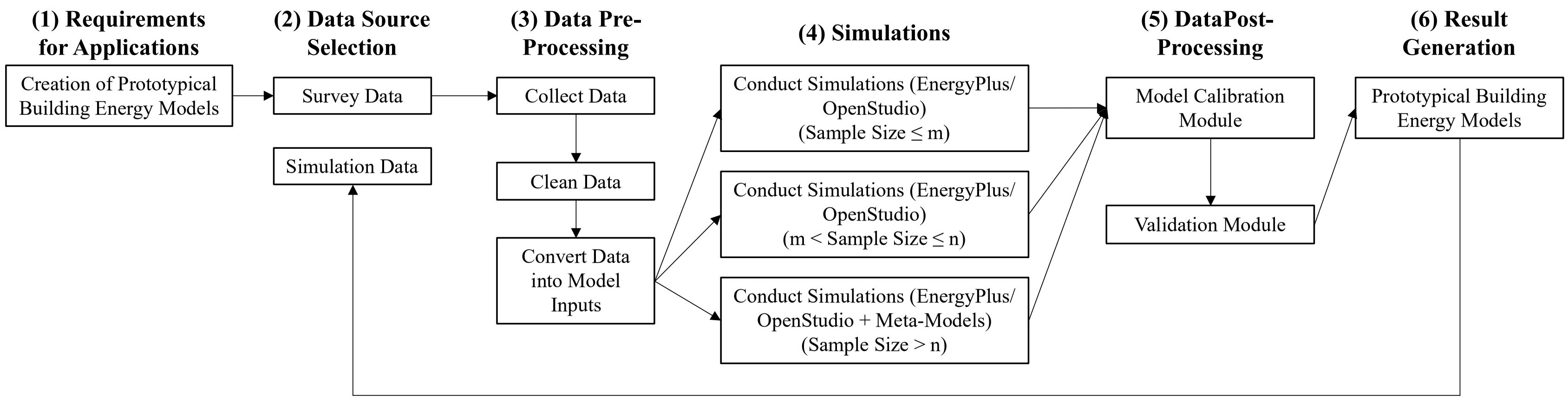


Figure 3.8: Application for prototypical building energy model creation

urban scale modeling. Second, the survey data or simulation data is selected based on the different requirements. Third, if survey data is selected, the framework will collect and clean data, and then convert data into required formats; if simulation data is selected, the framework will identify whether model inputs need to be modified. Fourth, based on the requirements and data provided in Step 3, regression models are created or simulations are conducted. Fifth, the framework decides which modules are used for the data post processing. Finally, the required results of building energy analyses are generated and sent to the users. Chapters 6 and 7 will provide two examples for the building energy analyses by using this framework.

3.4 Summary

This section details the structure of the standardized computational framework, and introduces potential applications of this framework about prototypical building energy model creation and building energy analyses. Chapter 4 provides the detailed methodology for prototypical building energy model creation. By using the framework, Chapter 5 creates prototypical building energy models for four U.S. commercial building types. The medium office buildings and religious worship buildings are used as two case studies to details the procedures of model creation. After that, Chapters 6 and 7 analyze the impacts of energy savings and electricity pricing programs on energy efficiency measure (EEM) selection. The models for U.S. medium office buildings are used as an example to analyze these impacts.

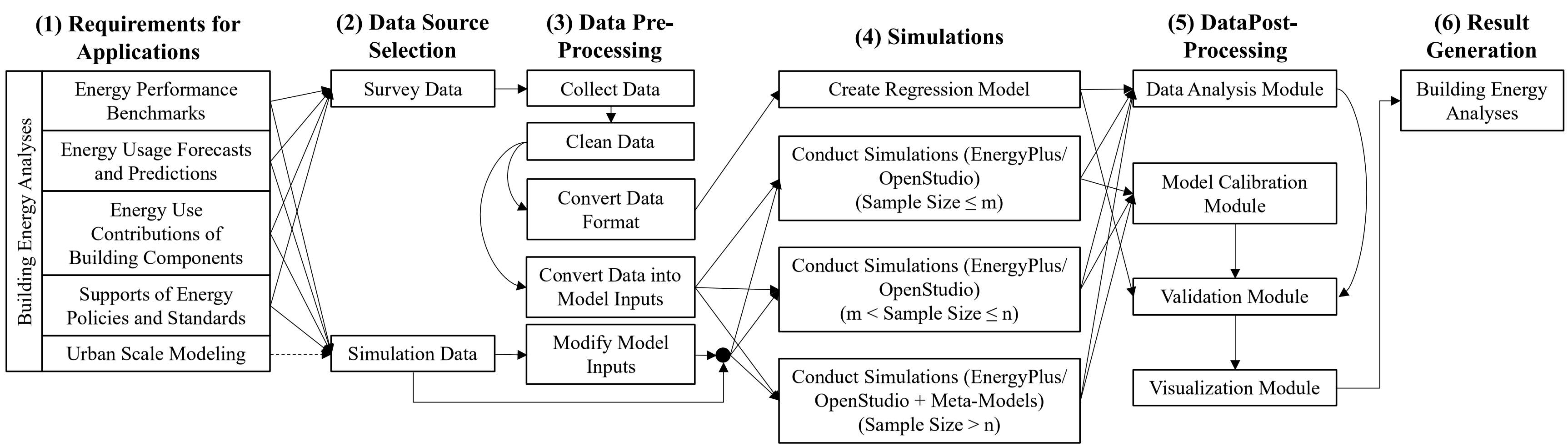


Figure 3.9: Applications for building energy analyses

Chapter 4

Methodology to Create Prototypical Building Energy Models

This chapter proposes a new methodology to create prototypical building energy models. This methodology can be implemented by using the standardized computational framework developed in this dissertation.

4.1 General Description

Prototypical building energy models of existing buildings should contain the typical building characteristics, include relevant operating schedules, and reflect the typical energy performance of that building type for a certain vintage at a given climate zone. This section proposes a new methodology to systematically create prototypical building energy models to meet the above requirements. To create prototypical building energy models, data analytics is applied to a rich set of building energy data sources. Figure 4.1 illustrates the six key steps of the proposed methodology for determining model inputs, and calibrating and validating the building energy models with the available data sources. Step 1 is to identify the requirements for model inputs based on the selected building energy simulation program. In order to determine the model input values, Step 2 is to collect data for the specific building type, location, and vintage from several data sources. Step 3 is to clean the data to exclude atypical and erroneous data. Because some data cannot directly be used as model inputs, Step 4 converts the data into model inputs. Steps 1 through 4 will be introduced in Section 4.2 in detail. After that, Step 5 calibrates the prototypical building energy models to obtain the energy results that represent the energy performance of typical buildings, which will be introduced in Section 4.3. Finally, Step 6 validates the energy results by using the empirical data, which will be introduced in Section 4.4.

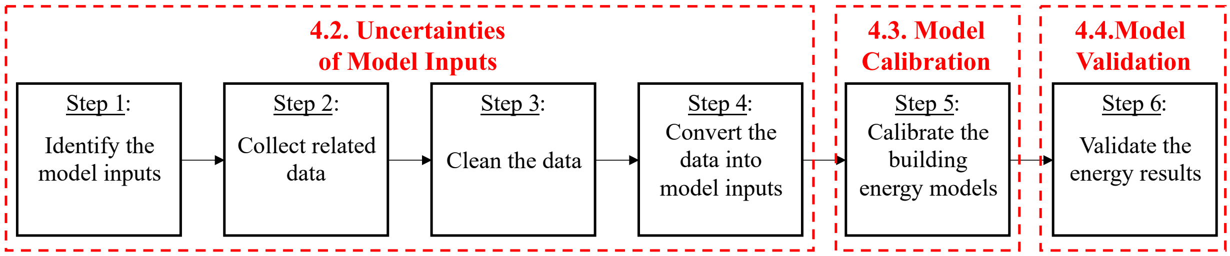


Figure 4.1: Workflow of the proposed methodology in creating prototypical building energy models

4.2 Model Inputs (Steps 1 - 4)

4.2.1 Step 1: Identify the Model Inputs

Figure 4.2 summarizes the possible model inputs of prototypical building energy models from high level frameworks to low level frameworks. The top level of the model inputs can be divided into the following six categories: *Weather Condition*, *Geometry*, *Envelope*, *Schedule*, *Internal Load*, and *System*. First, the *Weather Condition* consists of the ambient parameters, such as ambient temperature and wet bulb temperature. The hourly ambient parameters are needed if model developers plan to simulate hourly energy consumption of the buildings. Second, the *Geometry* contains dimensional and shape parameters, including total floor area and window location. Next, the *Envelope* is composed of two sub-levels; the upper sub-level contains the types of envelopes and the construction layers for specific envelope types, while the lower sub-level contains the detailed envelope parameters, including the thickness of each layer and R-value of insulation layers. Then, the *Schedule* is needed for occupants, lighting, plug loads, and building systems. To obtain the hourly energy consumption of the buildings, energy modelers need to provide the hourly schedules for model input files. Although the schedules of system operations and the occupants are related, they are not the same. For example, the HVAC system usually operates before the first person enters a building and stops after the last person leaves the building. After schedules, the *Internal Loads* are required as model inputs, which are comprised of power and occupant densities. Finally, the *System* category consists of the HVAC system, domestic hot water system, and refrigeration system. After determining the specific type of each system for an individual building, energy modelers then need to identify the parameters of all the components in each system.

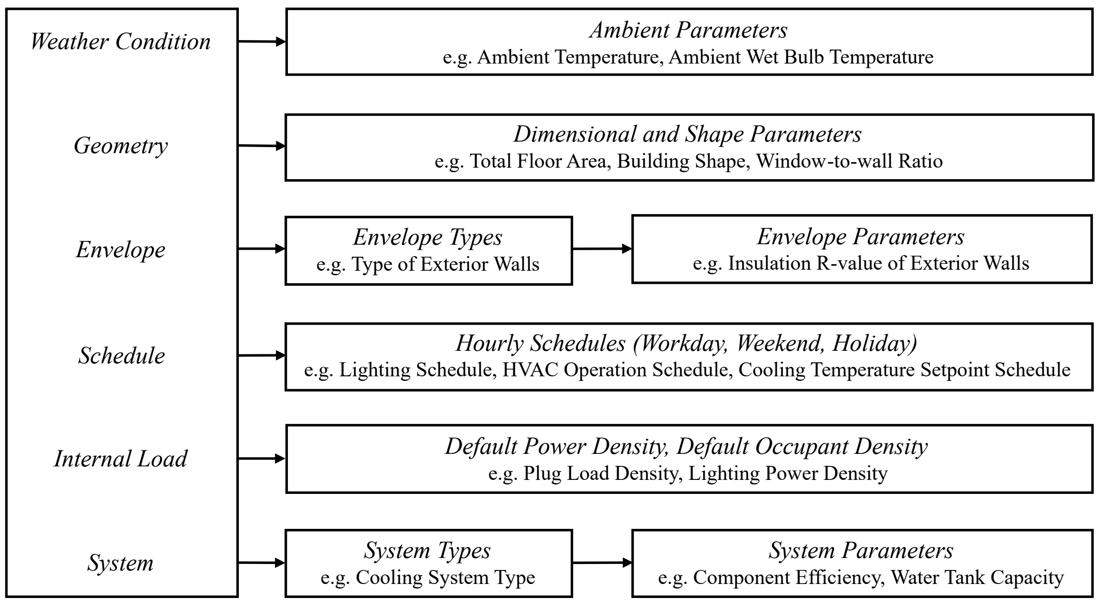


Figure 4.2: Inputs of prototypical building energy models from high level frameworks (left) to low level frameworks (right)

4.2.2 Step 2: Collect Related Data

Based on the required model inputs identified in Step 1, the related data can be collected from building energy databases, literature, and current building energy models of other building types. First, building energy databases provide building characteristics, operating schedules, and energy data of existing buildings. There are several commonly used databases for U.S. commercial buildings, such as Commercial Buildings Energy Consumption Survey (CBECS), Building Performance Database (BPD), and California Commercial End-Use Survey (CEUS) [59, 107, 22, 197].

The data in these databases is mainly collected from surveys and field measurements. However, the data availability varies depending on the databases. For example, CBECS, a national in-depth sample survey for the stock of U.S. commercial buildings, provides the building characteristics, operating schedules, and detailed energy data for individual building samples [59, 197]. On the other side, BPD gives the distributions of characteristics and energy data for different categories of commercial buildings [107]. Huang and Franconi [88] separated the model inputs into three categories: (1) the physical building characteristics, (2) the HVAC system characteristics, and (3) the building's internal conditions and operational patterns. Based on their analysis, the difficult levels to obtain the information of the model inputs in these three categories are:

(1) The physical building characteristics - **EASY**: They are static, observable and relatively straightforward to record and verify. The survey data is usually able to provide some information about these model inputs, such as total floor area and window-to-wall ratio.

(2) The HVAC system characteristics - **DIFFICULT**: They are affected by the control, operations, and maintenance, which are difficult to be recorded by survey data. The survey data is only able to record some simple information, such as system types.

(3) The building's internal conditions and operational patterns - **VERY DIFFICULT**: They are impossible to verify without detailed on-site monitoring and they greatly impact on the building energy consumption. Based on the methods to collect data, the survey data usually does not include the information of model inputs in this category.

Based on the categories provided in Figure 4.2 and the extent that data is available, this chapter evaluates the possibility of obtaining relevant data for model inputs from the databases. Table 4.1 summaries the possibility of related data for model inputs provided by the above-mentioned U.S. commercial building energy databases.

The sites and total floor areas of buildings are often readily obtained from the databases, while the details of envelopes, systems, and hourly operating schedules are sometimes either not available or require significant processing. For example, CBECS provides building characteristics, operating schedules, and energy data for individual building samples [59]. CBECS also provides detailed information on weather conditions, building geometries, and energy consumption for individual energy sources and end-uses. However, it is challenging to record the hourly schedules for thousands of building samples. Instead, CBECS provides information on total weekly work hours and whether the building is operated on weekdays and weekends. The general types of envelopes and building systems are also collected in CBECS; however, their details – such as insulation R-values, exterior wall thicknesses, and cooling and heating system efficiencies – are not included. Even if geometry information is included in detail, it is still difficult to obtain all the required data for model inputs, such as window-to-wall ratio and window location. Measured data collected from sensors can relieve this problem. However, using measured data for prototypical building energy models is not always feasible, since data from many similar buildings are required, and including many buildings can be prohibitive in terms of cost and time.

One solution to address the missing data in databases is to consult other sources, such as building energy-related papers, reports, building energy standards, and existing energy models for other building types. For example, the DOE Commercial Reference Building Models used some data from building energy-related papers, reports, and standards to implement the data related to the envelopes and equipment [36]. In addition, Griffith et al.[78] determined the values of model inputs by collecting data from various building energy-related papers and reports.

4.2.3 Step 3: Clean the Data

Before using the data collected in Step 2 to create building energy models, it is necessary to clean the data that is not suitable for model inputs and contains errors. Figure 4.3 displays the workflow to clean the related data, which begins with checking whether the data is representative for the typical buildings. Five aspects need to be inspected:

(1) **Are there typical building characteristics in the data set?** The data set usually

Table 4.1: Possibility of related data for model inputs provided by commonly used U.S. commercial building energy databases

Possibility of Data Provided by Building Energy Databases	Category of Model Inputs					
	Weather Condition	**Geometry**	**Envelope**	**Schedule**	**Internal Load**	**System**
Strong	- Climate Zone/Typical City/Typical HDD and CDD	- Total Floor Area				
Moderate		- Numbe of Floors - Building Shape	- Exterior Wall Type - Roof Type - Windows Type - Floors Type	- General Total Weekly Work Hours Wether Work on Workday and Weekend		- HVAC System Type - Water Heater Equipment Type
Weak or Unavailable		- Window-to-Wall Ratio - Aspect Ratio - Window Location - Floor Height - Orientation - Shading - Spaces or Thermal Zones	- Exterior Wall Insulation R-value - Roof Insulation R-value - Floors Insulation R-value - Window U-value - Window SHGC - Internal Partitions - Internal Mass - Infiltration	- Lighting Schedule - Electric and Natural Gas Equipment Schedule - Occupant Schedule - HVAC Schedule - Heating and Cooling Temperature Setpoints - Service Hot Water Schedule - Water Heater Setpoint - Daylighting Control	- Occupant Density - Lighting Power Density - Electric Equipment Power Density - Natural Gas Equipment Power Density	- HVAC System Detailed Components - HVAC System Component Efficiency - HVAC System Control - Water Heating Equipment Efficiency

provides either categories or numerical values for different building characteristics. If the building characteristics are categorical, then building samples with features that fall under those categories are assumed to be typical. If the building characteristics are numerical, then the building samples with characteristics between the 25^{th} and 75^{th} percentiles for the given building type are assumed to be typical. For atypical building characteristics, engineering judgment or on-site survey should be used to clean the data, such as special building shapes, extremely high total floor areas, and extremely high window-to-wall ratios. Building samples with atypical characteristics are deleted from the data sets directly.

(2) **Do the locations of the building samples and the prototypical building energy models have similar weather conditions?** Climates impact the values of some data, such as insulation of the envelopes. Thus, if the building samples have different weather conditions from the models, the data that is easily influenced by the climate must be cleaned. In these building samples, the climate-sensitive data is changed into the data from other building samples, which have required weather conditions and have similar building features.

(3) **Are there typical building assets of building samples in the dataset, and are the assets from representative building models?** The typical building assets have the same definition as the typical building characteristics. For example, high energy-efficient equipment should not be selected for models of old buildings, where the technology did not yet exist. In these building samples, the assets are changed into the data from other building samples, which have qualified assets and have similar building features.

(4) **Are there typical operating schedules present?** For instance, the data needs to be cleaned for the building samples with extremely low operating time. In these building samples, the schedules are changed into the data from other building samples, which have qualified schedules and have similar building features.

(5) **Is the energy consumption per area no much higher or lower than the median value?** If it is much higher or lower, the data will be cleaned. For the unchanged building samples, the samples are deleted if the values are three standard deviations away from the median value; for the building samples being modified based on aspects 2 through 4, the energy consumption is adjusted based on the rules. If the values are still 3 standard deviations away from the median value, the samples are deleted.

If the building energy databases provide the data for individual building samples, it is necessary to check whether there are missing data or errors. The recommended sequence to check data is: (1) energy data, (2) weather conditions, (3) geometries, (4) schedules, and (5) others. The erroneous data should be deleted. On the other hand, if a building sample is only missing a few data points, the remaining data can still be used for identifying the model inputs after the data adjustment based on expert knowledge. For example, even if the data of operating schedules for one building sample is not provided by the database, the geometry and envelope data are still useful to create the prototypical building energy models and can be used to determine model inputs in the subsequent steps.

4.2.4 Step 4: Convert the Data into Model Inputs

Not all the collected data can be directly used as model inputs; as such, this step converts the collected data into model inputs. The data are classified into four categories based on their sources and situations. Table 4.2 lists the methods to convert data into model inputs for each category.

Building energy databases provide the data for individual building samples or analysis data. If the data can be directly used as model inputs, this chapter selects median values for numerical data and the most frequent category for categories as model inputs, which is described in method M1 of Table 4.2. For example, the 2003 CBECS provides the total floor areas for individual building samples; the median total floor area will be used as the model input.

If the data cannot be directly used as model inputs, procedures need to be designed to convert

Table 4.2: Methods to convert related data into model inputs

Index	Data Source	Data Type	Method
M1	Building Energy Databases	Data can be directly used as model inputs	Numerical data: median value Categories: highest frequent category
M2		Data cannot be directly used as model inputs	Convert data into model inputs and determine ranges of model inputs
M3	Literature	-	Use the data to determine the ranges of model inputs
M4	Existing Building Energy Models	-	Adjust inputs and determine the ranges of existing building energy models to better represent prototypical building

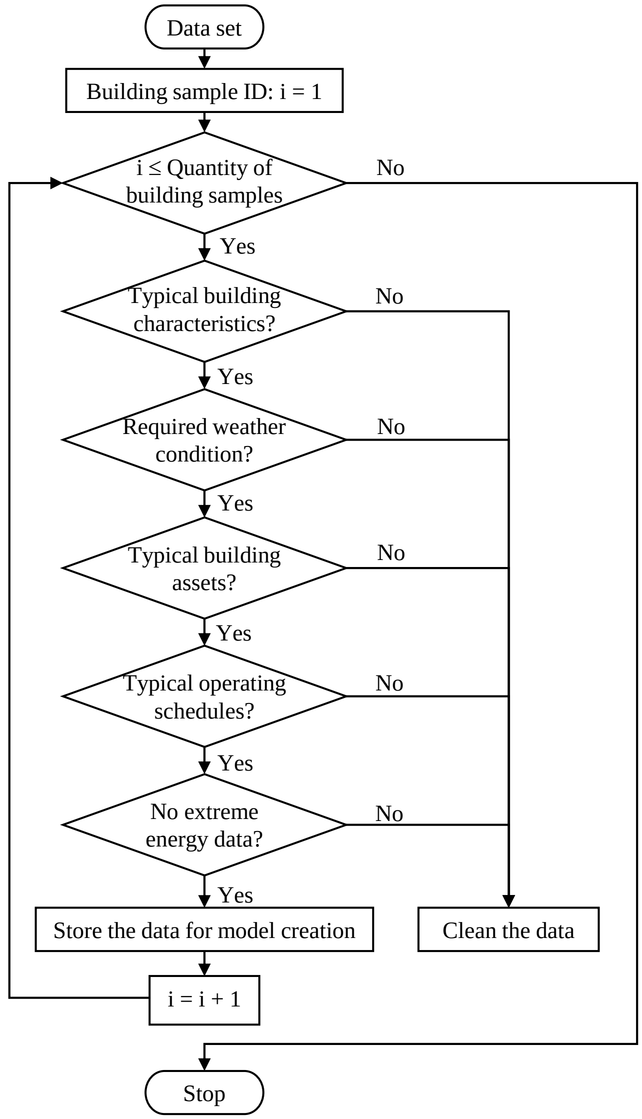


Figure 4.3: Inputs of prototypical building energy models from high level frameworks (left) to low level frameworks (right)

data into model inputs based on existing methods in literature as method M2. For instance, Winiarski et al. [186] and Winiarski et al.[187] determined the model inputs of envelopes and HVAC systems based on the 2003 CBECS. Further, the 2003 CBECS provides the building shapes for individual building samples instead of aspect ratios. However, the aspect ratio is required for model inputs. Thus, Winiarski et al. [186] identified the building shape category with the highest frequency and determined the aspect ratio based on the building shape. In addition, Griffith et al. [78] created over 4,000 building energy models to simulate the energy performance of individual building samples in the 2003 CBECS and introduced several methods to convert the survey data into model inputs. For instance, because the 2003 CBECS data only contains limited information on schedules (such as the total weekly operating hours or general workday/weekend operation), Griffith et al. [78] designed a workflow to identify the work hours every day, which is needed for the model. After that, the ranges of these model inputs are determined based on the converted model inputs and the best values of these model inputs will be identified by calibrating models (Step 5).

In addition to building energy databases, the data in Step 2 may also be collected from literature and existing model sources. Literature provides summaries of measured data or simulation data, which can be directly used as model inputs. Data in literature should be recorded from existing buildings when the prototypical building energy models represent the energy performance of existing buildings as described in method M3. For instance, Persily [140] provided the data for infiltration rate, which can be used for existing building models. Then, based on the data provided by literature, the ranges of the model inputs in this type are determined. The best values of these model inputs will be identified by calibrating models (Step 5).

Furthermore, inputs of existing building energy models for other building types, such as office and primary school models in the DOE Commercial Reference Building Models, can be used as reference, which is named as method M4. For example, the types of envelopes can be collected from the CBECS. The types of envelopes in the new models are usually used in some existing building energy models for other building types. Thus, the envelope details, such as insulation R-values, can be obtained from these existing building energy models. Based on the values in these existing building energy models, the ranges of the model inputs in this type are determined. The best values of these model inputs will be identified by calibrating models (Step 5).

4.3 Model Calibration (Step 5)

Section 4.2.2 has evaluated the possibility of related data for model inputs provided by the U.S. commercial building energy databases. The results shown in Table 4.1 indicate that the values of some model inputs are not able to be obtained from the data sources. Table 4.2 proposes the methods to convert related data into model inputs. For the model inputs, which are not provided by building energy databases directly, the ranges of model inputs are determined. This section introduces the method to calibrate the models and identify the best values among the ranges of these model inputs.

Before calibrating the prototypical building energy models, it is necessary to identify how to evaluate the performance of calibrated models. The criteria to evaluate the performance will be introduced in Section 4.4 in detail. Generally, there are two types of criteria, which are listed below:

(1) If there are a large set of the building samples after data cleaning, the empirical baselines are developed by using regression models, which are created by using the cleaned data. The criterion is that the coefficient of variation of the *root-mean-square deviation (CV(RMSD))* between the prototypical building energy models and regression models is lower than 0.05.

(2) If there are only a small set of the building samples after data cleaning, the performance metrics based on engineering judgment are developed to evaluate the calibrated prototypical building energy models.

After determining the criteria to evaluate the performance of model calibration, it is necessary to identify which model inputs need to be calibrated. Figure 4.4 shows the rules to determine the values and ranges of model inputs for model calibration. First, by reviewing existing research or conducting sensitivity analysis among the ranges of model inputs identified in Step 4, the model inputs can be divided into two categories: insensitive model inputs and sensitive model inputs. Based on Table 4.2, the model inputs in both categories contain data that is directly provided by data sources (M1) and data that is not directly provided by data sources (M2, M3 and M4). If the data is directly provided by data sources, the median value or highest category of data is selected. If the data is not provided by data sources but it is insensitive, the values provided by the literature or adjusted by existing building energy models for other building types are used as the model inputs. For the rest model inputs, which is not provided by data sources and is sensitive, the models are calibrated among the ranges of model inputs identified in Step 4. By calibrating the models, the best values of these model inputs are identified and the calibrated prototypical building models are the results for the application of prototypical building energy model creation.

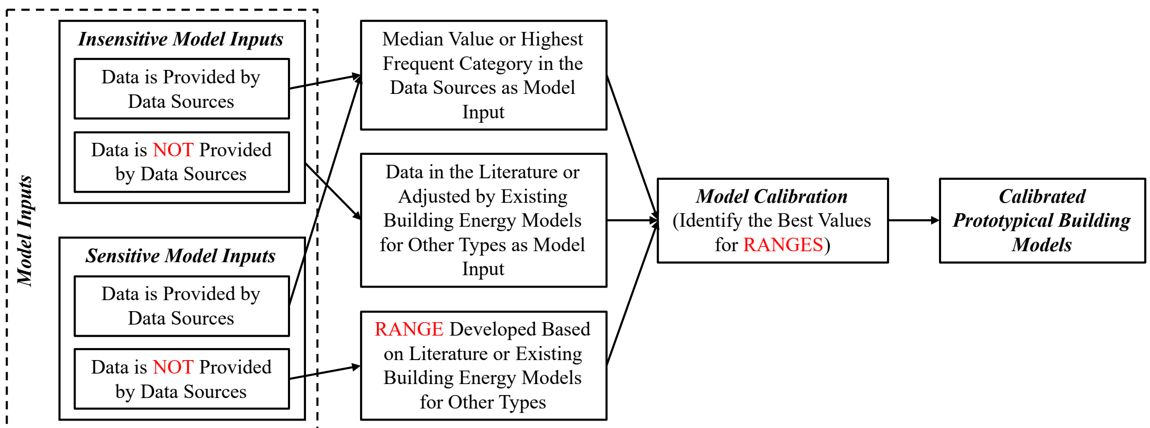


Figure 4.4: Rules to determine the values and ranges of model inputs for model calibration

After determining the values and ranges of model inputs, there is another question that needs to be solved. Since empirical databases, such as CBECS [59], only provides the yearly energy use intensity (EUI), it is unable to calibrate models by using the traditional method, which is based on monthly utility bills and sensors' data. Thus, a new methodology needs to be developed for calibrating prototypical building energy models, which is shown in Figure 4.5.

Though only yearly energy data is provided, there are relationships of model inputs between the prototypical building energy models in different climate zones and vintages. Thus, the prototypical building energy models in different climate zones and vintages are assembled into an

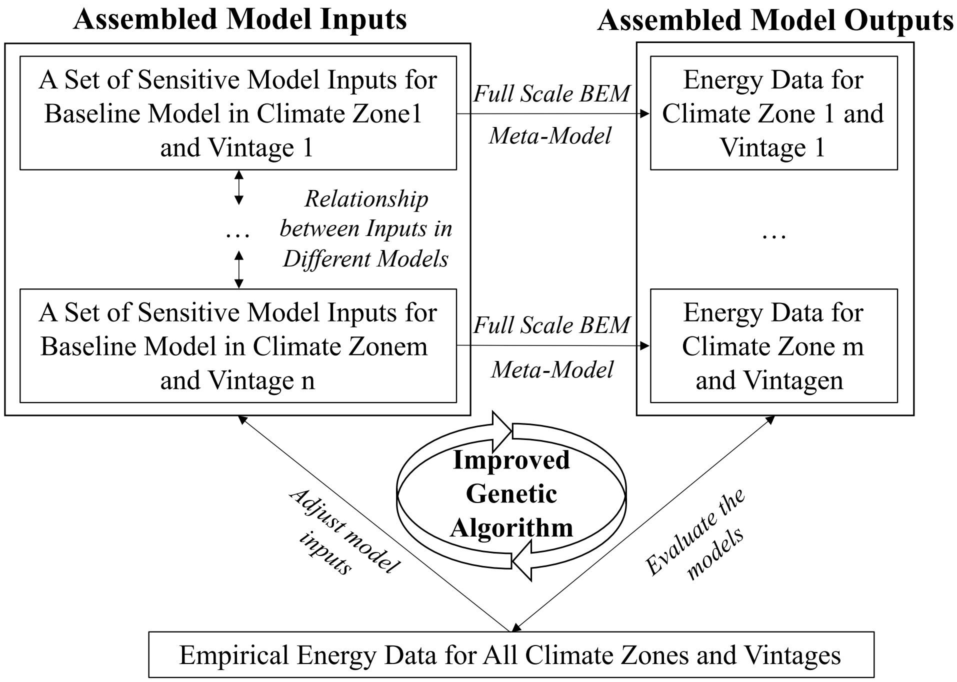


Figure 4.5: Methodology to calibrate the building energy models

assembled model. The relationships of models inputs become the links of the different prototypical building energy models in the assemble model. Table 4.3 shows an example about the relationships for prototypical building energy models for U.S. commercial buildings, which use ASHRAE climate zones and have two vintages (Pre- and post-1980).

For example, if the model input belongs to Type 1 of relationship, the values of this model input in all climate zones and vintages are the same. Thus, when a model input belonging to Type 1 is changed in one prototypical building energy model, this model input in all other prototypical building energy models has to be modified into the same value.

Based on these relationships, the samples of assemble model are selected, and full scale building energy modeling programs and meta-models are used to calculated energy data for each prototypical building energy model. In Figure 4.5, the empirical energy data is used as the indicator to evaluate the performance of model calibration.

Table 4.3: Example about relationships between inputs in different models

No.	**Type of Relationship**	**Example**	**Index**
1	Values are the same in all climate zones and both vintages	Aspect Ratio	Type 1
2	Values are the same in all climate zones; Values for post-1980 models are no higher than pre-1980 models	Electric Equipment Power Density	Type 2
3	Values are the same in all climate zones; Values for post-1980 models are no lower than pre-1980 models	Cooling COP	Type 3
4	Values in climate zones 5∼8 are no higher than the other climate zones	Window U-factor	Type 4
5	Values in climate zones 5∼8 are no lower than the other climate zones	Exterior Wall Insulation R-value	Type 5

Finally, the improved genetic algorithm (GA) is used to calibrate the assembled model and generate calibrated prototypical building energy models. Figure 4.6 shows the schematic diagram of improved GA. In improved GA, each sample for the assemble model has three dimensions: (1) model inputs, (2) climate zones, and (3) vintages. There are rule-based relationships between model inputs in different climate zones and vintages. The improved GA provides constraints to generate new populations by considering these relationships. In one loop, the improved GA conducts four steps: selection of samples based on rules, crossover, mutation, and new population generation. Till the energy results meet the requirements or the number of loops are larger than the setting value, the process will be stopped. Then some model inputs will be adjusted based on the engineering judgment. For example, U-factor and Solar Heat Gain Coefficient (SHGC) of window are discrete values in the real world based on the window types. Thus, the final values of U-factor and SHGC of window in the model are selected from the closest values in the set of existing window types. After that, the calibrated assemble model will be recorded. The prototypical building energy models are obtained from the calibrated assemble model.

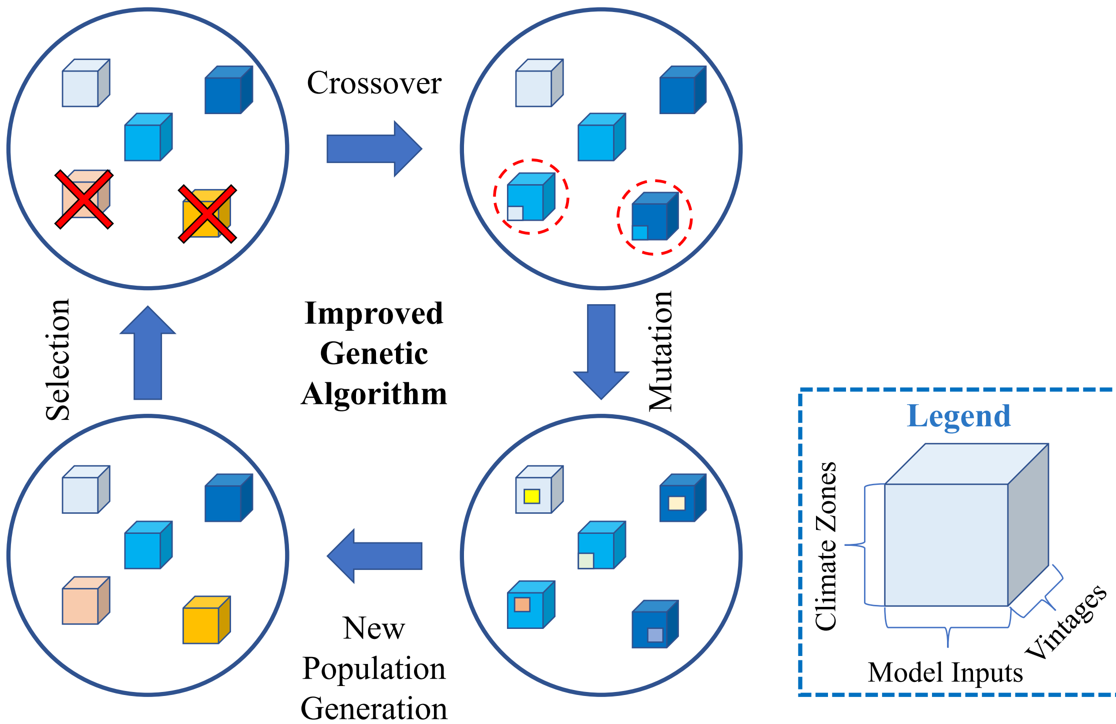


Figure 4.6: Schematic diagram of improved GA

4.4 Model Validation (Step 6)

As mentioned in Section 4.3, there are two types of criteria to evaluate the performance of calibrated prototypical building energy models. The first type of criteria are used when there are a large set of the building samples after data cleaning. The method provided by ENERGY STAR Portfolio Manager is used to create empirical baselines [66]. Figure 4.7 shows the methodology to create empirical baselines. First, the data is collected from data sources and filtered based on the rules. The objective to filter the data is to clean the atypical building samples or building samples with errors, which has been introduced in Section 4.2.3. Second, the sensitive variables need to be identified by conducting sensitivity analysis. Then the regression model is developed based on the sensitive variables in the filtered building samples. Finally, the typical values of these sensitive variables are used to calculate the energy data, such as empirical site EUIs by using the regression model. The median values are usually used as the typical values of the sensitive variables.

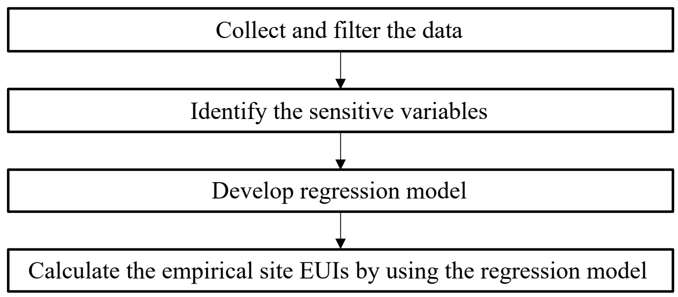


Figure 4.7: Methodology to create empirical baselines

After identifying the energy data for the empirical baselines, an indicator to evaluate baseline models needs to be selected. The indicator needs to be a value, which is able to evaluate the performance of the prototypical building energy models in all climate zones and vintages. As mentioned in Section 4.3, the *CV(RMSD)* is selected as the indicator to evaluate whether the baseline models have consistent energy estimation with empirical baseline. To calculate the *CV(RMSD)*, the first step is to calculate *root-mean-square deviation (RMSD)*. To illustrate the method to calculate the *CV(RMSD)*, the empirical site EUI is used as energy data here, and two vintages (pre- and post-1980) and 15 climate zones are considered for the prototypical building energy models. Thus, the *RMSD* is calculated by using the following equation:

$$RMSD_{Vint} = \sqrt{\frac{\sum_{i=1}^{15}\left(E\hat{U}I_{i,Vint} - EUI_{i,Vint}\right)^2}{15}} \tag{4.1}$$

where *Vint* is vintages, which consists of pre- and post-1980; i is climate zone i, i = *1, 2, ..., 15*; *EUI* is the empirical site EUI; $E\hat{U}I$ is the modeled site EUI.

Based on the results of *RMSD*, the *CV(RMSD)* can be calculated by using the following equation:

$$CV\left(RMSD_{Vint}\right) = \frac{RMSD_{Vint}}{max\left(EUI_{i,Vint}\right) - min\left(EUI_{i,Vint}\right)} \tag{4.2}$$

where $max(EUI_{i,Vint})$ is the maximum value of the empirical site EUI in the vintage *Vint*; $min(EUI_{i,Vint})$ is the minimum value of the empirical site EUI in the vintage *Vint*.

Usually, when the *CV(RMSD)* is lower than 0.05, the prototypical building energy models have consistent energy estimation with the empirical baseline. Section 5.2.4 will use this type of criteria to validate the prototypical building energy models for U.S. medium office buildings.

The second type of criteria are used when the building samples are limited. The rule-based criteria are developed based on the engineering judgment. Due to limitations in available survey data, the survey values do not always accurately represent the required model cities. Thus, the heating degree days (HDD) and cooling degree days (CDD) for the building samples from surveys and models are used to judge whether the models should have higher energy consumption for heating and cooling than the sample data. Section 5.3.4 will use this type of criteria to validate the prototypical building energy models for U.S. religious worship buildings. Finally, the prototypical building energy models will be stored into the database for simulation data sources in the standardized computational framework and will be used in the future research.

4.5 Summary

This section introduces the methodology to create prototypical building energy models in detail. The creation of prototypical building energy models consists of six steps: (1) identifying the model inputs, (2) collecting related data, (3) cleaning the data, (4) converting the data into model inputs, (5) calibrating the building energy models, and (6) validating the energy results. To implement the methodology, Section 5 will create prototypical building energy models for the four building types of U.S. commercial buildings: (1) medium office buildings, (2) religious worship buildings, (3) college/university buildings, and (4) mechanical shops. The medium office buildings and religious worship buildings will be used as two case studies.

Chapter 5

Creation of Prototypical Building Energy Models

By using the standardized computational framework, this chapter implements the methodology introduced in Chapter 4 and create prototypical building energy models for four types of U.S. commercial buildings: (1) medium office buildings, (2) religious worship buildings, (3) college/university buildings, and (4) mechanical shops. The medium office buildings and religious worship buildings are used as two case studies.

5.1 Introduction

Both commercial and residential buildings consume large amount of energy, and the International Energy Agency (IEA) stated that the global buildings sector was responsible for approximately 30% of primary energy consumption in 2017 [139, 2, 3]. Moreover, energy consumption of buildings all over the world is still rapidly growing. Conducting building energy analyses provides a quantitative understanding of building energy performance, which assists building owners and managers to avoid using energy inefficiently and to reduce energy consumption of buildings. Prototypical building energy models are the starting point in conducting these analyses for both existing and new buildings. The prototypical building energy models for existing buildings need to contain typical building features; meanwhile, the models for new buildings need to meet the requirements of building energy standards. Previous research has applied some current prototypical building energy models for various purposes. Field et al. [71] provided a variety of application examples of prototypical building energy models, such as evaluation of building energy standards and comparison of energy performance for buildings of different vintages. Glazer [74] analyzed the maximum technically achievable energy targets for commercial buildings by using prototypical building energy models as baselines. Similarly, Thornton et al. [173] evaluated the performance of energy and cost savings of the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 90.1-2010 based on prototypical building energy models.

Building energy simulation programs are frequently used to create prototypical building energy models and conduct building energy analyses. Brackney et al. [15] provided a history of building energy simulation program development. DOE-2 and EnergyPlus are two of the most popular building energy simulation programs [33, 42]. They can analyze the hourly energy consumption year-round for individual energy sources and end-uses. To simplify the model creation and perform detailed analyses for the buildings with complex characteristics and operations, graphical user interfaces eQUEST and OpenStudio were developed based on DOE-2 and EnergyPlus, respectively [41, 79]. Because of the various calculation methods, different building energy simulation programs have their own requirements for model inputs and varying accuracy of simulating results for building energy consumption. To compare the abilities and performance of popular building energy simulation programs, Crawley et al. [31] contrasted the capabilities of 20 simulation programs, which provides a valuable reference for energy modelers.

To facilitate building energy-related analyses, the U.S. Department of Energy (DOE) published several sets of prototypical building energy models. For example, to improve energy efficiency of commercial buildings, it is crucial to have a set of building energy models, which can represent the majority of U.S. commercial building types. Thus, the U.S. DOE created DOE Commercial Reference Building Models with EnergyPlus [39]. The models represent new and existing commercial buildings in the U.S. and can be used for various applications, including assessing new technologies, optimizing designs, and conducting studies of building components. The building models include three vintage categories: pre-1980, post-1980, and new construction. With these prototypical models, the U.S. DOE quantified the potential energy savings of U.S. commercial buildings with improving energy codes, such as ASHRAE Standard 90.1 [7, 9, 10, 11, 12] and the International Energy Conservation Code (IECC) [90, 91, 92, 93]. Accordingly, the U.S. DOE has been continuously updating the building models based on different editions of ASHRAE Standard 90.1 and IECC. The updated building energy models were then called the DOE Commercial Prototype Building Models [45]. Recently, the U.S. DOE developed a library called OpenStudio-Standards gem, which includes OpenStudio's version of the DOE Commercial Reference Building Models and the DOE Commercial Prototype Building Models [134, 150].

Although there is a rich set of existing prototypical building energy models in the U.S., there are still some building types missing, such as religious worship buildings, mechanic shops, and college or university buildings. Those missing building types still account for over 20% of the total energy consumption in the U.S. commercial building sector and approximately 20% of the floor space [173, 36]. Some researchers are currently working to create models of these missing building types, but overall, this work is not receiving sufficient attention [195, 196]. For example, religious worship buildings are approximately 25% of the total floor area and 13% of the total site energy use among the U.S. commercial building sector [51, 57]. Despite these relatively significant percentages, existing U.S. religious worship buildings have received minimal energy analysis attention, and there is a lack of prototypical building energy models [170, 171, 172]. Therefore, creating appropriate models for U.S. religious worship buildings is essential [194]. Furthermore, the existing prototypical building energy models may not be suitable for some specific building energy analyses, which has been discussed in Section 2.3.1.

Thus, based on the methodology to create prototypical building energy models introduced in Chapter 4, this chapter creates prototypical building energy models for four types of U.S. commercial buildings by using the standardized computational framework introduced in Chapter 3: (1) medium office buildings, (2) religious worship buildings [194], (3) college/university buildings [195], and (4) mechanical shops [196]. The medium office buildings and religious worship buildings are used as two case studies. The first case is to create prototypical building energy models for U.S. medium office buildings, which is introduced in Section 5.2. The energy performance of these models is compared with the existing prototypical building energy models. The second case is to create prototypical building energy models for U.S. religious worship buildings, which is introduced in Section 5.3. This case is complemented the database for data sources in the standardized computational framework.

5.2 Case Study 1: Model Creation for Medium Office Buildings

This section creates the prototypical building energy models for existing U.S. medium office buildings by using the methodology introduced in Chapter 4. The results are compared with the existing prototypical building energy models in the DOE Commercial Reference Building Models [39].

5.2.1 Model Inputs (Medium Office Buildings)

By using the methodology shown in Section 4.2, this section collects the model inputs for the prototypical building energy models of existing U.S. medium office buildings. First, the required model inputs are listed and the model inputs are classified into six categories, which have been shown in Figure 4.2. The first category is the *Weather Condition* and the 15 main climate zones in the U.S. are identified. Based on these climate zones, 15 typical cities are selected as the location of the prototypical building energy models. The 2003 historical weather data for these 15 typical cities is used. The standardized computational framework still needs to determine the values of model inputs in the other five categories. In the second step, the 2003 Commercial Buildings Energy Consumption Survey (CBECS) is selected from the database [51] and the related data is collected from the 2003 CBECS. Third, the selected data is cleaned based on the method introduced in Section 4.2.3. Then the selected data is converted into model inputs. Sensitive model inputs are identified based on the literature [74, 77, 184, 183, 185]. Based on the rules described in Figure 4.4, the framework determines the values or ranges of the model inputs. Table 5.1 provides examples to show the method for determining the values or ranges of sensitive model inputs in the other five categories.

The column of type of relationship has been introduced in Table 4.3. For the both sensitive

Table 5.1: Determine the values or ranges of sensitive model inputs

Category	**Sensitive Model Input**	**Whether Data Provided by the 2003 CBECS**	**Range/ Value**	**Type of Relationship**[1]
Geometry	Total Floor Area	Yes	Value	
	Aspect Ratio	No	Range	Type 1
	Floor to Floor Height	No	Range	Type 1
	Window-to-Wall Ratio	Yes	Value	
	Glazing Sill Height	No	Range	Type 1
Envelope	Exterior Wall Insulation R-value	No	Range	Type 5
	Roof Insulation R-value	No	Range	Type 5
	Window U-factor	No	Range	Type 4
	Window SHGC	No	Range	Type 5
	Foundation Insulation R-value	No	Range	Type 1
	Infiltration Rate	No	Range	Type 1
Schedule	Hourly Schedule	Design the schedule based on Figure 5.1	Value	
Internal Load	People Density	No	Range	Type 1
	Lighting Power Density	No	Range	Type 2
	Electric Equipment Power Density	No	Range	Type 2
System	Cooling COP	No	Range	Type 3
	Burner Efficiency	No	Range	Type 3
	Fan Total Efficiency	No	Range	Type 3
	Ventilation	No	Range	Type 1
	SWH Heater Thermal Efficiency	No	Range	Type 3

[1] Type of relationship is introduced in Table 4.3.

and insensitive model inputs provided by the 2003 CBECS, such as total floor area, the median values or highest frequent categories of the selected data from the 2003 CBECS are used as model inputs [51]. For the rest sensitive model inputs, the 2003 CBECS does not provide values. Thus, the ranges are determined based on the literature. Table 5.2 provides examples for ranges of sensitive model inputs in all five types of relationship. For example, the 2003 CBECS does not include information about the aspect ratio, but Winiarski [186] provides the values of the aspect ratio for office buildings. Furthermore, the Type 1 in Table 4.3 is that values are the same in all climate zones and both vintages. Thus, based on the engineering judgment, the range for the aspect ratio is [1.6, 2.4] and the value after calibration is 2.01 for all climate zones and both vintages.

Table 5.2: Examples for the ranges of sensitive model inputs

Type of Relationship	**Sensitive Model Input**	**Range**
Type 1	Aspect Ratio	[1.6, 2.4] for all climate zones and both vintages
Type 2	Electric Equipment Power Density	Pre-1980: [9.24, 14.81] W/m^2 Post-1980: [7.98, 13.34] W/m^2
Type 3	Cooling COP	Pre-1980: [2.52, 3.39] Post-1980: [2.61, 3.50]
Type 4	Window U-factor	Pre-1980: Climate Zones 1$\sim$4: [4.67, 7.00] W/m^2-K Climate Zones 5$\sim$8: [2.82, 4.23] W/m^2-K Post-1980: Climate Zones 1$\sim$4: [3.27, 7.00] W/m^2-K Climate Zones 5$\sim$8: [2.36, 4.03] W/m^2-K
Type 5	Exterior Wall Insulation R-value	Pre-1980: Climate Zones 1$\sim$4: [0.61, 1.18] m^2-K/W Climate Zones 5$\sim$8: [0.89, 1.69] m^2-K/W Post-1980: Climate Zones 1$\sim$4: [0.76, 2.26] m^2-K/W Climate Zones 5$\sim$8: [1.72, 4.69] m^2-K/W

It is noticeable that Griffith et al. [78] provides a methodology to design the hourly operating schedules based on the 2003 CBECS data. Based on the methodology, the hourly schedule is designed and thus, this case does not provide uncertainty of schedules here. Table 5.3 lists the four variables in the 2003 CBECS that are used to determine the operating schedules for the models, and Figure 5.1 shows the workflow to determine the modeled operating hours every day based on the 2003 CBECS data.

Table 5.3: Determine the values or ranges of sensitive model inputs[1]

No.	**Variable Name**	**Variable Description**	**Variable Type**
1	WKHRS8	Total weekly operating hours	Numerical Data *(0$\sim$168)*
2	OPEN248	Open 24 hours-a-day	Category *(Yes/No)*
3	OPNMF8	Open during the week	Category *(Open all five days/Open some of these days/Not open at all)*
4	OPNWE8	Open on weekends	Category *(Yes/No)*

[1] The information is provided by the document of All Layout Files and Format Codes in the 2003 CBECS [52]

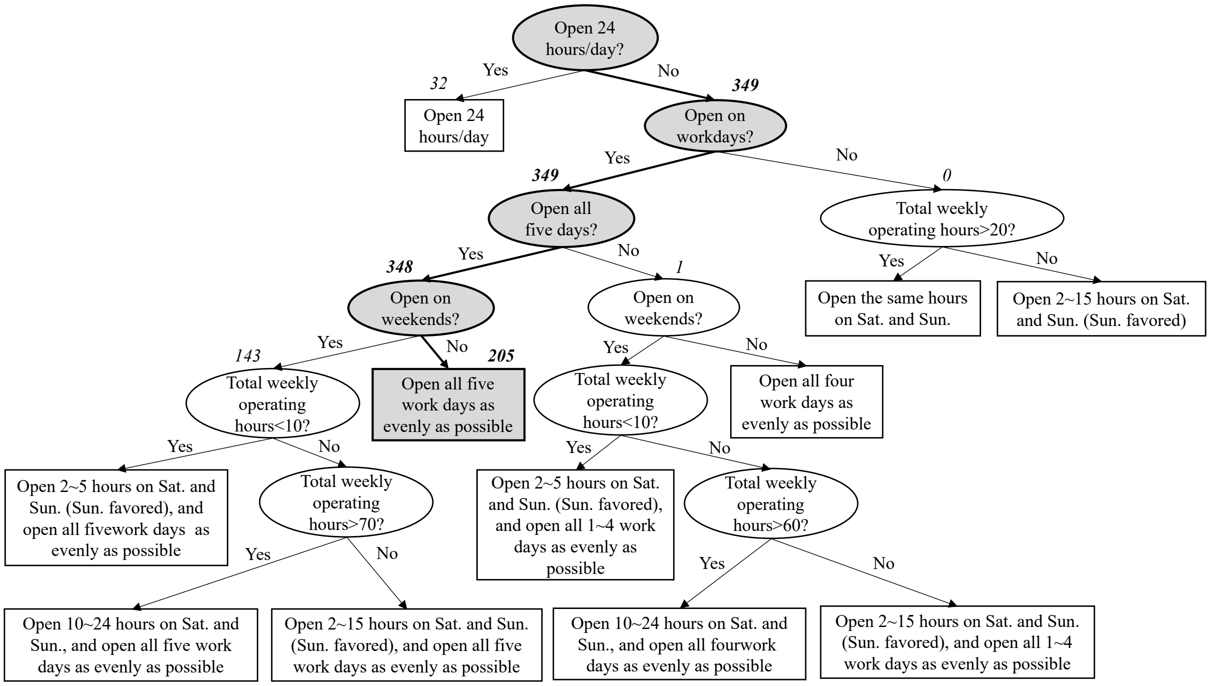


Figure 5.1: Workflow to determine operating hours for models (medium office buildings)

In Figure 5.1, the numbers shown above boxes and ovals are the quantities of remaining building samples in the 2003 CBECS after being classified. Based on the workflow, the models should open all five workdays as evenly as possible. Then the median value of total weekly operating hours (WKHRS8) is 50 hours for the selected building samples in the 2003 CBECS [51]. After that, the operating schedules are arranged by using DOE Commercial Reference and Prototype Building Models and engineering judgment [39, 45]. Finally, this case estimates that the occupants stay in the buildings from 8am $\sim$ 18pm and the system is operated from 7am $\sim$ 19pm, which are used for all prototypical building energy models of medium office buildings.

For the rest model inputs, which are all insensitive, the values provided by literature or adjusted based on other building energy models are used as the model inputs. After identifying the uncertainties of model inputs, it is necessary to calibrate and validate the models. Section 5.2.2 shows the workflow to develop the evaluation criteria for the prototypical building energy models of medium office buildings. Section 5.2.3 describes the prototypical building energy models of medium office buildings after being calibrated. Section 5.2.4 shows the results of the model validation.

5.2.2 Evaluation Criteria (Medium Office Buildings)

Based on the methodology introduced in Section 4.4, this case creates the evaluation criteria for the prototypical building energy models of medium office buildings. This case creates the empirical baselines to evaluate the performance of the models. After collecting and filtering the data from the 2003 CBECS [51], this case selects approximately 300 building samples for both pre- and post-1980 medium office buildings. Then, the site energy use intensities (EUIs) for these building samples are calculated. After that, the sensitivity analysis is conducted to identify the sensitive variables to the site EUIs. The seven variables are selected as the sensitive variables, which are listed below (The variable names and descriptions refer to the 2003 CBECS codebook [52]):

(1) SQFT8: Square footage;

(2) WKHRS8: Total weekly operating hours;

(3) NWKER8: Number of employees during main shift;

(4) PCNUM8: Number of computers;

(5) HDD658: Heating degree days (base 65 °F);

(6) CDD658: Cooling degree days (base 65 °F);

(7) PBAPLUS8: More specific building activity.

By referring to the ENERGY STAR Portfolio Manager [66], the sensitive variables are modified. The final version of the sensitive variables are listed as follow, which are used to create the regression model for the empirical baseline:

(1) Total floor area (SQFT8);

(2) Total weekly operating hours (WKHRS8);

(3) Number of employees per area (NWKER8/SQFT8);

(4) Number of computers per area (PCNUM8/SQFT8);

(5) Percent heated × Heating degree days (HEATP8 × HDD658);

(6) Percent cooled × Cooling degree days (COOLP8 × CDD658);

(7) Whether it is a bank (If PBAPLUS8 = 3, it is a bank; else, it is not a bank).

Then the regression model is created by using Equation 5.1:

$$SiteEUI = \sum a_i f\left(Variable_i\right) + b \tag{5.1}$$

where *Site EUI* is the site EUI for each building sample; $Variable_i$ is the value of each sensitive variable in each building sample; a_i is the coefficient for variable i; b is the residual value of the regression model.

The objective of this step is to find out the values of all a_i and b, which minimizes the distance between the real values of site EUIs and the estimated values calculated by the regression model. After determining the values of all a_i and b, this case uses the heating degree days and cooling degree days in the typical cities, and the median values or the highest categories for the rest selected variables to calculate the site EUIs for the empirical baselines. The results are summarized in Table 5.4.

ASHRAE Standard 90.1-2004 Climate Zones and two vintages (Pre- and Post-1980) are used for this research [17, 18, 88]. The climate zone 1 is the hottest area while the climate zone 8 is the coldest area. The character, "A", represents humid area; the character, "B", represents dry area; the character, "C", represents marine area. Table 5.4 shows that the hot and cold areas, such as climate zones 1A and 8, usually consume more energy than the mild area, such as climate zones 3 and 4. It is because the hot and cold areas usually use more energy for heating or cooling by

Table 5.4: Empirical baselines

	Climate Zone: Site EUI (Unit: $MJ/m^2 - yr$)							
Pre-1980	1A: 908.83	2A: 886.99	3A: 851.66	4A: 894.70	5A: 940.47	6A: 1,032.64	7: 1,132.51	8: 1,375.41
		2B: 935.48	3B: 863.82	4B: 868.40	5B: 897.18	6B: 939.41		
			3C: 726.35	4C: 786.81				
Post-1980	1A: 726.15	2A: 701.28	3A: 695.41	4A: 747.91	5A: 808.07	6A: 914.88	7: 995.50	8: 1,215.80
		2B: 736.86	3B: 689.42	4B: 682.56	5B: 734.53	6B: 804.76		
			3C: 569.30	4C: 646.08				

compared with the mild area. Furthermore, the cold area usually consumes more energy than hot area, which is because the energy efficiency of cooling system is usually higher than 1 while the heating system is lower than 1. Moreover, the marine area usually consumes less energy than the humid and dry areas.

5.2.3 Model Description (Medium Office Buildings)

Figure 5.2 shows the geometry and thermal zones of the prototypical building energy models of medium office buildings. The models have three floors and there are five thermal zones in each floor.

Then Table 5.5 lists all key model inputs of the prototypical building energy models for U.S. medium office buildings. The first column shows the name of each model input. The second column shows the values of each model input. Since there are 30 building energy models (15 climate zones $\times$ 2 vintages), the values are provided if the model inputs have the same value in all climate zones, such as the total floor area; otherwise, the ranges are provided, such as the insulation R-value of exterior walls. The third column shows the methods to convert related data into model inputs, which has been introduced in Table 4.2. Some model inputs are identified by using more than one method. It is because the 2003 CBECS only provides limited information for these model

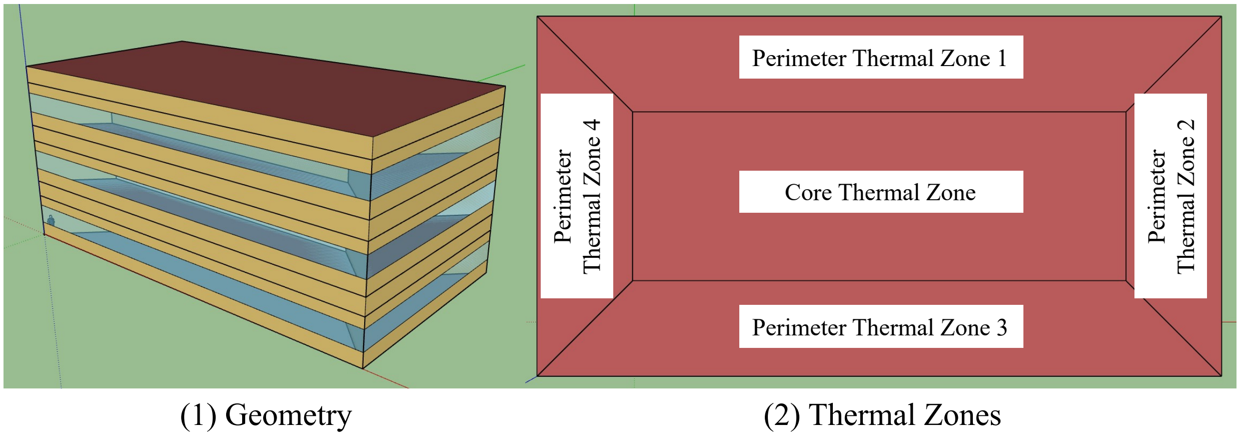


Figure 5.2: Geometry and thermal zones of the prototypical building energy models for the U.S. medium office buildings

inputs and the detailed information needs to be collected from other sources. For example, the 2003 CBECS provides the types of the exterior walls and roof. However, the prototypical building energy models need more detailed information, such as the insulation R-value. Thus, by using the method, M2, this case converts the types of the exterior walls and roof, which are used in the 2003 CBECS, into the types used by ASHRAE [186]. Then, based on the existing prototypical building energy models for various commercial building types, the ranges of the R-values for these types of the exterior walls and roof can be estimated [39, 45]. Then the models are calibrated in these ranges and obtain the best values of the insulation R-values, which are summarized in Table 5.5.

Table 5.5: Model inputs of prototypical building energy models for U.S. medium office buildings

Input	**Value**	**Method** [1]
Location	1A, Miami, FL 2A, Houston, TX 2B, Phoenix, AR 3A, Atlanta, GA 3B, El Paso, TX 3C, San Francisco, CA 4A, Baltimore, MD 4B, Albuquerque, NM 4C, Seattle, WA 5A, Chicago, IL 5B, Denver, CO 6A, Minneapolis, MN 6B, Helena, MT 7, Duluth, MN 8, Fairbanks, AK	M4
Vintage	Pre-1980 Post-1980	M4
Geometry	Total floor area: 3,130 m^2 Building shape: Wide rectangle Aspect ratio: 2.01 Window fraction: 27.5% Window locations: Equal percentages on all sides Number of floors: 3 Shading: No Floor-to-ceiling height: 4.47 m (Include the height of plenum)	M1, M2, M3
Schedules	Calculated based on Figure 5.1 and engineering judgment	M2, M4

Input	Value	Method [1]
Envelope	Exterior walls: steel frame walls - Insulation R-value of exterior walls (m^2-K/W): - Pre-1980: [0.76, 1.37] - Post-1980: [0.83, 1.56] Roof: Insulation Entirely Above Deck (IEAD) - Insulation R-value of roof (m^2-K/W): - Pre-1980: [1.80, 2.31] - Post-1980: [2.55, 2.88] Windows: hypothetical window - U-value of glazing (W/m^2-K): - Pre-1980: [3.80, 5.96] - Post-1980: [3.52, 6.13] - SHGC of glazing (unitless): - Pre-1980: [0.40, 0.77] - Post-1980: [0.25, 0.49]	M2, M4
Plug and process loads	Pre-1980: 14.74 W/m^2 Post-1980: 11.83 W/m^2	M2
Occupant density	20.48 m^2/person	M2
Lighting power density	Pre-1980: 16.34 W/m^2 Post-1980: 11.95 W/m^2	M3
Infiltration rate	0.00031 m/s for the whole building (Flow per exterior surface area)	M3
Ventilation requirement	0.0242 m^3/s-person for the whole building	M4
HVAC system	Cooling: packaged A/C units - Rated COP: - Pre-1980: 3.11 - Post-1980: 3.17 Heating: furnaces - Efficiency: - Pre-1980: 0.68 - Post-1980: 0.78	M3
Water heating equipment	Natural gas centralized water heater	M1, M4

[1] The explanation of the index of the method column is in Table 4.2 and the main data sources consist of:
M1: EIA [51];
M2: EIA [51], Griffith et al. [78], Winiarski et al. [186];
M3: Griffith et al. [78], Winiarski et al. [186], Deru et al. [36];
M4: DOE [39], NREL [134].

5.2.4 Model Evaluation (Medium Office Buildings)

This section evaluates the performance of the prototypical building energy models of medium office buildings. The building models from the DOE Commercial Reference Building Models are used as reference [39]. Figure 5.3 shows the values of site EUIs for the reference and new models. The black bars are the site EUIs for the reference building models and the white bars are the new building models created in this chapter. The red "X"s are empirical baselines listed in Table 5.4.

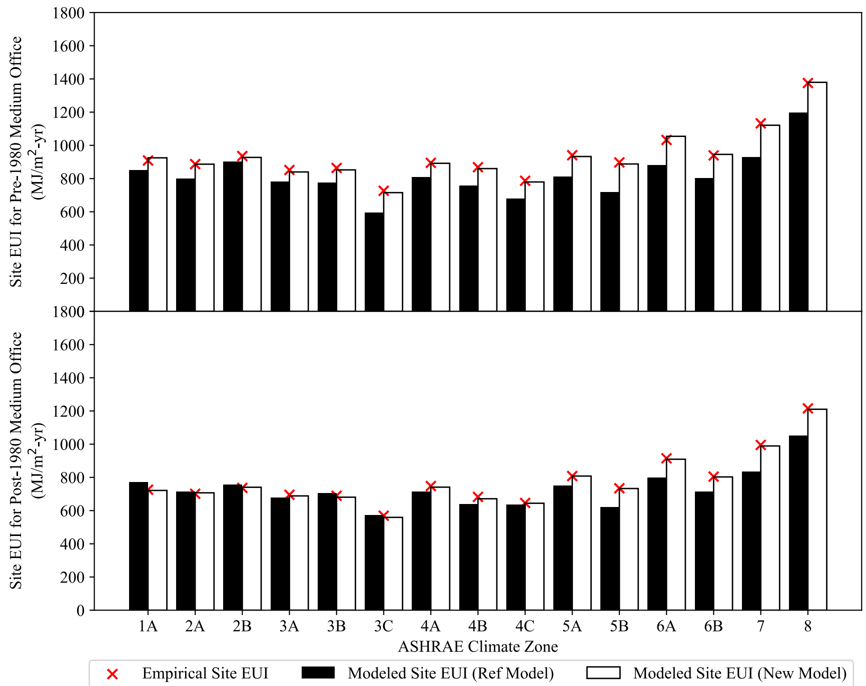


Figure 5.3: Comparison of site EUIs for the reference and new prototypical building energy models

The results show that the site EUIs of the new models are much closer to the empirical baselines. Then it is necessary to calculate *CV(RSMD)* and quantitatively evaluate the performance of the new models. The results are shown in Table 5.6.

Table 5.6: Evaluation of the new baseline models

Evaluation Index	**Unit**	**Pre-1980**		**Post-1980**	
		Ref Model	**New Model**	**Ref Model**	**New Model**
CV(RSMD)	-	0.194	0.016	0.123	0.009

The *CV(RSMD)* of both pre- and post-1980 new models are lower than 0.05, which meets the requirement provided in Section 4.4. By compared with the reference models, the values of *CV(RSMD)* is only approximately 0.075 times for the new models. Furthermore, this case compares the EUIs for heating and cooling in the reference and new models. The modeled EUIs are compared with the EUIs of building samples in the 2003 CBECS. To make the models and the 2003 CBECS data comparable, the 15 typical cities are put into the 2003 CBECS Climate Zones based on the cooling degree day 65 °F (CDD65) and heating degree day 65 °F (HDD65). Equations 5.2 and 5.3 express the method to calculate CDD65 and HDD65:

$$CDD65 = \sum_{Day=1}^{365} \left(\frac{1}{24} \sum_{hr=1}^{24} T_{hr} - 65 \right)^{+} \tag{5.2}$$

where T_{hr} is the ambient temperature in °F at a given hour in a day, and the + means that only the days with positive values for $\left(\frac{1}{24} \sum_{hr=1}^{24} T_{hr} - 65 \right)$ are included in the annual summation.

$$HDD65 = \sum_{Day=1}^{365} \left(65 - \frac{1}{24} \sum_{hr=1}^{24} T_{hr} \right)^{+} \tag{5.3}$$

where, similarly to CCD65, T_{hr} is the ambient temperature in °F at a given hour in a day, and the + means that only the days with positive values for $\left(65 - \frac{1}{24} \sum_{hr=1}^{24} T_{hr} \right)$ are included in the annual summation.

Figure 5.4 shows the results of comparison. By using the similar procedure of model creation, the data in the 2003 CBECS is cleaned [51]. Then the EUIs are adjusted by considering the impacts caused by some factors, such as the operating hours, occupant density, and plug load density. After that, for both pre- and post-1980 data, to evaluate the EUIs for heating, this case divides the data into five categories based on the HDD65; to evaluate the EUIs for cooling, the data is divided into five categories based on the CDD65. The boxplots are created and the red horizontal lines in the figure are the median values for boxplots. The red circles for Ref Model in the figure are the EUI for DOE Commercial Reference Building Models (reference models) while the blue triangles for New Model are the EUI for the new prototypical building energy models created in this case.

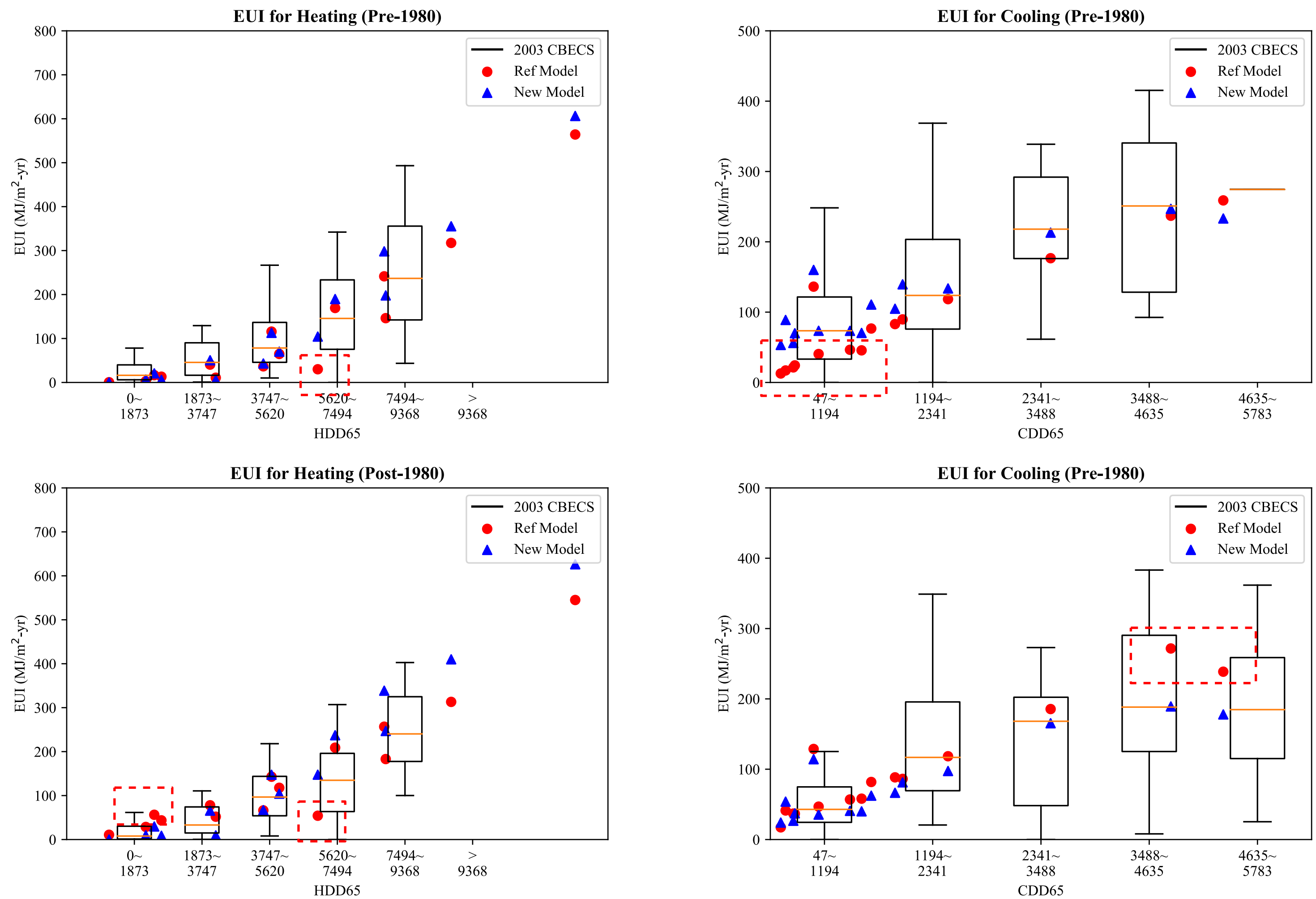


Figure 5.4: Analysis about the heating and cooling loads in the models and the 2003 CBECS

The results show that, in most of cases, the EUIs for heating and cooling in the new models are closer to the median values of the 2003 CBECS data. For example, in the figure, *EUI for Heating (Pre-1980)*, one case for a reference model in the red box has much lower EUI than the most of the 2003 CBECS data for building samples with the similar HDD65. Furthermore, the pre-1980 reference models tend to have lower EUIs for cooling in the cases with 47 $\sim$ 1194 CDD65 by compared with the 2003 CBECS data. Moreover, the post-1980 reference models tend to have higher EUIs for heating in the area with low HDD65 and higher EUIs for cooling in the are with high CDD65. The new models have a better performance for these problems.

Furthermore, Table 5.7 shows the differences between the DOE Commercial Reference Building Models (Ref Model) and the models created in this chapter (New Model) by using pre-1980 building model in climate zone 5A as an example. The column, "Material or Equipment for New Model", also provides some potential materials or equipment, which can be used to match the values of model inputs. Table 5.7 shows that the changes of geometry and system make great contributions to increase the site EUI of this model while the changes of envelope and schedule reduces the site EUI based on the Ref Model.

This section evaluates the performance of the new prototypical building energy models and shows that the new models meet the requirement. The next two chapters will provide two use cases about the building energy analyses for the U.S. medium office buildings. The models created in this section will also be used in these analyses to identify whether the new models will cause different analysis results.

5.3 Case Study 2: Model Creation for Religious Worship Buildings

This section creates the prototypical building energy models for existing U.S. religious worship buildings by using the methodology introduced in Chapter 4. The models are complemented the database for data sources in the standardized computational framework.

Table 5.7: Example of model input comparison (Pre-1980 building model in climate zone 5A)

Baseline (Empirical) Site EUI: 940.47 MJ/m²-yr						
Item		**Unit**	**Ref Model** *Site EUI: 812.26 MJ/m²-yr*	**New Model** *Site EUI: 932.75 MJ/m²-yr*	**Material or Equipment for New Model**	**Energy Impact** $NewModel_{SiteEUI} - RefModel_{SiteEUI}$
Geometry	Total Floor Area	m^2	4,982	3,130	-	+158.29 MJ/m^2-yr
	Aspect Ratio	-	1.50	2.01	-	
	Window fraction	-	33.00%	27.50%	-	
Envelope	Exterior Wall Insulation R-value	m^2-K/W	1.13	1.01	R-6 Steel Frame Wall Insulation	-39.14 MJ/m^2-yr
	Roof Insulation R-value	m^2-K/W	2.50	2.05	R-12 IEAD Roof Insulation	
	Window U-value	W/m^2-K	3.53	4.26	Double Glazed Window with Air Vent	
	Window SHGC	-	0.41	0.60		
	Infiltration	m^3/s-m^2	0.00113	0.00031	-	
Schedule	Schedule	-	The schedules are simplified in the New Models		-	-57.07 MJ/m^2-yr
Internal Load	Lighting Power Density	W/m^2	16.90	16.34	-	+2.85 MJ/m^2-yr
	Electricity Equipment Power Density	W/m^2	10.76	14.74	-	
	People Density	m^2/person	18.58	20.48	-	
System	Ventilation Rate	m^3/s-person	0.0125	0.0242	-	+193.76 MJ/m^2-yr
	Cooling COP	-	3.38	3.11	Direct Expansion (DX) Cooling System (Rated COP=3.11)	
	Heating Efficiency	-	0.78	0.68	Gas Furnace over 120 MBH (Eff=0.68)	
	Water Heater Efficiency	-	0.80	0.69	Commercial Water Heater, 100 gallon (Eff=0.69)	

5.3.1 Model Inputs (Religious Worship Buildings)

Based on reviewing the existing prototypical building model sets [39, 45, 134], this section selects one typical city for each ASHRAE Climate Zone. The existing prototypical building model sets for existing buildings, such as DOE Commercial Reference Building Models and OpenStudio-Standards gem [39, 134], use the ASHRAE Standard 90.1-2004 Climate Zones [17, 18]. To be consistent with their settings, the same version of ASHRAE Climate Zones is used in this section, and 15 typical cities are selected for the 15 climate zones based on the typical cities selected in the existing data sets and engineering judgments. Because empirical energy data is used to evaluate the modeled energy results, 2003 historical weather files of the typical cities are used for the prototypical building energy models. Based on the methodology described in the Chapter 4, model input files are created for the 30 models by using SketchUp for the geometries and OpenStudio, and the uncertainties of sensitive model inputs are identified.

Based on the methodology introduced in the Chapter 4, the model inputs are determined by using the 2003 CBECS data, the data provided by building energy-related papers and reports, and model inputs of DOE Commercial Reference Building Models [39, 51, 170, 171, 172, 78, 186, 187]. This case collects these data into a data set. Then the data set needs to be cleaned. For example, approximately 50% religious worship building samples have wide-rectangle shape while lower than 1% samples have "E" shape. Thus, the samples with "E" shapes should be deleted. Furthermore, only 25% religious worship building samples are smaller than 235 m^2, and only 25% samples are bigger than 4,000 m^2. Thus, the samples smaller than 235 m^2 or bigger than 4,000 m^2 are deleted. Since the 2003 CBECS data only provides 311 samples for religious worship buildings, which is insufficient to develop the building models, some building samples are implemented by selecting from other survey data sources, such as the 2012 CBECS data [57]. The buildings constructed after 2003 are not selected. Ultimately, the initial sample size is approximately 550 buildings, and after cleaning, there are approximately 300 samples remaining. Over 200 samples were modified based on the rules introduced in Section 4.2.3. Since most of the building samples come from the 2003

CBECS data set, this case uniformly refers to the survey building samples by this name. After cleaning the related data, the data is classified into four categories and converted into model inputs by using various methods identified in Table 4.2. For example, through method M1 introduced in Table 4.2, the median total floor area of the religious worship building samples is used as the modeled total floor area. Because the total floor area is not impacted by the climate, the same settings are applied to all models regardless of the climate zone, which avoids the problem of insufficient building samples. Next, by using methods M2 and M4, operating schedules in the models are determined. Just as with total floor area, the models have the same profiles for operating schedules in all the climate zones. By using the same procedure shown in Figure 5.1, Figure 5.5 shows the workflow to determine the modeled operating hours every day based on the 2003 CBECS data.

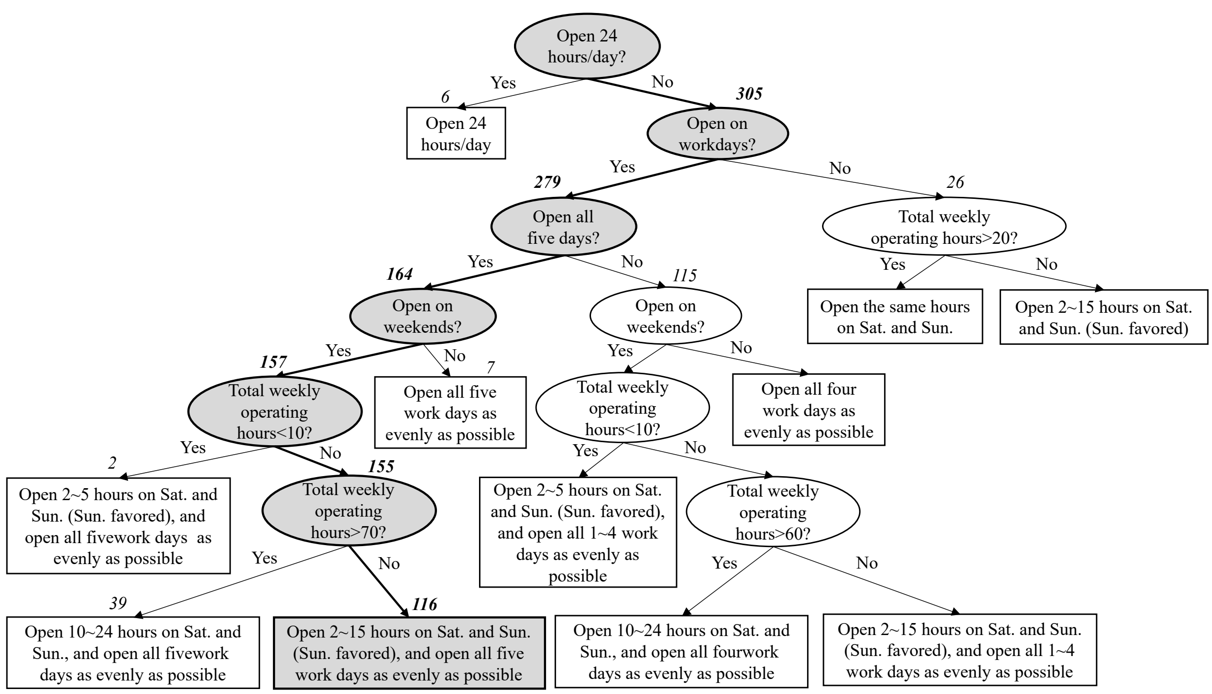


Figure 5.5: Workflow to determine operating hours for models (religious worship buildings)

In Figure 5.5, the numbers shown above boxes and ovals are the quantities of remaining building samples in the 2003 CBECS after being classified. Based on the workflow, the models should operate 2∼15 hours each weekend and all five workdays as evenly as possible. After that, the operating schedules are adjusted by using DOE Commercial Building Models and engineering judgement. Then by using method M3 in Table 4.2, the models' infiltration rate is identified [78]. Finally, the 2003 CBECS provides the general types of exterior walls and roofs for individual building samples, but it does not give the details of the envelopes; thus, the method M4 is used to identify the details of the envelopes in the models. Winiarski et al. [186] provided the matchup of envelope types between the 2003 CBECS and ASHRAE Standard. Since the classification of envelope types in DOE Commercial Reference Building Models follows ASHRAE Standard, the insulation R-values of exterior walls and roof in DOE Commercial Reference Building Models can be used as references to create the prototypical building energy models of existing U.S. religious worship buildings [39]. Finally, this section identifies the values or ranges of model inputs for the prototypical building energy models of religious worship buildings.

5.3.2 Evaluation Criteria (Religious Worship Buildings)

It is essential to evaluate the performance of prototypical building energy models by using the energy data of building samples with the similar weather conditions. Due to the limited building samples in the 2003 CBECS, this case uses the rule-based criteria to evaluate the performance of the prototypical building energy models of religious worship buildings. ASHRAE classifies the U.S. into 15 climate zones [17, 18], which are used to select the 15 typical cities; however, since the 2003 CBECS divides the U.S. into 5 climate zones [56], a method is required correlate these different zone identifications. To accomplish this, the 15 typical cities are put into the 2003 CBECS Climate Zones based on the cooling degree day 65 °F (CDD65) and heating degree day 65 °F (HDD65). Equations 5.2 and 5.3 express the method to calculate CDD65 and HDD65.

To allocate the 15 typical cities across the 5 climate zones available in the 2003 CBECS dataset, the 2003 historical weather files of the typical cities are used to identify CDD65 and HDD65. Figure 5.6 shows the location distribution of typical cities and building samples in the 2003 CBECS.

Due to limitations in available survey data, the survey values available do not always ac-

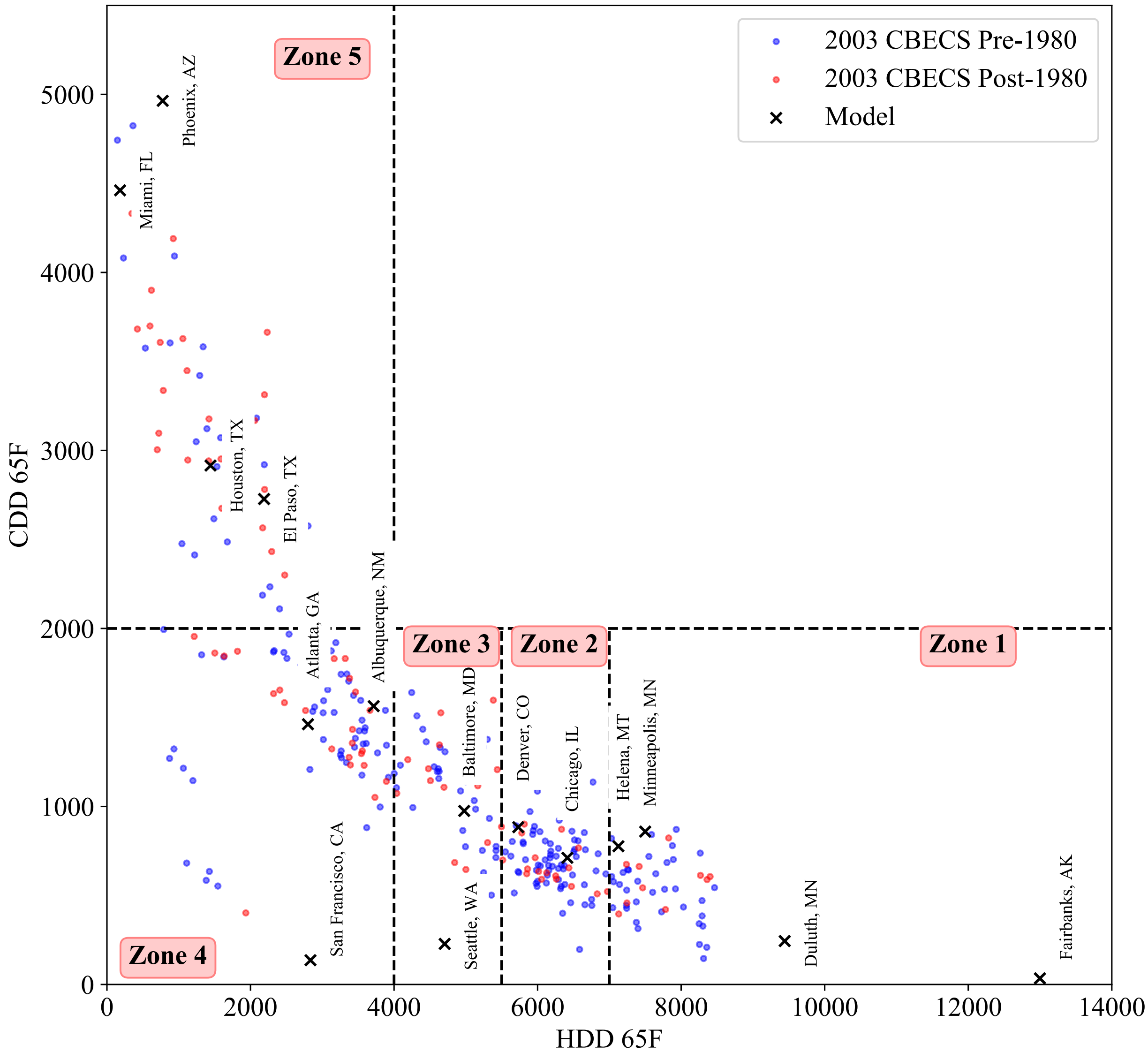


Figure 5.6: Location distribution of building samples in CBECS climate zones and prototypical building energy models

curately represent the required model cities. Figure 5.6 shows that the most building samples in the 2003 CBECS are located in areas with HDD65 less than 9,000, and there is a lack of building samples in locations over 9,000 HDD65. However, two model cities, Duluth, MN and Fairbanks, AK, have HDD65 over 9,000. Thus, it can be expected that the building energy models in 2003 CBECS Climate Zone 1 will have higher energy consumption for heating than the building samples.

Similarly, the CDD65 of San Francisco, CA is far lower than the median value of building samples in the 2003 CBECS Climate Zone 4, and the CDD65 of Seattle, WA is lower than median value in the 2003 CBECS Climate Zone 3. Because of this, the models in the San Francisco, CA and Seattle, WA probably consume less energy per area for cooling compared to the building sample data. Thus, based on these rules, the performance of the models will be evaluated.

5.3.3 Model Description (Religious Worship Buildings)

Based on the values and ranges of model inputs, and criteria for model validation, the prototypical building energy models of religious worship buildings are calibrated. Figure 5.7 shows the geometry of the calibrated models.

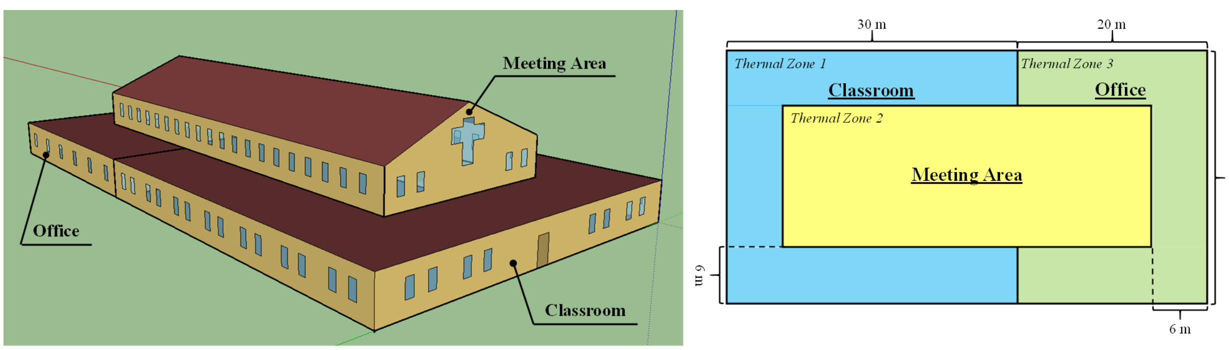


Figure 5.7: Geometry of the building energy models for the U.S. religious worship buildings

To perform the energy analysis of religious worship building, the geometry is created based on the information provided by the 2003 CBECS and several relevant papers [51, 170, 171, 172]. The total floor area of the building energy model is 1,300 m^2 with a wide rectangular shape and 1.93 aspect ratio. It contains three space types and three thermal zones. The perimeters are offices and classrooms, and the core is a meeting area. The window-to-wall ratio is 11.5%, and windows are distributed with equal percentages on all four sides. The front of religious worship model faces to west. The floor-to-ceiling heights of offices and classrooms are both 3 m, while the height of meeting area is 6∼9 m.

Then, the models are calibrated in the ranges of uncertainties of sensitive model inputs. This case selects more than 10 sensitive model inputs with their uncertainties for the model calibration, such as electrical equipment power density, lighting power density, insulation R-value of envelopes, and rated COP for cooling system. The ranges of the sensitive model inputs for prototypical building models have been determined in Section 5.3.1. These ranges are decided based on the CBECS data, literature, DOE Commercial Reference Building Models, and engineering judgment [39, 51, 170, 171, 172, 36, 78]. The building models with different vintages in various climate zones have their own specific ranges for individual inputs, and this case assumes normal distributions for all inputs. Furthermore, the links of these model inputs in different models are considered.

In total, there are approximately 10^7 possible combinations for each prototypical building model. Although the genetic algorithm (GA) can identify the global best solution much faster than exhaustive simulations, it is still time consuming to conduct simulations. Thus, to reduce computational time, the Latin Hypercube Sampling (LHS) method is used to select the building samples and the simulations are conducted for all samples by using OpenStudio. Next, the values of sensitive model inputs and site EUIs for individual building samples are used to train and test the Support Vector Regression (SVR) meta-models. Then this case conducts simulations by using meta-models and use genetic algrithom to identify the best solutions. Finally, based on the rule-based criteria, the standardized computational framework selects the best combinations as the prototypical building models with the two vintages in the 15 climate zones. By comparing the simulation results with the survey data, the average difference between the modeled site EUIs and the 2003 CBECS median site EUIs is reduced by approximately 10%. However, there are still differences between the modeled site EUIs and the 2003 CBECS median site EUIs. The reason will be analyzed in Section 5.3.4. Table 5.8 lists the inputs of prototypical building energy models for existing U.S. religious worship buildings after model calibration. The Method column shows the relevant method index corresponding to those listed in Table 4.2.

Table 5.8: Model inputs of prototypical building energy models for U.S. religious worship buildings

Input	**Value**	**Method** [1]
Location	1A, Miami, FL 2A, Houston, TX 2B, Phoenix, AR 3A, Atlanta, GA 3B, El Paso, TX 3C, San Francisco, CA 4A, Baltimore, MD 4B, Albuquerque, NM 4C, Seattle, WA 5A, Chicago, IL 5B, Denver, CO 6A, Minneapolis, MN 6B, Helena, MT 7, Duluth, MN 8, Fairbanks, AK	M4
Vintage	Pre-1980 Post-1980	M4
Geometry	Total floor area: 1,300 m^2 Building shape: Wide rectangle Aspect ratio: 1.93 Window fraction: 11.5% Window locations: Equal percentages on all sides Number of floors: 1 Shading: No Floor-to-ceiling height: - Meeting area: 6 - 9 m - All other areas: 3 m	M1, M2, M3
Schedules	Calculated based on Figure 5.5 and engineering judgment	M2, M4

Input	Value	Method [1]
Envelope	Exterior walls: mass walls - Insulation R-value of exterior walls (m^2-K/W): - Pre-1980: [0.35, 0.99] - Post-1980: [0.10, 3.32] Roof: Insulation Entirely Above Deck (IEAD) - Insulation R-value of roof (m^2-K/W): - Pre-1980: [1.56, 2.74] - Post-1980: [2.18, 5.48] Windows: hypothetical window - U-value of glazing (W/m^2-K): - Pre-1980: [3.53, 5.84] - Post-1980: [2.96, 5.84] - SHGC of glazing (unitless): - Pre-1980: [0.41, 0.54] - Post-1980: [0.25, 0.62]	M2, M4
Plug and process loads	2.5 W/m^2 for the whole building	M2
Occupant density	7.00 m^2/person for meeting area 23.22 m^2/person for other area	M2
Lighting power density	10.00 W/m^2 for meeting area 15.10 W/m^2 for other area	M3
Infiltration rate	0.00027 m/s for the whole building (Flow per exterior surface area)	M3
Ventilation requirement	0.0094 m^3/s-person for the whole building	M4
HVAC system	Cooling: packaged A/C units (Rated COP: 3.27) Heating: furnaces (Efficiency: pre-1980: 0.78, post-1980: 0.8)	M3
Water heating equipment	Natural gas centralized water heater	M1, M4

[1] The main data sources consist of:
M1: EIA [51];
M2: EIA [51], Griffith et al. [78], Winiarski et al. [186];
M3: Griffith et al. [78], Winiarski et al. [186], Deru et al. [36], Terrill et al. [170], Terrill and Rasmussen [172];
M4: DOE [39], NREL [134].

5.3.4 Model Evaluation (Religious Worship Buildings)

After calibrating the building energy models, the site EUIs of models are compared with the EUIs of building samples for each climate zone. Figure 5.8 shows the site EUIs of the prototypical building energy models and the building samples in the 2003 CBECS.

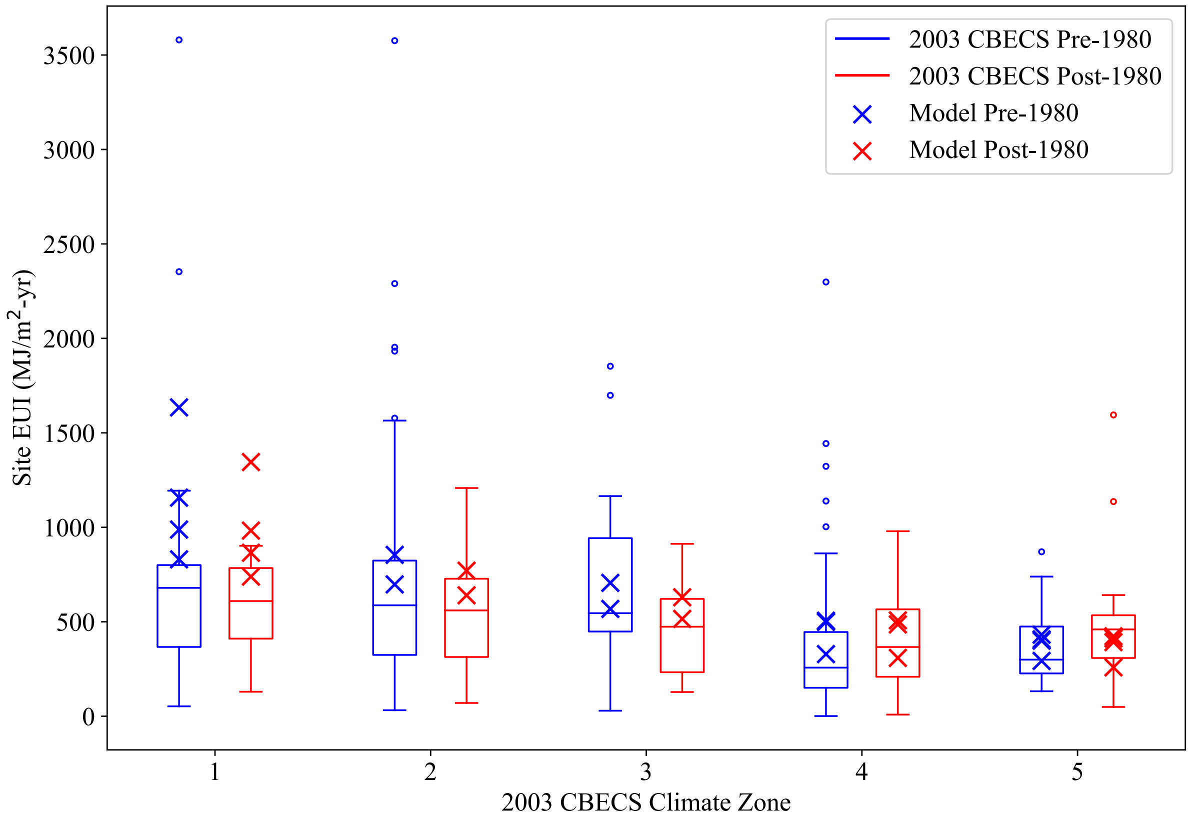


Figure 5.8: Site EUIs of building samples and prototypical building energy models (religious worship buildings)

While the site EUIs of the prototypical building energy models are mainly in the $25^{th}\sim75^{th}$ percentiles of building samples' site EUIs (Figure 5.8), some discrepancies between model and sample EUIs exist due to misalignment in locations available and low sample sizes in some categories. Typical cities in the 2003 CBECS Climate Zone 1 have higher HDD65 than the locations of most building samples; as a result, the models in these cities consume more energy per area for heating, and the site EUIs of these models will also be higher than the building samples in this climate zone. In addition to misalignments such as this, some discrepancies between the model and building sample EUIs are caused by low sample sizes. The total number of both pre-1980 and post-1980 building samples in the 2003 CBECS is around 300; however, the number of building samples is insufficient for some climate zones and vintages. For example, only 14 post-1980 building samples are in 2003 CBECS Climate Zone 3. The median site EUI is easily affected by individual building samples when there are insufficient samples. To address these limitations and avoid over-fitting, this case compares the energy performance of prototypical building energy models to the building samples from the CBECS data using engineering judgments.

Table 5.9 summarizes the performance metrics for select cities to exemplify how this case uses engineering judgment to evaluate the calibrated typical building models. These selected cities demonstrate median and extreme cases when comparing the typical models and CBECS sample buildings. As can be seen in Figure 5.7, Houston has average CDD65 and HDD65 among the building samples in the 2003 CBECS Climate Zone 5. As such, pre-1980 and post-1980 religious worship building models in Houston have similar EUIs for cooling and heating compared to the survey median data, as shown in Table 5.9. Conversely, Phoenix has higher cooling EUIs compared to the survey data. This difference is due to the higher CDD65 in Phoenix than the median level of building samples in the 2003 CBECS Climate Zone 5. Thus, the Phoenix prototypical building energy model is qualified after being calibrated. Another example is that the models in Fairbanks have higher HDD65 than the survey buildings, as can be seen in Figure 5.7; both pre-1980 and post-1980 models have higher EUIs for heating compared to the corresponding median empirical EUIs. Repeating this process for all 15 typical cities, it is confirmed that the calibrated building energy models meet the criteria based on engineering judgment. Therefore, the developed models of existing U.S. religious worship buildings are good representations of prototypical building energy models. However, it is noted that due to the limited number of building samples, it is necessary to avoid over-fitting and accept large variation between the survey and simulation data.

5.4 Summary

Based on the methodology introduced in Chatper 4, this chapter creates the prototypical building energy models for U.S. medium office and religious worship buildings. Since there are enough building samples for the medium offices in the 2003 CBECS [51], the prototypical building

Table 5.9: Possibility of related data for model inputs provided by commonly used U.S. commercial building energy databases

Typical City	**2003 CBECS Climate Zone**	**Vintage (Pre/Post)**	**Criteria**[1]	**Model**[2] **(MJ/m²-yr)**		**Survey**[2,3] **(MJ/m²-yr)**			**Meet the Criteria (Y/N)**
				Cooling	**Heating**	**Cooling**	**Heating**	**# Samples**	
Houston	5	Pre	Both	70.82	27.12	69.99	20.21	25	Y
Phoenix	5	Pre	Cooling	132.98*		69.99		25	Y
San Francisco	4	Pre	Cooling	4.52		39.11*		56	Y
Seattle	3	Pre	Cooling	6.81		12.35*		34	Y
Denver	2	Pre	Both	30.81	186.41	4.70	294.39	40	Y
Duluth	1	Pre	Heating		845.95*		158.48	37	Y
Fairbanks	1	Pre	Heating		1,291.55*		158.48	37	Y
Houston	5	Post	Both	67.04	28.73	88.84	16.21	31	Y
Phoenix	5	Post	Cooling	131.27*		88.84		31	Y
San Francisco	4	Post	Cooling	3.39		34.45*		22	Y
Seattle	3	Post	Cooling	4.96		27.82*		14	Y
Denver	2	Post	Both	26.03	168.14	11.80	378.87	33	Y
Duluth	1	Post	Heating		698.50*		426.88	10	Y
Fairbanks	1	Post	Heating		1,051.45*		426.88	10	Y

[1] *The criteria listed indicates which EUI is being compared (Cooling or Heating).*
[2] *The asterisks indicate which EUI is larger between the Model and Survey.*
[3] *EUIs in the survey columns are the median empirical EUIs for cooling and heating.*

energy models for U.S. medium office buildings are validated by using the regression model created based on the 2003 CBECS data. However, there are not enough building samples for U.S. religious worship buildings in the 2003 CBECS. Thus, the second case provides the loose rule-based criteria to validate the energy performance of the models for U.S. religious worship buildings. Furthermore, the performance of these models are compared with the existing models from the DOE Commercial Reference Building Models [39]. The new models of religious worship buildings are stored into the database in the standardized computational framework.

Besides creation of prototypical building energy models, the standardized computational framework is also able to conduct different types of building energy analyses. Chapters 6 and 7 will provide two case studies to research on two types of the building energy analyses. Chapters 6 will study the impacts of the energy savings on energy efficiency measure (EEM) selection while Chapters 7 will study the impacts of the electricity pricing programs on energy efficiency measure (EEM) selection. The medium offices are used to do the research. Furthermore, this dissertation will discuss about the impact of the baseline models on the results and will compare the prototypical building energy models created in this chapter with the models from existing data sources.

Chapter 6

Impacts of Energy Savings on EEM Selection

This chapter provides one example for the standardized computational framework about building energy analyses and analyze the impacts of building energy savings on the selection of energy efficiency measures (EEMs). The DOE Commercial Prototype Building Energy Models for medium office buildings are used as the baseline models [45]. Three global sensitivity analysis methods are used: Standardized Regression Coefficients (SRC), Morris, and Sobol. Furthermore, this chapter also discusses how different baseline models impact the energy saving in relationship to the EEM selections.

6.1 Introduction

The 2012 Commercial Buildings Energy Consumption Survey (CBECS) showed that U.S. office buildings consume over 3×10^6 GJ of primary energy annually, and approximately 50% of this is from medium office buildings, which have total floor areas from 1,000 m^2 to 10,000 m^2 [57]. With over 80% of all medium office buildings constructed before 2000, there is a great potential to reduce energy consumption by conducting existing building retrofits [74, 77, 173].

Detailed building energy models are usually used in the retrofit projects for the large buildings. However, these are often not cost-effective for small retrofit projects, such as medium office buildings. Instead, small retrofit projects typically rely on prescriptive methods for energy reduction strategies, which have their limitations. First, building owners often make independent retrofit decisions, but their knowledge may be limited in selecting EEMs that are most effective while minimizing cost. Second, building engineers have potential biases when selecting EEMs based on previous experience. Without comprehensive analyses, they tend to select some high-efficiency measures, which from past projects demonstrated strong energy saving performance with the short payback periods; however, these techniques may not be suitable for the current project. Furthermore, by using prescriptive methods, it is possible to neglect some important factors, such as climates or occupancy schedules, and interactive relationships between EEMs. Therefore, the actual payback period of energy retrofit of medium office buildings may be longer than the expectations.

To identify which measures have the highest energy saving potentials, it is useful to have readily-available knowledge about which EEMs are most effective for the target building type and climate zone. A priori knowledge can help various types of users – such as building owners, architects, and engineers – select prioritized EEMs in specific climate conditions. Furthermore, the knowledge provides focused EEMs to streamline the building energy modeling process. A detailed building energy model usually contains hundreds of EEM-related data. In order to develop accurate predictive models within budgeted timeframes, a priori knowledge can inform modelers which EEMs need the most attention and, more importantly, which EEMs they can suitably assign default or estimated values with minimal impacts to building energy consumption. Moreover, a streamlined building energy modeling process for medium office buildings can help designers achieve creative energy-saving designs; energy modeling provides greater flexibility in evaluating EEM combinations than other methods and can be used to quantitatively investigate advanced design strategies [126].

Energy performance indicators (EPIs) are often used to quantify the impacts of the EEMs on building energy consumption. Source and site energy use intensities (EUIs) are the two most common EPIs. While EUI is defined as the energy use per area in a year, the system boundary where that energy is evaluated changes between site and source methods. Site energy is the combination of primary (typically natural gas and fuel oil) and secondary energy (electricity) that is used directly at a building [67]. Expanding out from the building level (site), source energy is the total amount of raw fuel that is consumed through the building's operation. As such, the transmission, delivery, and production losses are also included in the calculation. There are various pros and cons to using site or source energy as the basis for evaluation. For example, site EUI is metered directly and contains less uncertainty, while source EUI is not fully metered, contains greater uncertainty, and is inherently more complex. On the other hand, source EUI considers all of the energy use through its encompassing scope, while site EUI does not fully represent the true energy cost. Since the energy costs are important considerations for building owners and these costs accrue at the site utility meters, this chapter selects site EUI to quantify EEM impacts on building energy consumption.

There are multiple methods to guide EEM selection in retrofit applications, such as engineering judgment, building energy codes, and published guidelines. While these methods are frequently used and often effective, their effectiveness can be limited by human biases and their generalized nature. To this end, a guideline based on large-scale simulations and sensitivity analysis can provide unbiased recommendations that are appropriate for the target climate. Furthermore, such recommendations allow us to identify the interactive relationships between various EEMs. Existing research provides a rich set of references to identify effective EEMs for individual buildings by conducting large-scale simulations and sensitivity analysis [126, 63, 89, 34, 161, 16]. For example, based on 100,000 energy model simulations, the New Buildings Institute (NBI) developed a prescriptive guide for small to medium sized new construction projects that can achieve up to 40% energy savings over ASHRAE 90.1-2007/IECC 2009 [126].

One popular method to quantitatively guide EEM development at a large scale is sensitivity analysis. Using sensitivity analysis to conduct building energy analyses is well studied [63, 34, 161, 16, 137, 28, 81, 82, 128, 154, 174, 175, 142]. In the existing research, different sensitivity analysis methods have been applied. To provide a guideline to select sensitivity analysis methods, Table 6.1 summarizes the advantages and disadvantages of individual sensitivity analysis methods.

Generally, sensitivity analysis methods can be classified as either local or global approaches, and the global approach can be further classified into four categories: regression, screen, variance based, and meta-model. Although the local sensitivity analysis method is straightforward and has low computational cost, the sensitivity levels are only for the input factors around certain base cases, and interactions between inputs cannot be detected [174]. Furthermore, self-verification is

Table 6.1: Advantages and disadvantages of sensitivity analysis methods

Type	Subtype	Method	Advantage	Disadvantage
Local	**-**	Local	(1) Straightforward and low computational cost [174]	(1) The sensitivity levels are only for the input factors around certain base cases [174] (2) The interactions between inputs cannot be detected [174] (3) No self-verification [174]
Global	**Regression**	SRC/SRRC/ PCC/PRCC[1]	(1) Fast computational speed [165] (2) Good interpretability [165]	(1) Have a poor performance where the underlying relationship is far from linear [165]
		t-value		
	Screen	Morris	(1) Low computation cost among the global sensitivity analysis [174]	(1) Have no self-verification [174]
	Variance based	Sobol	(1) Have a relatively good performance to analyze nonlinearity and interaction effects [123]	(1) Have high computational costs [174] (2) Be weak for the models with large number of inputs and complex model structure [123]
		FAST[2]	(1) Have a relatively good performance to analyze nonlinearity [174]	(1) Be weak to analyze interaction effects [174]
	Meta-model	Generalized Additive Models	(1) Have a relatively good performance to analyze nonlinearity [164]	(1) Be weak to analyze interaction effects [164]
		Response Surface Regression	(1) Be able to identify a certain degree of interaction [164]	(1) Be weak to analyze some types of nonlinearity [164]
		Recursive Partitioning Regression	(1) Have a relatively good performance to analyze nonlinearity and interaction effects for discrete variables [164]	(1) Be high computational cost [164] (2) Do not performance well for continuous variables [108] (3) Have the risk to overfit data [72]

[1] SRC: Standardized Regression Coefficients; SRRC: Standardized Rank Regression Coefficients; PCC: Partial Correlation Coefficients; PRCC: Partial Rank Correlation Coefficients.
[2] FAST: Fourier Amplitude Sensitivity Testing.

not available to support the results generated by local sensitivity analysis methods, which makes the results fragile. Most of the global sensitivity analysis methods avoid these disadvantages. However, they still have some limitations for specific situations. For example, Standard Regression Coefficient (SRC), Morris, and Sobol are three popular global sensitivity analysis methods used in building energy analyses. The SRC method has the lowest computational cost among the three methods and good interpretability [165, 166]. However, it has a poor performance where the underlying relationship is far from linear. The computational cost of the Morris method is also low among the global sensitivity analysis methods, but it does not have self-verification; this is similar to the local sensitivity analysis method [174]. Furthermore, the Sobol method demonstrates relatively good performance analyzing nonlinearity and interaction effects. However, it has high computational costs and is weak for models with a large number of inputs or complex model structure [174, 123]. With these considerations in mind, this chapter proposes using these three different types of global sensitivity analysis methods (SRC, Morris, and Sobol) in order to avoid biases from individual sensitivity analysis methods.

This chapter aims to evaluate the energy saving potential of several EEMs for retrofits of U.S. medium office buildings through large-scale simulations and sensitivity analyses. This a priori knowledge can help building owners identify promising EEMs in their given climate and engineers develop predictive models to evaluate the energy savings in retrofit applications. The remainder of this chapter is structured as follows. Section 7.2 describes the methodology. Section 6.3 presents the analysis results for medium office buildings in 15 climate zones and provides climate-specific EEM evaluations. Section 6.4 compares the selection of EEMs by using the prototypical building energy models created in Section 5.2 and the models from the DOE Commercial Reference Building Models [39]. Finally, Section 7.5 makes a conclusion of this chapter and discusses the potential applications for the results.

6.2 Methodology to Evaluate the Impacts of Energy Savings on EEM Selection

As shown in Figure 6.1, the methodology consists of four sections: (1) model preparation, (2) large-scale simulation, (3) sensitivity analysis, and (4) energy impact evaluation. The first step develops baseline models and selects EEMs with their range of uncertainties. The second step generates large-scale building samples by using sampling methods, conducts uncertainty analysis of site EUIs, and develops a meta-model. The third step calculates the energy savings by individual EEMs and the interactive effects of two EEMs on energy savings. Furthermore, this chapter identifies the sensitive EEMs based on the aggregated results calculated by three sensitivity analysis methods. The last step provides the recommendations for building modeling and retrofits of existing buildings.

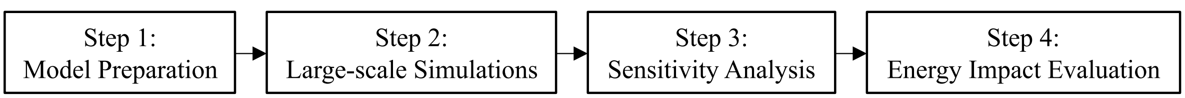


Figure 6.1: Methodology to generate recommendations

6.2.1 Step 1: Model Preparation

Model preparation consists of two tasks: developing baseline models and selecting EEMs. There are many sets of prototypical building energy models, which can be used as baseline models [39, 45, 134, 195, 196, 194]. For example, the DOE Commercial Reference Building Models, Commercial Prototype Building Models, and OpenStudio-Standards gem provide many prototypical building energy models for various U.S. commercial buildings [39, 45, 134]. Furthermore, some researchers created prototypical building energy models for other commercial building types to complement the existing datasets, which are also suitable to be used as baseline models [195, 196, 194]. Based on the required building types, vintages, and areas, the computational framework selects the prototypical building models from these sets. For instance, it is recommended to select models from the DOE Commercial Reference Building Models if existing U.S. medium office buildings constructed in 1980s need to be analyzed.

Existing research conducted data analyses for subsets of EEMs of buildings with various characteristics under different climates. The research is used to select possible sensitive EEMs and identify the uncertainty ranges that can be expected for these EEMs. Some existing research conducts analyses for energy saving potentials of existing buildings [74, 103, 184, 183, 185]. The sensitive EEMs need to be identified before analyzing the energy saving potentials, which are used as references to select the EEMs. Furthermore, the DOE Commercial Reference Building Models and Commercial Prototype Building Models are developed according to different editions of building energy standards or codes [173, 45, 39, 36]. The values of the selected EEMs in these models are used to determine the ranges of these EEMs. Uniform distributions are assumed for all EEMs.

6.2.2 Step 2: Large-scale Simulations

The large-scale simulations conduct thousands of building energy simulations, which prepares for the sensitivity analysis. The large-scale simulation methods consist of six sub-steps (Figure 6.2). In Step 2.1, based on the uncertainties of the selected EEMs, this chapter selects building samples by using the Latin Hypercube Sampling (LHS) method [163]. In Step 2.2, full-scale building energy models of these samples are developed by using EnergyPlus. By including detailed inputs in the model, accurate outputs can be generated.

In Step 2.3, this chapter conducts uncertainty analysis to evaluate the ranges of site EUIs of the building samples caused by the uncertainties of the selected EEMs. If the ranges of site EUIs are too narrow, this chapter considers that there are no sensitive EEMs. In other word, the building energy consumption is not impacted by the selected EEMs. As a result, the standardized computational framework will have to restart Step 1 to select other EEMs. Otherwise, the framework will move to Step 2.4.

A large number of building samples is needed for the sensitivity analysis, especially when

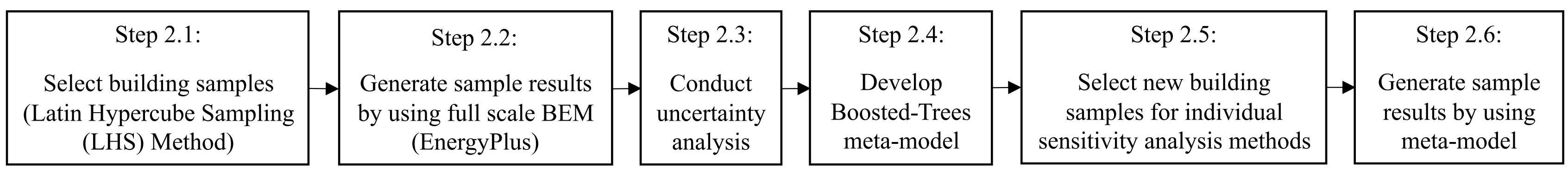


Figure 6.2: Six steps of large-scale simulation methods

using the Sobol method. For instance, approximately 20,000 samples are needed if eight EEMs are considered in each climate zone. Thus, Step 2.4 is to create a meta model to reduce the computation time. This study adopts a Booted-Trees meta-model. The Boosted-Trees meta-model is developed based on the building samples and results generated in Steps 2.1 and 2.2. The objective of Boosted Trees is to generate a model that can capture all the useful information with minimal complexity. To achieve this objective, the function consists of two parts:

$$obj\left(\theta\right) = L\left(\theta\right) + \Omega\left(\theta\right) \tag{6.1}$$

where $L(\theta)$ is training loss, represented by the difference between the training values and the real values, and controls the accuracy of the model; the Mean Squared Error (MSE) is used as the criterion to minimize $L(\theta)$; $\Omega(\theta)$ is the regularization term, which controls the complexity of the model and is used to avoid over-fitting.

Step 2.5 generates building samples based on the requirements of individual sensitivity analysis methods. At the end, Step 2.6 calculates energy results of these samples generated by Step 2.5 by using the meta-model.

6.2.3 Step 3: Sensitivity Analysis

Figure 6.3 shows the methodology to conduct sensitivity analysis and evaluate the potential energy impact, which are Steps 3 and 4. In Step 3, first, it is needed to calculate the energy savings caused by improving individual EEMs and the interactive effects of two EEMs. After that, this chapter identifies sensitive EEMs. As mentioned in the introduction, to avoid bias of an individual method, three sensitivity analysis methods (SRC, Morris, and Sobol) are selected to identify sensitive EEMs. The methodology, shown in Figure 6.3, depicts the unique sampling method for each sensitivity analysis method. For sampling methods, LHS is used to select building samples in the SRC method [163]; Morris provides its own sampling method; and the Saltelli's sampling scheme is used to select building samples in the Sobol method [83]. Based on the sensitivity analysis results, Step 4 conducts the energy impact evaluation, which will be described further in

Section 2.4. The energy savings for individual EEMs, the interactive effects of multiple EEMs, and the three sensitivity analysis methods will be explained in further detail in the following subsections.

6.2.3.1 Energy Savings for Individual EEMs and Interactive Effects

Before identifying the sensitive EEMs by using global sensitivity analysis methods, it is necessary to calculate the energy savings caused by improving individual EEMs and interactive effects of two EEMs on energy savings. First, the standardized computational framework uniformly selects five values for each EEMs in the ranges of EEMs. Second, based on the baseline models, a one-at-a-time (OAT) method is used to calculate the energy savings caused by improving individual EEMs. Then this chapter changes values of two EEMs at the same time. The interactive effects are calculated by using the following equation:

$$Diff_{EEM_{i+j}} = EEM_{i+j} - EEM_i - EEM_j, \quad i \neq j \quad \text{and} \quad i, j = 1, 2, \cdots, 11 \tag{6.2}$$

where i and j are the number of the EEM for each option; EEM is the percentage of energy saving. Thus, EEM_{i+j} is the percentage of energy saving by using i^{th} and j^{th} EEMs, and EEM_i or EEM_j is the percentage of energy saving by only using i^{th} or j^{th} EEM. If the $Diff_{EEM_{i+j}}$ is positive, it means that the two EEMs have a positive effect on energy saving; a negative value means a negative effect; and zero is no interactive effect.

6.2.3.2 SRC Method

The SRC method provides a measure to evaluate the importance of EEMs for EUIs. It uses a linear regression model to identify the relationship between EEMs and EUIs. The regression model is expressed as:

$$\left(E\hat{U}I_i - E\bar{U}I\right)/\hat{s} = \sum_{j=1}^{m} \left(b_j \hat{s}_j / \hat{s}\right) \left(EEM_{ij} - E\bar{E}M_j\right)/\hat{s}_j = \sum_{j=1}^{m} SRC_j \left(EEM_{ij} - E\bar{E}M_j\right)/\hat{s}_j \tag{6.3}$$

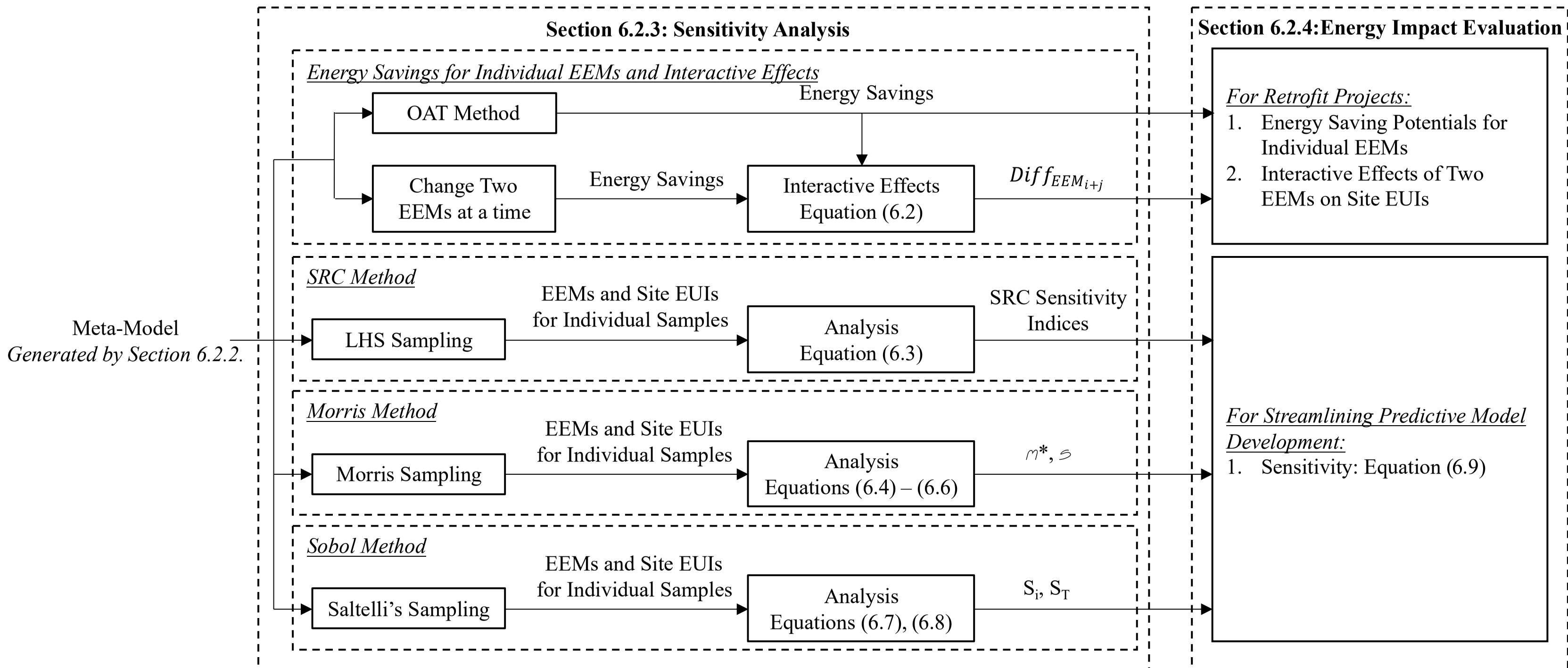


Figure 6.3: Methodology to conduct sensitivity analysis and provide recommendations

where m is the quantity of the EEMs; $E\hat{U}I_i$ is the estimated site EUI of sample i, calculated based on the regression model; and EEM_{ij} is the value of EEM j in the sample i. The sample mean $E\bar{U}I$ corresponds to the site EUIs, where $E\bar{U}I = \frac{1}{n}\sum_{i=1}^{n} EUI_i$, and n is the quantity of the building samples. The value $E\bar{E}M_j$ is the mean of EEM j in all the samples, where $E\bar{E}M_j = \frac{1}{n}\sum_{i=1}^{n} EEM_{ij}$. The standard deviation for EUIs is represented by $\hat{s}$, where $\hat{s} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(EUI_i - E\bar{U}I\right)^2}$. Lastly, $\hat{s}_j$ is the standard deviation for EEM_j, where $\hat{s}_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(EEM_{ij} - E\bar{E}M_j\right)^2}$.

The regression model for SRC aims to minimize the *Root Mean Square Error (RMSE)* between estimated site EUIs from regression models and samples' EUIs from the meta-model developed in Step 2.5. The SRC of EEM j is $b_j\hat{s}_j/\hat{s}$, and $|b_j\hat{s}_j/\hat{s}|$ can be used as a measure of variable importance. This chapter refers to $b_j\hat{s}_j/\hat{s}$ as the SRC sensitivity index and $|b_j\hat{s}_j/\hat{s}|$ as the absolute SRC sensitivity index. The range of the SRC sensitivity index is -1 to 1. If the absolute value is close to 1, the EEM is sensitive; if it is close to 0, the EEM is insensitive. To enhance the accuracy of the SRC results, the bootstrap method is used to re-sample the building samples [175]. Based on the original sample set created with the meta-model, the standardized computational framework generates 1,000 sample sets by randomly sampling from the original sample set with replacement. Then, each bootstrap sample set will obtain a vector of SRC sensitivity indices. The set of such vectors shows the sensitive ranges of individual EEMs, while avoiding sampling biases.

6.2.3.3 Morris Method

As a popular sensitivity analysis method for building energy analyses [34, 28, 81, 82, 154], the Morris method classifies the EEMs into the three groups – negligible effects, large linear and non-interaction effects, and large non-linear and/or interaction effects. Several steps are followed to calculate two indices for sensitivity in Equation 6.4, 6.5, and 6.4. First, the spaces of individual EEMs need to be discretized into n grid levels. Then, a given number of One-At-A-Time (OAT) designs need to be performed before the experiment designs are randomly chosen in the EEM spaces. After that, the elementary effects are calculated. The elementary effect of the variable j

obtained at the repetition i is expressed as:

$$E_j^{(i)} = \frac{EUI\left(EEM^{(i)} + \Delta e_j\right) - EUI\left(EEM^{(i)}\right)}{\Delta} \tag{6.4}$$

where Δ is a pre-defined trajectory, and e_j is a vector of the canonical base. Finally, the two sensitivity indices are obtained as follows:

$$\mu_j^* = \frac{1}{r}\sum_{i=1}^{r}\left|E_j^{(i)}\right|, \tag{6.5}$$

$$\sigma_j = \sqrt{\frac{1}{r}\sum_{i=1}^{r}\left(E_j^{(i)} - \frac{1}{r}\sum_{i=1}^{r}E_j^{(i)}\right)^2} \tag{6.6}$$

where $E_j^{(i)}$ is the elementary effect, and r is the number of trajectories. The quantity of building samples is $r{\times}(m+1)$, where m is the quantity of EEMs being evaluated.

It is worth mentioning that, as a qualitative method, the Morris method cannot quantify the sensitivity of the EEMs. The indicator μ_j^* shows whether the EEM is sensitive to site EUIs or not. If μ_j^* is a high value, the EEM is more sensitive to site EUIs, while lower values imply that the EEM is less sensitive to site EUIs. σ_j is the indicator to show whether the EEM has a linear relationship with site EUIs. If σ_j is low, the EEM follows a close linear relationship with site EUIs, while high values indicate that either the EEM has a nonlinear relationship with site EUIs or that the site EUI is dependent on other EEMs.

6.2.3.4 Sobol Method

The Sobol method is another common approach employed in building energy analyses. While computationally intensive, this method can determine the sensitive variables when the model is non-linear and non-monotonic. The first-order and total Sobol indices, expressed in equations (5) and (6), respectively, are typically used to evaluate the sensitivity of the variables.

$$S_i = \frac{D_i\left(EUI\right)}{Var\left(EUI\right)} \tag{6.7}$$

For index i, *Var(EUI)* is the total variance of EUI and $D_i(EUI)$ represents partial variance caused by the uncertainty of EEM_i, where $D_i(EUI) = Var[E(EUI|EEM_i)]$. The total Sobol index, S_{T_i}, is expressed as:

$$S_{T_i} = S_i + \sum_{j \neq i} S_{ij} + \sum_{j \neq i, k \neq i, j < k} S_{ijk} + \cdots = \sum_{l \in \# i} S_l \tag{6.8}$$

where $\# i$ represents all subsets of $\{1, \ldots, m\}$ including i, and m is the quantity of the EEMs.

The ranges of both S_i and S_{T_i} are 0 to 1. The EEM is sensitive when both values are close to 1, while the insensitive EEMs have S_i and S_{T_i} values near 0. The S_i of an independent factor is lower than or equal to S_{T_i}, but it is possible that the S_i of a dependent factor is larger than S_{T_i}.

6.2.4 Step 4: Energy Impact Evaluation

In order to assist the EEM selection for medium office retrofits, this chapter evaluates the energy saving potentials and sensitivity of the EEMs for retrofit projects and for streamlining predictive model development. Based on the results calculated in Step 3, two metrics are used. First, in support of building energy retrofit projects, this chapter provides the energy saving potentials for individual EEMs and the interactive effects of two EEMs on site EUIs. Engineers can calculate the payback period by combining the energy-related information provided by this chapter and cost information obtained from the market. Then they can select EEMs for the building energy retrofit projects.

Second, to assist the development of predictive energy models, this chapter calculates the weighted indices for EEM sensitivity as follows:

$$Sensitivity_i = \frac{1}{3} \times \sum_{j}^{N} \left(\frac{Index_{i,j} - \min_{i \in M}(Index_{i,j})}{\max_{i \in M}(Index_{i,j}) - \min_{i \in M}(Index_{i,j})} \right) \tag{6.9}$$

where i is the index for each EEM; N is the set of the sensitivity analysis methods, where $N \in \{SRC, Morris, Sobol\}$; M is the quantity of the EEMs; and *Index* is the sensitivity index generated by each sensitivity analysis method (the sensitivity index of SRC is the *absolute SRC* *sensitivity index*; the sensitivity index of Morris is μ_j^*; and the sensitivity index of Sobol is S_i).

6.3 EEM Selections for Existing U.S. Medium Office Buildings

The methodology described in Section 7.2 is applied in order to provide unbiased and climate-specific EEM recommendations for retrofits and developing predictive models of medium office buildings.

6.3.1 Model Preparation

The baseline models of medium office buildings are selected from the DOE Commercial Prototype Building Models [45]. Figure 6.4 shows the geometry and thermal zones of the baseline models for medium office buildings. The baseline models have rectangle shape and three stories. Each story contains five thermal zones (one core zone and four perimeter zones).

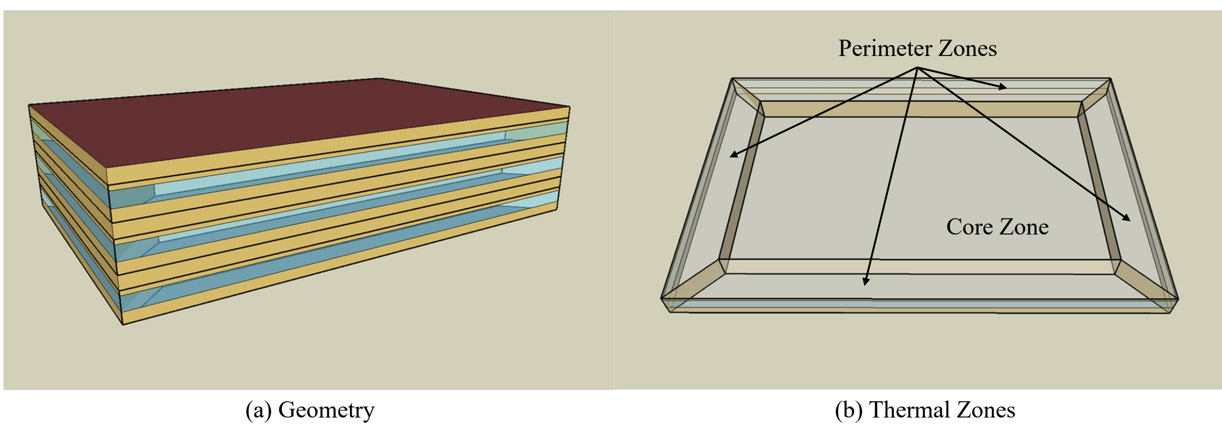


Figure 6.4: Geometry and thermal zones of the baseline medium office building models

Table 6.2 lists the key parameters of the baseline models of medium office buildings. One typical city is selected for each ASHRAE climate zone. Since there are 15 ASHRAE climate zones in the U.S., 15 baseline models are selected for the 15 typical cities. The total floor area for each baseline model is 4,980 m^2 with a 33% window-to-wall ratio. The models have steel-frame exterior walls and insulation entirely above deck (IEAD) roofs. Furthermore, the models use packaged air conditioning units and VAV terminal boxes.

Table 6.2: Key parameters of the baseline medium office building models

Parameter Name	**Value**		
Location (Climate Zone: Typical City)	1A: Honolulu	3C: San Diego	5B: Denver
	2A: Tampa	4A: New York	6A: Rochester
	2B: Tucson	4B: Albuquerque	6B: Great Falls
	3A: Atlanta	4C: Seattle	7: International Falls
	3B: El Paso	5A: Buffalo	8: Fairbanks
Total Floor Area	4,980 m^2 (50 m $\times$ 33.2 m)		
Aspect Ratio	1.5		
Number of Floors	3		
Window-to-Wall Ratio	33%		
Floor-to-Floor Height	3.96 m		
Envelope	Exterior Walls: Steel-Frame Walls Roof: IEAD Roof Windows: Hypothetical Windows		
Lighting Power Density	10.76 W/m^2		
Plug Load Density	8.07 W/m^2		
HVAC System	Heating: Packaged Air Conditioning Unit, Gas Furnace Cooling: Packaged Air Conditioning Unit, DX Cooling Terminal Units: VAV Terminal Boxes		
Service Water Heating	Tank-type, Natural Gas Water Heater		

Based on the outcomes of existing research [74, 77, 185, 75], this chapter selects eight EEMs, which potentially have significant impacts on the site energy use intensities (EUIs) for U.S. medium office buildings across all climate zones. Then, based on the different editions of ASHRAE Standards and related literature, the standardized computational framework determines the uncertainties of these EEMs [7, 9, 10, 11, 12, 6, 59].

Table 6.3 lists the uncertainties of the eight selected EEMs, which are all uniformly distributed. The R-value of Exterior Wall Insulation, R-value of Roof Insulation, and U-value and SHGC of Glazing are climate-dependent; thus, this chapter provides them with unique ranges for different climate zones. Lighting power density, electric equipment power density, gas burner efficiency, and cooling COP are not climate-specific, and as such, the same range of values are considered in all climate zones.

Table 6.3: Uncertainties of the eight selected EEMs

NO.	EEM	Unit	Range
1	R-value of Exterior Wall Insulation	m^2-K/W	1A: [0.40, 1.42] 2A: [0.77, 2.10]; 2B: [0.73, 2.10] 3A: [0.78, 2.29]; 3B: [0.77, 2.29]; 3C: [0.79, 2.29] 4A: [0.99, 2.75]; 4B: [0.96, 2.75]; 4C: [1.01, 2.75] 5A: [1.13, 3.21]; 5B: [1.09, 3.21] 6A: [1.22, 3.60]; 6B: [1.22, 3.60] 7: [1.30, 3.60] 8: [1.41, 4.76]
2	R-value of Roof Insulation	m^2-K/W	1A: [1.76, 3.72] 2A: [1.76, 4.57]; 2B: [1.76, 4.57] 3A: [1.76, 4.57]; 3B: [1.76, 4.57]; 3C: [1.76, 4.57] 4A: [2.04, 5.56]; 4B: [1.98, 5.56]; 4C: [2.07, 5.56] 5A: [2.50, 5.56]; 5B: [2.37, 5.56] 6A: [2.85, 5.56]; 6B: [2.85, 5.56] 7: [2.79, 6.33] 8: [2.99, 6.33]
3	U-value of Glazing	W/m^2-K	1A: [3.36, 5.84] 2A: [3.29, 5.84]; 2B: [3.29, 5.84] 3A: [2.85, 5.84]; 3B: [2.85, 5.84]; 3C: [2.85, 5.84] 4A: [2.37, 5.84]; 4B: [2.37, 5.84]; 4C: [2.25, 5.84] 5A: [2.25, 3.53]; 5B: [2.25, 3.53] 6A: [2.22, 3.53]; 6B: [2.22, 3.53] 7: [1.75, 3.53] 8: [1.75, 3.53]
4	SHGC of Glazing	-	1A: [0.23, 0.54] 2A: [0.23, 0.54]; 2B: [0.23, 0.54] 3A: [0.22, 0.54]; 3B: [0.22, 0.54]; 3C: [0.22, 0.54] 4A: [0.36, 0.54]; 4B: [0.36, 0.54]; 4C: [0.37, 0.54] 5A: [0.37, 0.43]; 5B: [0.37, 0.43] 6A: [0.37, 0.43]; 6B: [0.37, 0.43] 7: [0.41, 0.50] 8: [0.30, 0.62]
5	Lighting Power Density	W/m^2	[8.50, 16.90]
6	Electric Equipment Power Density	W/m^2	[8.07, 10.76]
7	Gas Burner Efficiency	-	[0.70, 0.80]
8	Cooling COP	-	[2.68, 3.23]

6.3.2 Large-scale Simulations

Over 30,000 building samples are selected by using the LHS method, which this chapter introduced in Step 2.1 of Figure 6.2. As described in the methodology, the standardized computational framework conducts simulations using EnergyPlus, collect site EUIs, and conduct uncertainty analysis for the site EUIs in order to quantify the impact of EEM uncertainties on the site EUIs across all 15 climate zones. The results are shown in Figure 6.5 by using the violin plot. The outer shape of the violin plot represents all possible results, with the thickness indicating how common the value is. The highest, middle, and the lowest horizontal lines respectively indicate the maximum, median, and minimum values.

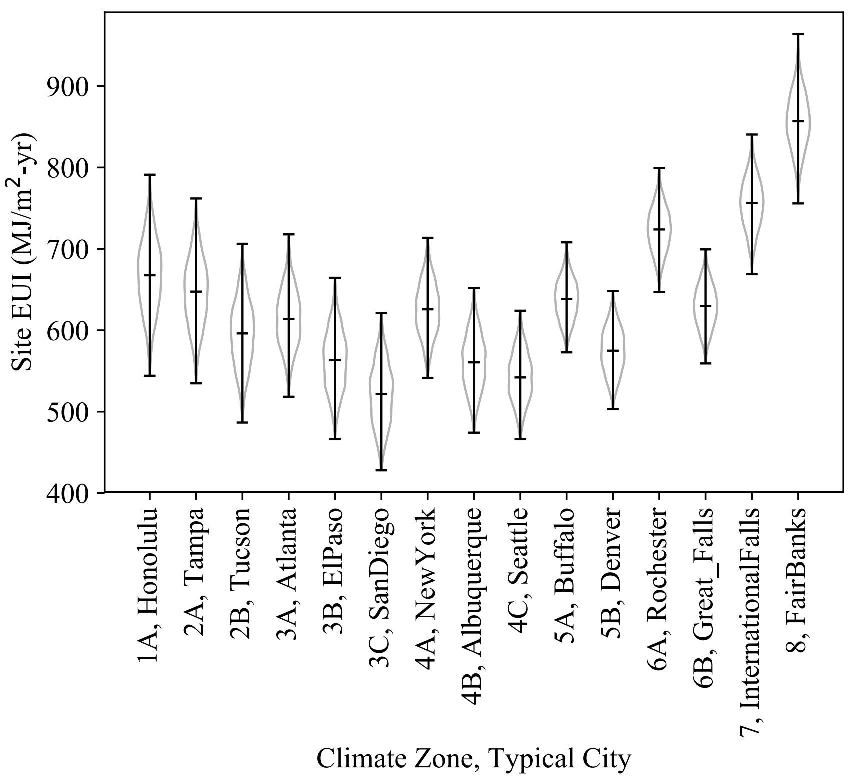


Figure 6.5: Uncertainties of site EUIs for medium office buildings in the 15 climate zones

The uncertainties of the site EUIs represent the energy saving potential of existing medium office buildings in different climate zones. Both the climates' temperatures (correlated to the numerical zone listings 1 through 8) and humidity ranges (correlated to the letter keys A through C) affect site EUIs. In cold climate zones (zones 7 and 8), medium office buildings have the highest median site EUIs, while the site EUIs in temperate climate zones (zones 3 and 4) and warm climate zones (zones 1 and 2) are relatively low. This is primarily because more energy will be consumed for heating in cold areas, and the heating devices have lower efficiency relative to the cooling devices. In the ASHRAE climate zones, "A" represents the moist locations that are mainly the east and middle areas of the U.S.; "B" is the dry locations that are mainly the mountain areas; and "C" is the marine locations that are mainly the west coast areas. Based on Figure 6.5, it is can be found that medium office buildings in moist areas usually have the highest site EUIs among the buildings with a similar latitude, while the medium office buildings in marine areas (e.g. 3C and 4C) have the lowest site EUIs. This is primarily caused by the different climate conditions of the geography. Furthermore, the uncertainties of site EUIs for the buildings in all the 15 climate zones are in the range of 100 $\sim$ 200 MJ/m^2-yr, which indicates that these eight EEMs notably impact site EUIs. As such, it is important to understand how EEM changes affect the buildings' energy performance, which can be learned through sensitivity analysis. By following the instruction of Section 6.2.2, the standardized computational framework conducts approximately 500,000 building energy simulations by using the Boosted-Trees meta-model. Figure 6.6 shows the performance of the meta-model. The relative errors of site EUIs between the EnergyPlus simulations and meta-model simulations are mostly lower than 5%. The output data is used to conduct sensitivity analysis and the results are shown in the next section.

6.3.3 Sensitivity Analysis

The sensitivity analysis results for the eight selected EEMs are as follows. First, this chapter calculates the energy savings for individual EEMs and interactive effects of two EEMs. While all 15 climate zones are included in the analysis, three climate zones that represent the extreme and mean climate conditions (1A, 5A, and 8) are selected for demonstration. Then, the sample sizes of the three sensitivity analysis methods are discussed. Finally, this chapter summarizes the results

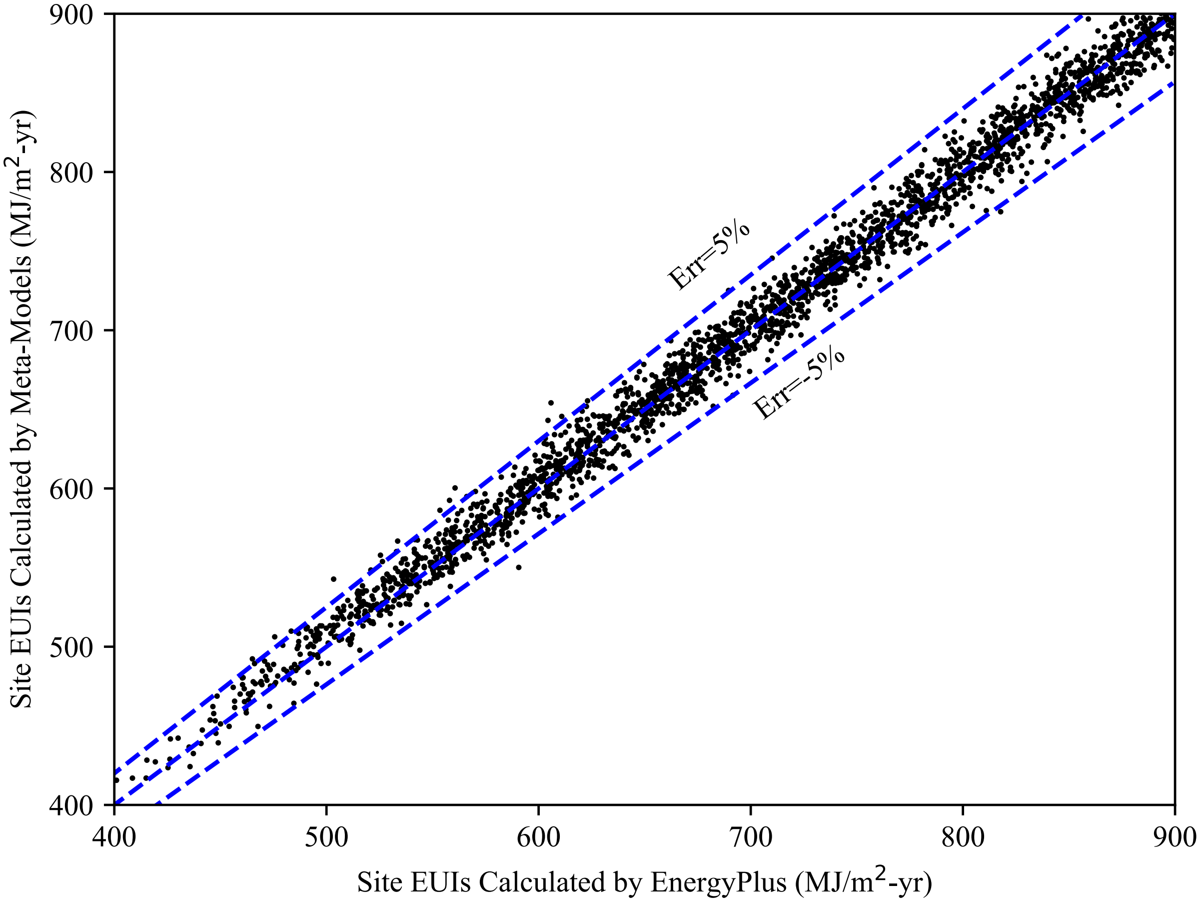


Figure 6.6: Performance evaluation of meta-model

calculated by the SRC, Morris, and Sobel methods.

6.3.3.1 Energy Savings for Individual EEMs and Interactive Effects

To evaluate the energy savings for individual EEMs, this chapter uniformly divides the ranges of EEMs and select the extreme EEM values for baseline models that result in the highest energy consumption. Table 6.4 shows the No. of point for EEMs in the three climate zones.

Based on the points selected for EEMs, this chapter evaluates the energy savings for individual EEMs. The percentage of site EUI reduction for each EEM in each point is evaluated. Figure 6.7 shows the results in the three climate zones.

Table 6.4: No. of point for EEMs in the three climate zones

Climate Zone	EEM	Unit	No. of Point for EEMs					
			0 (Baseline)	1	2	3	4	5
1A, Honolulu	R-value of Exterior Wall Insulation	m^2-K/W	0.40	0.60	0.81	1.01	1.22	1.42
	R-value of Roof Insulation	m^2-K/W	1.76	2.15	2.54	2.94	3.33	3.72
	U-value of Glazing	W/m^2-K	5.84	5.34	4.85	4.35	3.86	3.36
	SHGC of Glazing	-	0.54	0.48	0.42	0.35	0.29	0.23
	Lighting Power Density	W/m^2	16.90	15.22	13.54	11.86	10.18	8.50
	Electric Equipment Power Density	W/m^2	10.76	10.22	9.68	9.15	8.61	8.07
	Gas Burner Efficiency	-	0.70	0.72	0.74	0.76	0.78	0.80
	Cooling COP	-	2.68	2.79	2.90	3.01	3.12	3.23
5A, Buffalo	R-value of Exterior Wall Insulation	m^2-K/W	1.13	1.55	1.96	2.38	2.79	3.21
	R-value of Roof Insulation	m^2-K/W	2.50	3.11	3.72	4.34	4.95	5.56
	U-value of Glazing	W/m^2-K	3.53	3.27	3.02	2.76	2.51	2.25
	SHGC of Glazing	-	0.43	0.42	0.41	0.39	0.38	0.37
	Lighting Power Density	W/m^2	16.90	15.22	13.54	11.86	10.18	8.50
	Electric Equipment Power Density	W/m^2	10.76	10.22	9.68	9.15	8.61	8.07
	Gas Burner Efficiency	-	0.70	0.72	0.74	0.76	0.78	0.80
	Cooling COP	-	2.68	2.79	2.90	3.01	3.12	3.23
8, Fairbanks	R-value of Exterior Wall Insulation	m^2-K/W	1.41	2.08	2.75	3.42	4.09	4.76
	R-value of Roof Insulation	m^2-K/W	2.99	3.66	4.33	4.99	5.66	6.33
	U-value of Glazing	W/m^2-K	3.53	3.17	2.82	2.46	2.11	1.75
	SHGC of Glazing	-	0.62	0.56	0.49	0.43	0.36	0.30
	Lighting Power Density	W/m^2	16.90	15.22	13.54	11.86	10.18	8.50
	Electric Equipment Power Density	W/m^2	10.76	10.22	9.68	9.15	8.61	8.07
	Gas Burner Efficiency	-	0.70	0.72	0.74	0.76	0.78	0.80
	Cooling COP	-	2.68	2.79	2.90	3.01	3.12	3.23

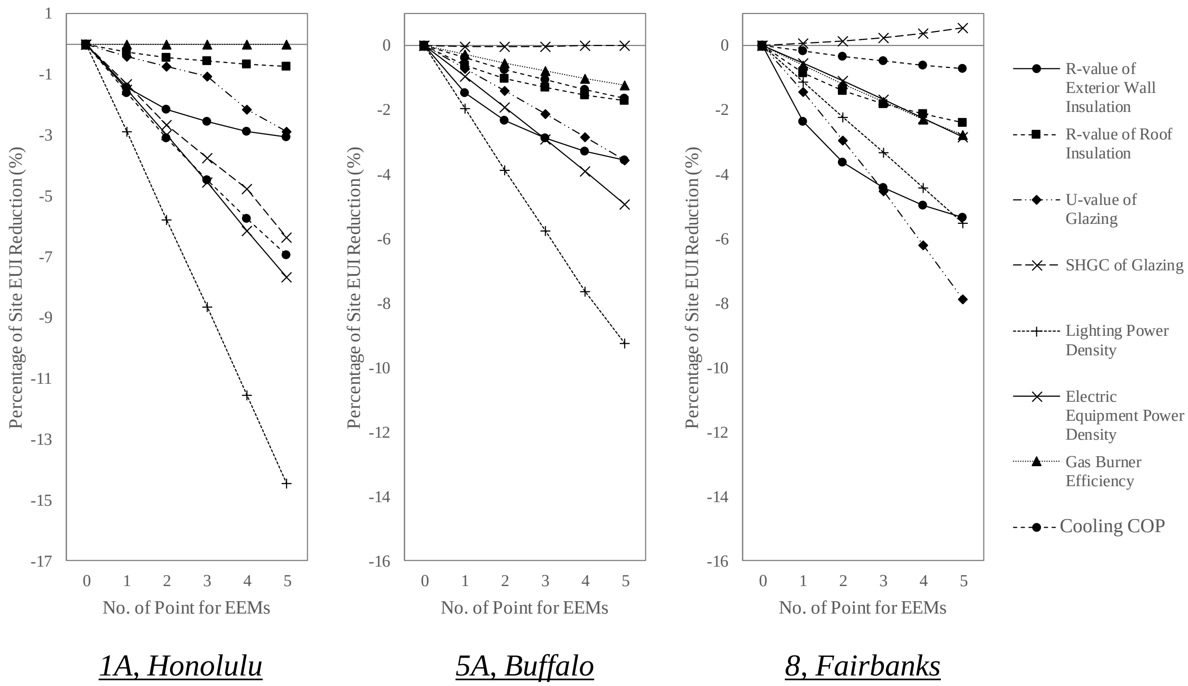


Figure 6.7: Energy savings for individual EEMs in the three climate zones

In climate zones 1A and 5A, lighting power density has the greatest potentials to reduce energy consumption. It is approximately 15% and 10% of site EUI reduction respectively from the worst case to the best case. In climate zone 8, the U-value of glazing is more dominant and 8% of site EUI reduction is obtained by decreasing the U-value of glazing. Furthermore, some EEMs, such as lighting power density, has the linear relationship to the site EUI, while the others, such as cooling COP, has the nonlinear relationship to the site EUI. Thus, it is important for the nonlinear EEMs to identify the existing value and the proposed value. Moreover, some EEMs are affected by climate greatly. For example, when decreasing the SHGC of glazing in climate zone 1A, the site EUI is decreased; when doing so in climate zone 8, the site EUI is increased. Thus, it is important to consider the impact of climate in the building retrofit projects. After that, it is still needed to identify the interactive effects between two EEMs on the site EUI. Figure 6.8 shows the interactive effects in the three climate zones. The Point 0 (baseline) for each EEM is used to represent the existing value and Point 5 is used to represent the proposed value.

(a) Percentage of Energy Saving (%) in Honolulu (ASHRAE Climate Zone 1A)

	Individual EEMs
EEM1	3.08
EEM2	0.72
EEM3	2.88
EEM4	6.35
EEM5	14.44
EEM6	7.67
EEM7	0.00
EEM8	6.93

Two EEMs	EEM8	EEM7	EEM6	EEM5	EEM4	EEM3	EEM2
EEM1	9.58	3.08	10.78	17.59	9.48	5.92	3.84
EEM2	7.54	0.72	8.41	15.16	7.10	3.63	
EEM3	9.43	2.88	10.57	17.42	7.71		
EEM4	12.43	6.35	14.06	20.90			
EEM5	20.76	14.44	22.11				
EEM6	14.27	7.67					
EEM7	6.93						

$Diff_{EEM_{i+j}}$	EEM8	EEM7	EEM6	EEM5	EEM4	EEM3	EEM2
EEM1	-0.42	0.00	0.03	0.08	0.05	-0.04	0.04
EEM2	-0.11	0.00	0.01	0.00	0.02	0.03	
EEM3	-0.37	0.00	0.02	0.10	-1.52		
EEM4	-0.85	0.00	0.04	0.11			
EEM5	-0.61	0.00	0.00				
EEM6	-0.33	0.00					
EEM7	0.00						

Positive Effect No Effect Negative Effect

(b) Percentage of Energy Saving (%) in Buffalo (ASHRAE Climate Zone 5A)

	Individual EEMs
EEM1	3.55
EEM2	1.69
EEM3	3.55
EEM4	-0.01
EEM5	9.24
EEM6	4.91
EEM7	1.23
EEM8	1.65

Two EEMs	EEM8	EEM7	EEM6	EEM5	EEM4	EEM3	EEM2
EEM1	5.18	4.78	8.55	12.85	3.56	6.97	5.21
EEM2	3.31	2.94	6.64	10.92	1.68	5.18	
EEM3	5.22	4.79	8.56	12.90	3.52		
EEM4	1.56	1.31	4.85	9.15			
EEM5	10.63	10.80	13.96				
EEM6	6.43	6.25					
EEM7	2.88						

$Diff_{EEM_{i+j}}$	EEM8	EEM7	EEM6	EEM5	EEM4	EEM3	EEM2
EEM1	-0.02	0.00	0.09	0.05	0.02	-0.14	-0.03
EEM2	-0.03	0.01	0.05	-0.01	0.00	-0.06	
EEM3	0.01	0.00	0.10	0.10	-0.03		
EEM4	-0.08	0.09	-0.04	-0.09			
EEM5	-0.26	0.32	-0.19				
EEM6	-0.12	0.11					
EEM7	0.00						

Positive Effect No Effect Negative Effect

(c) Percentage of Energy Saving (%) in Fairbanks (ASHRAE Climate Zone 8)

	Individual EEMs
EEM1	5.34
EEM2	2.38
EEM3	7.86
EEM4	-0.55
EEM5	5.49
EEM6	2.84
EEM7	2.77
EEM8	0.72

Two EEMs	EEM8	EEM7	EEM6	EEM5	EEM4	EEM3	EEM2
EEM1	6.06	8.06	8.19	10.80	4.66	13.03	7.70
EEM2	3.09	5.09	5.24	7.89	1.78	10.30	
EEM3	8.61	10.58	10.77	13.41	7.28		
EEM4	-0.04	2.69	2.14	4.23			
EEM5	6.09	8.56	8.25				
EEM6	3.50	5.71					
EEM7	3.49						

$Diff_{EEM_{i+j}}$	EEM8	EEM7	EEM6	EEM5	EEM4	EEM3	EEM2
EEM1	0.00	-0.05	0.01	-0.03	-0.14	-0.18	-0.02
EEM2	-0.01	-0.06	0.02	0.02	-0.05	0.06	
EEM3	0.03	-0.05	0.07	0.05	-0.04		
EEM4	-0.21	0.47	-0.15	-0.71			
EEM5	-0.11	0.30	-0.08				
EEM6	-0.05	0.10					
EEM7	0.00						

Positive Effect No Effect Negative Effect

# of EEM	Name of EEM	# of EEM	Name of EEM	# of EEM	Name of EEM	# of EEM	Name of EEM
1	R-value of Exterior Wall Insulation	3	U-value of Glazing	5	Lighting Power Density	7	Gas Burner Efficiency
2	R-value of Roof Insulation	4	SHGC of Glazing	6	Electric Equipment Power Density	8	Cooling COP

Figure 6.8: Interactive effects of two EEMs in the three climate zones

The energy savings could have positive or negative interactive effects by using two EEMs. For example, improving cooling COP will counteract part of energy savings obtained by using higher R-value of exterior wall and roof insulations in climate zone 1A, while the higher-efficiency lighting fixtures and higher R-value of exterior wall insulation assist each other in climate zone 1A. Furthermore, the interactive effects could be different in various climates. For instance, higher R-value of exterior wall and roof insulations have positive interactive effects in climate zone 1A while they have negative effects in climate zones 5A and 8.

6.3.3.2 Impact of Sample Size for Sensitivity Analysis Methods

Before generating the sensitive indices for individual EEMs, it is necessary to identify the number of building samples that are needed to minimize the margin of error for each method. Naturally, when the sample size becomes larger, the sensitivity results become gradually more stable [128, 123, 95, 121]. Iooss and Lemaître [95] estimated the number of samples required for various global sensitivity analysis. If the total number of variables is *d*, the number of samples required is on the scale of 10d for the SRC and Morris methods, while it is on the scale of *1,000d* or greater for the Sobol method. Since there are eight EEMs (*d=8*) in this study, approximately 80 samples for SRC and Morris methods and 8,000 samples for Sobol method will be needed. In this chapter, the samples sizes were selected for each method based on the point when the standard deviation of the sensitivity indices stabilized. Our results show that the SRC and Morris methods need 500 samples for each climate zone, while the Sobol method needs 20,000 samples for each climate zone. These numbers of samples are higher than the estimated values of 80 and 8,000, which ensures the sensitivity analysis results are independent of sample size.

6.3.3.3 Results by the SRC Method

To avoid biases caused by random selection of samples, this chapter calculates the SRC sensitivity index by using the bootstrap method [175]. Figure 6.9 shows the sensitivity analysis results of the eight EEMs in three climate zones.

The SRC sensitivity indices indicate the relative sensitivity of the eight EEMs. Each bootstrap sample set generates one value of the SRC sensitivity index for a certain EEM. Thus, based on multiple bootstrap sample sets, the standardized computational framework will obtain a set of values for the EEM's SRC sensitivity index. In Figure 6.9, the circle shows the median value and the vertical line shows the range of the EEM's SRC sensitivity index. Positive SRC sensitivity indices indicate positive relationships between the EEM and the site EUIs, while negative values

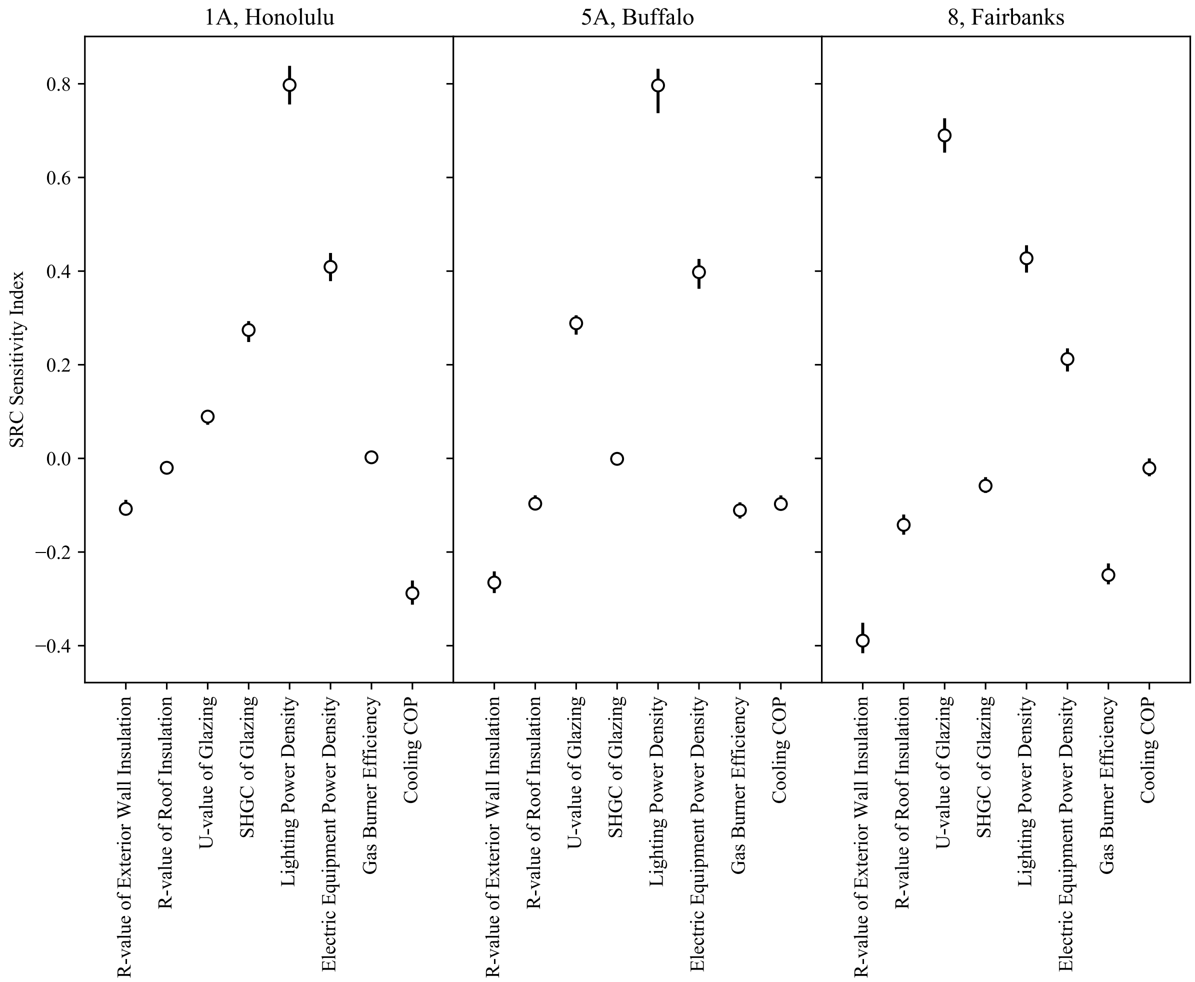


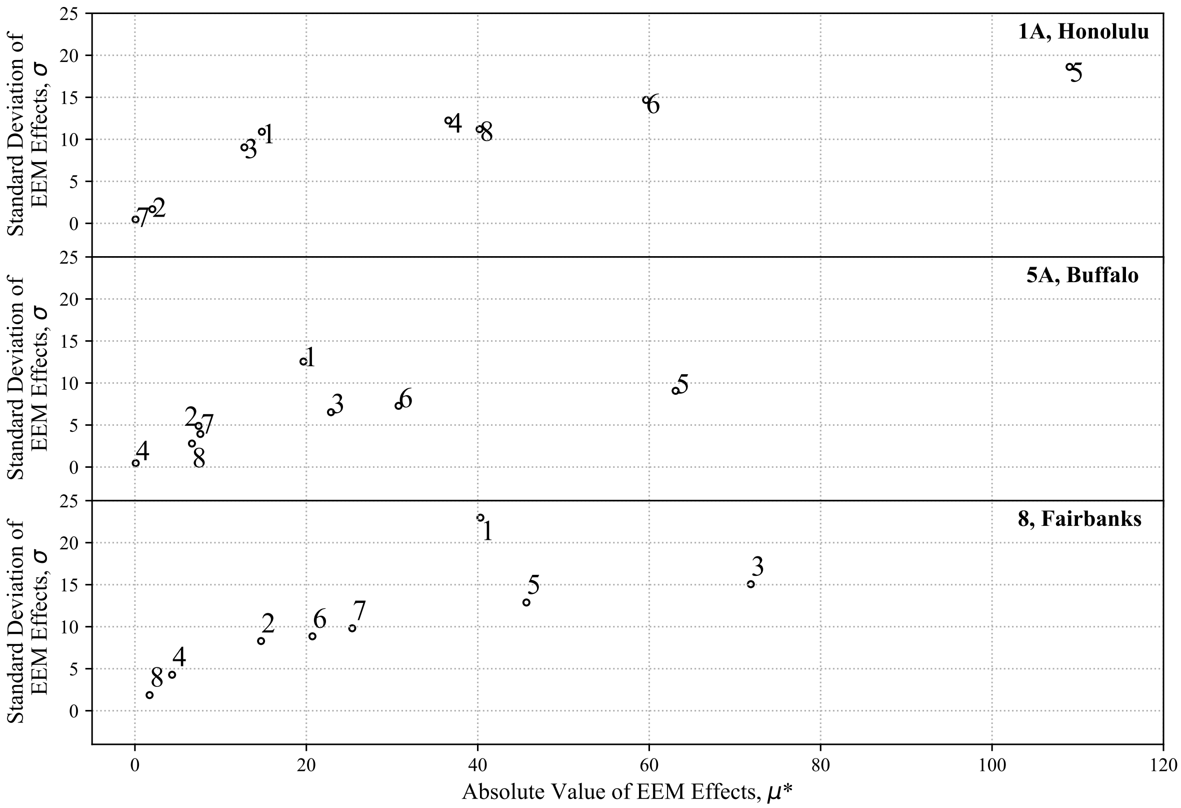
Figure 6.9: SRC sensitivity indices of the eight EEMs in the three climate zones

indicate negative relationships. This chapter uses the absolute SRC sensitivity index to measure the sensitivity level of each EEM. For example, the lighting power density is the most sensitive EEM in climate zones 1A and 5A, while the U-value of glazing has the highest sensitivity in climate zone 8. Both lighting power density and U-value of glazing have positive relationships with site EUI in the three climate zones. Cooling COP has a negative relationship with site EUI in the climate zone 1A, while the absolute indices of cooling COP are lower than 0.1 in climate zones 5A and 8, indicating weak correlations. Furthermore, the electric equipment power density in all three climate zones and SHGC of glazing in climate zone 1A have relatively high positive effects on site

EUI, while the R-value of exterior wall insulation has relatively high negative effects on site EUI in climate zones 5A and 8.

6.3.3.4 Results by the Morris Method

Both μ^* and σ are the sensitivity indices used in the Morris method. Figure 6.10 displays the values of Morris sensitivity indices of the eight EEMs in the three climate zones.



1: R-value of Exterior Wall Insulation	2: R-value of Roof Insulation	3: U-value of Glazing
4: SHGC of Glazing	5: Lighting Power Density	6: Electric Equipment Power Density
7: Gas Burner Efficiency	8: Cooling COP	

Figure 6.10: Morris sensitivity indices of EEMs of the eight EEMs in the three climate zones

The Morris method results are similar to those from the SRC method. The most sensitive EEMs, which have the highest values of μ^*, are lighting power density in climate zones 1A and 5A and U-value of glazing in climate zone 8. Furthermore, the Morris method can identify whether the relationships between EEMs and site EUIs are linear. For example, cooling COP is not sensitive to site EUIs but has a near linear relationship with site EUI in climate zone 5A. Contrarily, lighting power density, electric equipment power density, R-value of exterior wall insulation, and U-value of glazing have nonlinear relationships with site EUI or are dependent on other EEMs. By comparing with the sensitivity results of SRC, there are still some minor differences. For example, in Figure 6.9, the median absolute SRC index for the roof insulation's R-value (0.0967) is slightly lower than the index for the cooling COP (0.0974) in climate zone 5A. By using the Morris method, the roof insulation's R-value is slightly more sensitive to the site EUI than the cooling COP in climate zone 5A. Since there is no EEM that has the highly nonlinear relationship with site EUIs, the SRC and Morris sensitivity results do not have significant differences.

6.3.3.5 Results by the Sobol Method

As mentioned in Section 6.2.3, both first-order and total Sobol indices are typical metrics to evaluate EEM sensitivity. Figure 6.11 shows the values of Sobol sensitivity indices of the eight EEMs in the three climate zones.

The Sobol method results as similar to the SRC and Morris method results. Since the first-order and total Sobol indices provide similar values for all EEMs, this chapter uses first-order indices to evaluate the sensitivity levels of the EEMs. Figure 6.11 shows that the lighting power density is the most sensitive in climate zones 1A and 5A, while the U-value of glazing is the most sensitive in climate zone 8. The Sobol sensitivity results tend to distinguish the values of sensitivity indices for sensitive and insensitive EEMs. Since all the selected EEMs do not have highly nonlinear relationship with site EUIs and there is no strong correlation between the EEMs, the Sobol method does not have significant difference compared with the sensitivity results generated by the SRC and Morris methods.

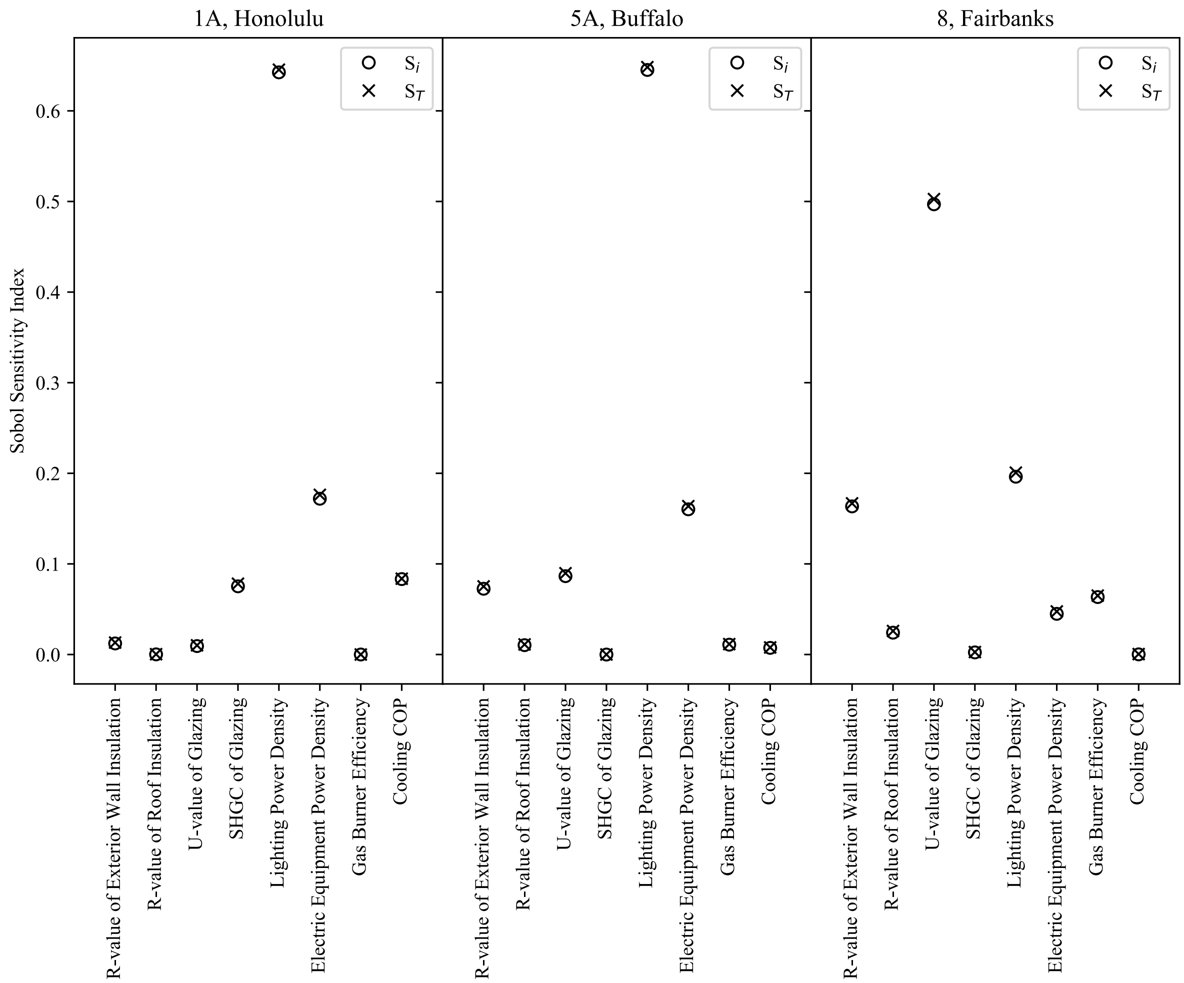


Figure 6.11: Sobol sensitivity indices of EEMs of the eight EEMs in the three climate zones

6.3.3.6 Summary for the Sensitivity Analysis Methods

Figure 6.12 summarizes the sensitivity results for the three methods, eight EEMs, and 15 climate zones. The absolute SRC sensitivity index, μ^* of the Morris method, and first-order sensitivity index of the Sobol method are selected to evaluate the sensitivity of the eight EEMs.

The three sensitivity analysis methods generate similar results for all eight EEMs and 15 climate zones. However, there are still some minor differences. For instance, the Sobol method shows the insensitive EEMs with the lightest colors. This is because the scales and definitions of

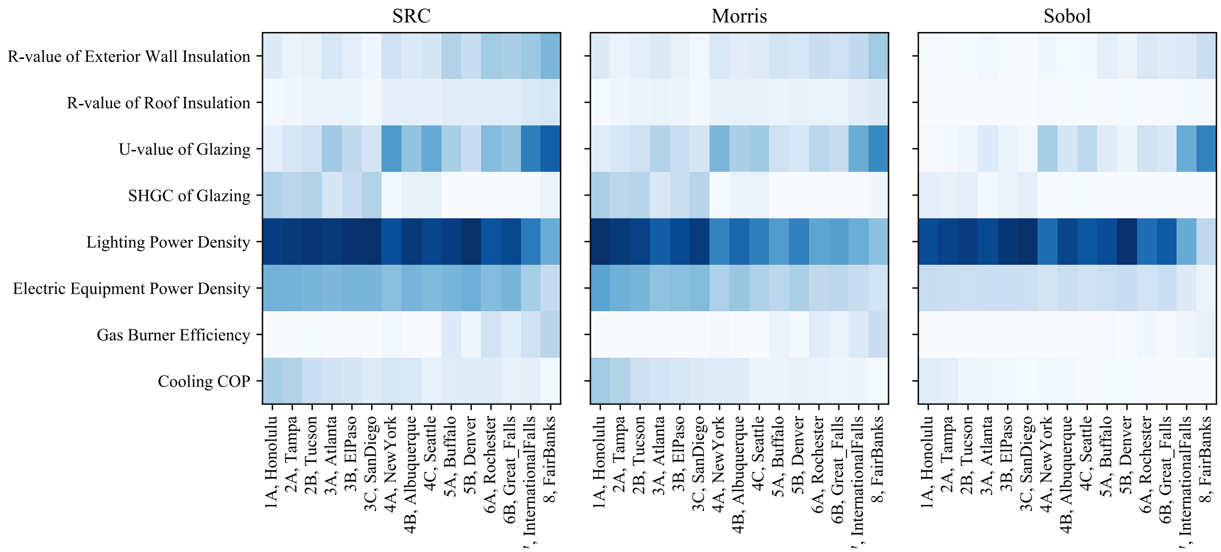


Figure 6.12: Evaluation of sensitivity of the eight EEMs in the 15 climate zones

the sensitivity indices from different sensitivity analysis methods differ. While these differences are present, they do not influence the primary results. Generally, the EEM sensitivity levels vary among the climate zones. Noticeably, lighting power density is the most sensitive EEM in most climate zones. The U-value of glazing and R-value of exterior wall insulation are more sensitive in cold climate zones, while the SHGC of glazing has greater impacts on site EUI in hot climate zones. Furthermore, the electric equipment power density has slightly lower impacts on site EUI in climate zone 8. The other three EEMs have weak impacts on site EUI. However, this chapter still finds that the gas burner efficiency is more relevant to the site EUIs in cold areas, while the cooling COP affects site EUIs more in hot areas.

6.3.4 Energy Impact Evaluation

6.3.4.1 Analysis of Energy Savings

Based on the sensitivity results for the eight EEMs in the 15 climate zones, this chapter evaluates the potential impact on energy consumption to support retrofit decisions of existing U.S. medium office buildings. To assist the users in selecting EEMs, Figure 6.13 shows the energy savings for individual EEMs in the 15 climate zones. Table 6.5 lists the top three positive and negative interactive effects of two EEMs in the 15 climate zones.

The energy impact information shown in Figure 6.13 and Table 6.5 can help users determine which of the eight EEMs are appropriate for their climate zone. For example, lighting power density is one of the most important EEMs to reduce energy consumption in all 15 climate zones. In cold area, the U-value of glazing is also an EEM with a high energy saving potential. Furthermore, the lighting power density and gas burner efficiency strongly assist each other in cold areas. Therefore, it is worth considering improving both lighting fixtures and the gas burner at the same time. Moreover, in hot areas, reducing the U-value and SHGC of glazing at the same time have counterproductive effects; therefore, building owners and architects need to select windows with suitable a U-value and SHGC. Based on the information provided by Figure 6.13 and Table 6.5, and the cost information from the market, users are able to decide which EEMs are appropriate for retrofit projects in their target climate zone.

6.3.4.2 Sensitivity of EEMs

In addition to identifying the energy saving potentials of EEMs in retrofits, developing building energy models for retrofit applications can be beneficial to quantify potential energy savings. The sensitivity of EEMs will provide information for which EEM values significantly impact the accuracy of the predicted energy consumption. Thus, modelers need to spend more time on identifying the values of these EEMs, while general estimates or typical values for the remaining EEMs are sufficient. Table 6.6 summarizes the aggregated sensitivity of the eight EEMs.

For developing building energy models, only 43.3% of the selected EEMs have sensitive impacts on site EUIs for all 15 climate zones; thus, using general estimates for the remaining 56.7% of the selected EEMs can save modelers valuable time and money. Lighting power density is highly sensitive for all climate zones. Electric equipment power density is also sensitive for all climate zones. Furthermore, U-value of glazing is sensitive for most climate zones. Moreover, in some climate zones, R-value of exterior wall insulation, SHGC of glazing, gas burner efficiency, and cooling

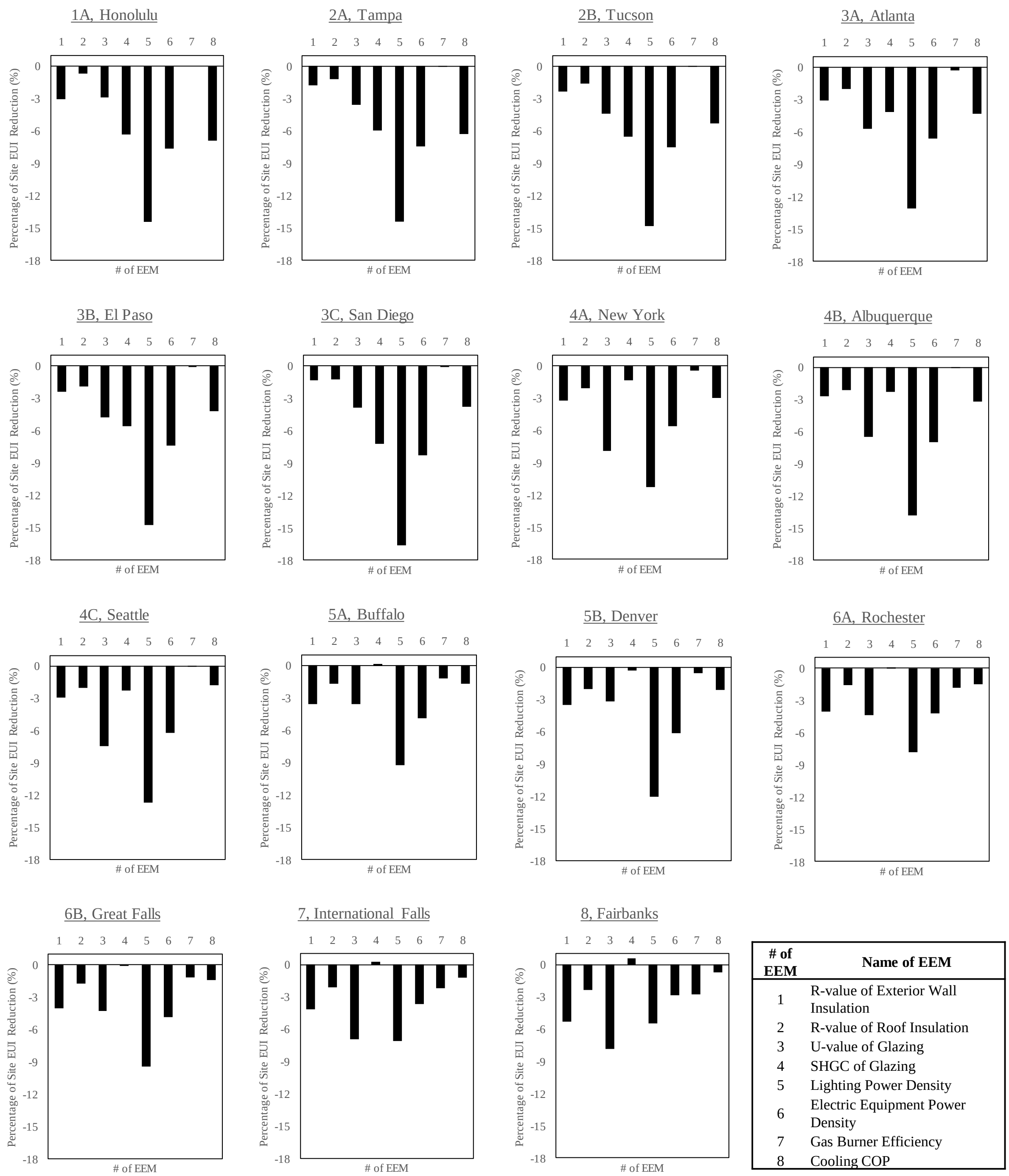
Table 6.5: Interactive effects of two EEMs in the 15 climate zones

Climate	**Top 3 Positive**			**Top 3 Negative**		
	1	**2**	**3**	**1**	**2**	**3**
1A, Honolulu	EEM4 & EEM5	EEM3 & EEM5	EEM1 & EEM5	EEM3 & EEM4	EEM4 & EEM8	EEM5 & EEM8
2A, Tampa	EEM1 & EEM5	EEM3 & EEM5	EEM2 & EEM5	EEM3 & EEM4	EEM4 & EEM8	EEM5 & EEM8
2B, Tucson	EEM2 & EEM8	EEM1 & EEM4	EEM3 & EEM5	EEM3 & EEM4	EEM4 & EEM8	EEM5 & EEM8
3A, Atlanta	EEM4 & EEM7	EEM1 & EEM5	EEM1 & EEM6	EEM3 & EEM4	EEM4 & EEM8	EEM4 & EEM5
3B, El Paso	EEM1 & EEM4	EEM3 & EEM6	EEM3 & EEM5	EEM3 & EEM4	EEM4 & EEM8	EEM4 & EEM5
3C, San Diego	EEM3 & EEM4	EEM3 & EEM6	EEM1 & EEM5	EEM3 & EEM4	EEM4 & EEM8	EEM4 & EEM5
4A, New York	EEM5 & EEM7	EEM4 & EEM7	EEM3 & EEM6	EEM4 & EEM5	EEM1 & EEM3	EEM5 & EEM8
4B, Albuquerque	EEM3 & EEM6	EEM3 & EEM5	EEM1 & EEM5	EEM1 & EEM3	EEM4 & EEM5	EEM5 & EEM8
4C, Seattle	EEM3 & EEM6	EEM5 & EEM7	EEM2 & EEM6	EEM4 & EEM5	EEM1 & EEM3	EEM5 & EEM6
5A, Buffalo	EEM5 & EEM7	EEM6 & EEM7	EEM3 & EEM5	EEM5 & EEM8	EEM5 & EEM6	EEM1 & EEM3
5B, Denver	EEM5 & EEM7	EEM3 & EEM6	EEM1 & EEM6	EEM5 & EEM6	EEM4 & EEM5	EEM5 & EEM8
6A, Rochester	EEM5 & EEM7	EEM6 & EEM7	EEM3 & EEM5	EEM5 & EEM8	EEM5 & EEM6	EEM6 & EEM8
6B, Great Falls	EEM5 & EEM7	EEM6 & EEM7	EEM4 & EEM7	EEM5 & EEM6	EEM4 & EEM5	EEM1 & EEM5
7, International Falls	EEM5 & EEM7	EEM4 & EEM7	EEM6 & EEM7	EEM5 & EEM6	EEM4 & EEM5	EEM5 & EEM8
8, Fairbanks	EEM4 & EEM7	EEM5 & EEM7	EEM6 & EEM7	EEM4 & EEM5	EEM4 & EEM8	EEM1 & EEM3

Table 6.6: Aggregated sensitivity levels of the EEMs for medium office buildings in the 15 climate zones

EEM	Climate Zone														
	1A	2A	2B	3A	3B	3C	4A	4B	4C	5A	5B	6A	6B	7	8
R-value of Exterior Wall Insulation	.10	.05	.06	.12	.07	.03	.15	.10	.13	.25	.18	.35	.29	.44	.48
R-value of Roof Insulation	.01	.03	.04	.06	.04	.02	.07	.08	.07	.08	.08	.09	.08	.15	.14
U-value of Glazing	.08	.12	.16	.30	.19	.13	.59	.35	.48	.29	.18	.43	.35	.98	1.0
SHGC of Glazing	.27	.23	.24	.13	.19	.24	.00	.06	.06	.00	.00	.00	.00	.00	.03
Lighting Power Density	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	.99	.54
Electric Equipment Power Density	.44	.42	.40	.41	.39	.38	.39	.41	.39	.41	.41	.42	.43	.40	.22
Gas Burner Efficiency	.00	.00	.00	.00	.00	.00	.01	.00	.00	.09	.03	.16	.08	.20	.27
Cooling COP	.29	.25	.17	.16	.13	.09	.12	.11	.05	.08	.08	.09	.06	.08	.00

	1.00∼0.80	0.79∼0.60	0.59∼0.40	0.39∼0.20	0.19∼0.00
Sensitivity Levels					



# of EEM	Name of EEM
1	R-value of Exterior Wall Insulation
2	R-value of Roof Insulation
3	U-value of Glazing
4	SHGC of Glazing
5	Lighting Power Density
6	Electric Equipment Power Density
7	Gas Burner Efficiency
8	Cooling COP

Figure 6.13: Energy savings for individual EEMs in the 15 climate zones

COP are sensitive.

6.4 Discussion

This section compares the results of sensitivity analysis based on different medium office building energy models. The prototypical building energy models of U.S. medium office buildings created in Section 5.2.1 are used to conduct sensitivity analysis. The same workflow is used and this chapter uses 5A (Buffalo) as an example to show the results. Figure 6.14 shows the comparison results of sensitivity analysis by using the DOE Commercial Prototype Building Models and new models created in Section 5.2.1 [45]. The aggregated sensitivity levels of the EEMs are compared.

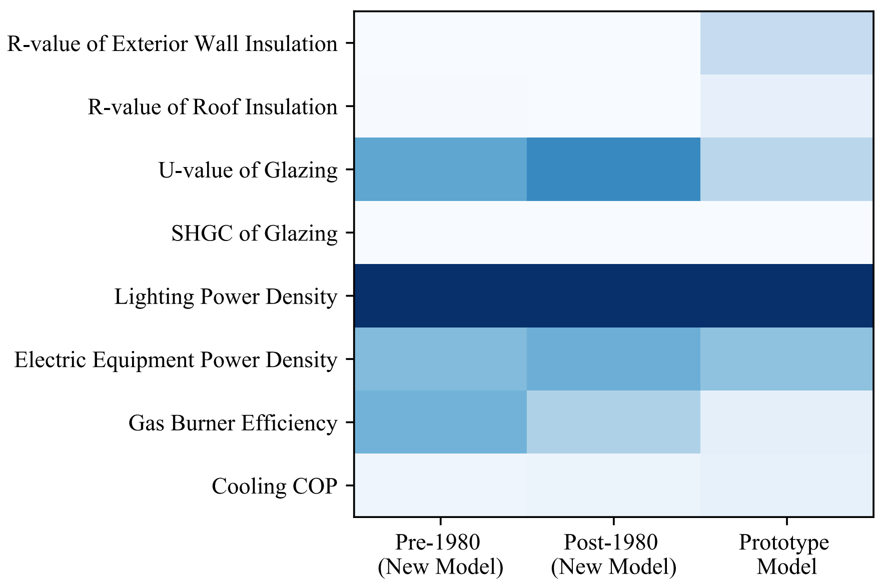


Figure 6.14: Comparison of sensitivity analysis results by using different baseline models

The results show that the EEMs with the high sensitivity levels are similar in different models, such as lighting power density. There are some different results for the EEMs with the low sensitivity levels. The EEMs with the high sensitivity levels are more important for building energy retrofits and energy savings than the EEMs with the low sensitivity levels. Thus, the results are summarized in this chapter can be used as reference for the building energy retrofits. Furthermore, the rankings of the sensitivity levels of the EEMs are also necessary during the EEM selections. Table 6.7 shows the rankings calculated by using the different baseline models.

Table 6.7: Rankings of the sensitivity levels of the EEMs by using different baseline models

EEM	**Pre-1980 (New Model)**	**Post-1980 (New Model)**	**Prototype Model**
R-value of Exterior Wall Insulation	7	4	8
R-value of Roof Insulation	8	6	6
U-value of Glazing	2	3	2
SHGC of Glazing	6	8	7
Lighting Power Density	1	1	1
Electric Equipment Power Density	3	2	4
Gas Burner Efficiency	4	5	3
Cooling COP	5	7	5
	1∼3	4∼6	7∼8
Ranking			

The results show that U-value of glazing and lighting power density belong to Ranking 1∼3 in all three models. Then electricity equipment power density and gas burner efficiency belongs to Ranking 1∼3 in some models while Ranking 4∼6 in the other models. The rest EEMs have low rankings in most situations. It is noticeable that the prototype models are more sensitive on the insulation of envelopes by compared with the new models while the new models are more sensitive on system. Thus, when building energy analyses are conducted and the accurate results are required, it is important to select suitable baseline models as the starting points.

6.5 Summary

This chapter provides the energy saving potentials of eight EEMs to advise EEM selections in retrofit projects. To fulfill these targets, the standardized computational framework conducts large-scale simulations and sensitivity analyses of typical U.S. medium office buildings in the 15 climate zones. This energy impact evaluation can help building owners and architects select EEMs during existing medium office building retrofits, and help engineers develop predictive models, which are used to evaluate energy savings in existing medium office building retrofits:

(1) *Support of EEMs Selection for Retrofits.* The results in Figure 6.13 and Table 6.5 provide climate-appropriate energy saving potentials for eight EEMs that can help the owners, architects, and engineers identify EEMs that can produce deep energy savings for existing medium office retrofits. Based on the results, users can check the EEMs during the existing medium office building retrofits. If the EEMs have high energy saving potentials and have low-efficient energy performance in the existing building, then upgrading them should be considered. For example, if the lighting power density is the highest priority and the lighting fixtures in the existing building have low efficacy ratings, such as incandescent lamps, building owners should consider retrofitting the lighting system with high-efficient fixtures, such as LED. It is noted that the table only provides suggestions based on the energy considerations. The users also need to evaluate the payback period of the retrofits, which is out of the scope of this chapter. Furthermore, in the special situations, the owners, architects, and engineers still need to use their own judgments based on prior experience. As an application example, an owner decides to retrofit his medium office building in Denver, CO, which is in climate zone 5B. Based on the data in Figure 6.13 and Table 6.5, the first step is to check whether the lighting fixtures and windows have poor energy performance ratings. If so, they need to consider changing the lighting fixtures into the high-performance ones, such as LED, and replacing the windows with low U-value windows. Next, they need to check the insluated R-values of the envelopes. Then, if the initial cost is still lower than the budget, they can consider upgrading the rest EEMs.

(2) *Identification of Critical EEMs for Predictive Modeling.* These results in Table 6.6 provide a guideline for identifying the most important EEMs in the development of predictive models to estimate the energy savings of retrofits. For small retrofit projects, it is often not cost-effective for engineers to provide accurate values for all EEMs. To address this, Table 6.6 quantifies EEM importance, which can advise engineers which EEMs need more attention. If the time is limited to develop models, users can apply the default or evaluated values for

insensitive EEMs. However, in the special situations, the engineers still need to use their own judgments based on prior experience. For an application example, building engineers are creating a predictive model for retrofitting an existing medium office in Miami, FL, which is in the climate zone 1A. From Table 6.6, it is found that there are four EEMs with aggregated sensitivity larger than 0.20. Among them, the lighting power density (1.00) is the most sensitive EEM, followed by the electric equipment power density (0.44), the cooling coil coefficient of performance (0.29), and the window solar heat gain coefficient (0.27). If extra energy savings are needed, then the R-value of exterior wall insulation (0.10) and U-value of glazing (0.08) can also be explored. Thus, the engineers need to spend more effort on these model inputs in order to achieve an accurate energy model, while general estimates for the other EEMs are sufficient. This saves the engineers valuable time and can help make modeling more accessible for building retrofit applications.

Furthermore, this chapter compares the results by using different building energy models as the baselines. The results indicate that it is necessary to select suitable baseline models for the building energy analyses with the highly accurate requirements. Moreover, it is noted that the cost information from the market is also needed to calculate the payback period of retrofit options, which will be analyzed in Chapter 7.

Chapter 7

Impacts of Electricity Pricing Programs on EEM Selection

This chapter provides one example for the standardized computational framework about building energy analyses and analyze the impacts of electricity pricing programs on the selection of energy efficiency measures (EEMs). The DOE Commercial Prototype Building Energy Models for medium office buildings are used as the baseline models [45]. Five electricity pricing programs are studied: static, general, critical peak, time-of-use, and high renewable penetration electricity pricing programs. Furthermore, this chapter also discusses how different baseline models impact the cost savings in relationship to the EEM selections.

7.1 Introduction

Building energy retrofit has great potential to save energy [80, 181, 74, 77, 173]. For example, Glazer [74] analyzed 272 buildings and climate combinations, and stated that the energy retrofit of commercial buildings in the U.S. had the potential to achieve approximately 50% site energy saving compared to ASHRAE Standard 90.1-2013 [11]. Furthermore, the study by Chen et al. [24] shows that replacing lighting with LED in office and retail buildings in San Francisco will save more than 300 GWh energy consumption annually. According to simulations conducted by Friess et al. [73], an appropriate wall insulation strategy is able to save up to 30% of energy consumption. Moreover, energy saving with improved lighting systems was found to be 8.3% in the research conducted by Houri and El Khoury [86]. However, energy saving is only one of the considerations for building owners. They also consider cost saving when selecting EEMs. To optimize energy and cost savings, it is crucial to select appropriate EEMs during building energy retrofits.

Currently, a lot of research has studied how to select appropriate EEMs for buildings by considering various factors, such as energy and cost savings [70, 97, 99, 106, 129]. Taking into account energy consumption and net present value (NPV), Liu et al. [111] introduced a framework to optimize the design of building energy systems. Moreover, using energy saving or cost saving as the main objective, Tan et al. [169] studied how to select the right EEMs for existing buildings. Mahlia et al. [115] analyzed the life cycle cost and the payback period of lighting retrofit at the University of Malaya.

The studies mentioned above mainly applies static energy price (or a fixed energy price) to evaluate the cost performance of building retrofits. However, more and more commercial buildings adopt dynamic electricity pricing programs instead of static pricing programs [191, 1, 65, 180, 198]. For example, commercial buildings in Colorado, U.S. adopt various dynamic electricity pricing programs, such as critical peak pricing and time of use pricing [192]. In this case, electricity prices are different for individual buildings according to the power peak load demanded by each building. Electricity prices vary during different time periods. Generally, electricity price is higher during the daytime than at night. Another example is that real time electricity pricing programs are being adopted in Texas, U.S. [68, 198]. Electricity prices fluctuate over short intervals (typically an hour), and building users are charged at a specific price for each interval. Dynamic pricing programs can generate savings if building users respond to the fluctuations in electricity prices and adjust their usage accordingly.

Apparently, for building adopting dynamic electricity pricing programs, the conventional approach of selecting EEMs based on static pricing programs may not be valid anymore. The return on investment (ROI) of EEMs, which could reduce the peak power load or shift the time period of energy consumption, may be underestimated under static pricing programs. For example, there is an EEM can shift the electricity consumption from noon to night. This feature does not bring cost savings under the static pricing program as the energy consumption is the same. However, it can generate cost saving under the time of use pricing program by shift the load from the peak to non-peak period.

To understand how electricity pricing programs impact the selection of EEMs, this chapter studies the ROIs of EEMs under different pricing programs using U.S. medium office buildings as an example. This research selected four typical cities with different climate features and designed five electricity pricing programs. To simplify the research process, the electricity pricing programs in different cities are similar, which are designed based on a review about existing electricity pricing programs used in the U.S. This chapter is organized as follows: Section 7.2 introduces the methodology to select EEMs. Section 7.3 provides a case study to select EEMs for U.S. medium office buildings. The four studied cities and five electricity pricing programs are used for this study. Furthermore, Section 7.4 analyzes how the selection of EEMs are changed when the medium office building models created in Section 5.2 are used as baselines. Finally, findings are concluded in Section 7.5.

7.2 Methodology to Evaluate the Impacts of Electricity Pricing Programs on EEM Selection

7.2.1 General Description

Figure 7.1 presents a general description of selecting EEMs for an existing building based on the ROI for different pricing programs. Although this paper focuses on the U.S. medium office buildings, the methodology presented in this section can be applied for other building types. This chapter first establishes a baseline model and calculates its energy consumption. Secondly, this chapter upgrades the baseline models with EEM i. Then, energy costs are calculated based on energy predictions and different pricing programs. After that, annual cost saving by applying EEM i can be determined. Finally, ROI for EEM i can be calculated by using initial investment and annual cost saving. The EEMs can be selected based on a threshold defined the users. A detailed introduction is shown in Sections 7.2.2, 7.2.3, and 7.2.4.

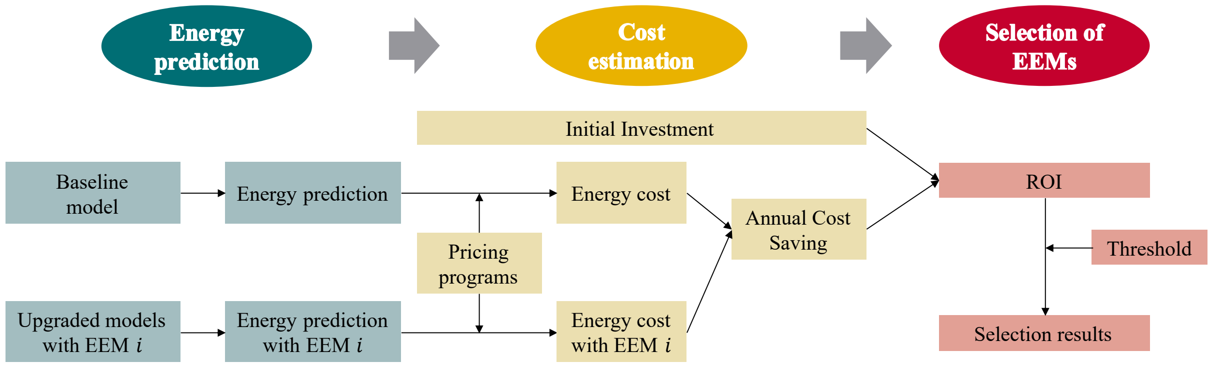


Figure 7.1: General description of calculating ROI of EEM for an existing building

7.2.2 Energy Prediction

As mentioned in section 7.2.1, energy consumption is predicted based on (1) baseline models and (2) upgraded models by adopting individual EEMs. The baseline model can be the model of the actual building if users are only interested in a single building. For large-scale analysis, the baseline models can be prototypical building models, such as Commercial Reference Building Models (Deru et al. 2011; DOE 2019b), Commercial Prototype Building Models [45, 173], other prototypical models for religious worship[194], mechanical shop [196], and college and university buildings [195].

The EEMs can be selected by engineering experience or referring to literature. A rich set of research identified possible sensitive EEMs, which may have great impacts on energy consumption in buildings [74, 103, 184, 185, 183, 197].

Depending on the pricing programs, different data will be extracted from the building energy simulations of baseline models and upgraded models with EEM i. This study extracts three types of data: (1) hourly electricity consumption; (2) monthly peak power load; (3) annual natural gas consumption.

7.2.3 Cost Estimation

Cost estimation consists of two types of cost: initial investment and energy cost. Initial investment is the total cost during the retrofit period, including material cost, installation cost, and transport cost. Energy cost includes electricity cost and natural gas cost.

7.2.3.1 Initial Investment

The investment estimation of EEMs is an important area of research for building energy retrofit [35, 125]. Some existing reports provide the estimated values of the initial investment (I_i) for EEMs. For example, the Advanced Energy Retrofit Guide provides strategies and costs to retrofit existing office buildings [111]. The RSMeans also provides cost estimations for the initial investment of EEMs [76]. This study referred the retrofit guides and used RSMeans as a tool to estimate initial investment.

7.2.3.2 Energy Cost

Energy cost consists of two types of cost: electricity cost and natural gas cost. In order to analyze the impact of electricity pricing programs on the selection of EEM, electricity cost is calculated under different pricing programs, while natural gas cost is calculated under one static pricing program.

There are different ways to define electricity pricing programs [5, 46, 98]. This study considered electricity pricing programs consist of three types of charge: basic charge, demand charge, and energy charge. Basic charge is a monthly fixed charge. Demand charge is the charge for each month's peak power load. Energy charge is the charge for electricity consumption. Therefore, annual electricity cost $C_{electricity}$ under a typical electricity pricing program is:

$$C_{electricity} = P_B \times 12 + \sum_{j=1}^{12} P_{D,j} \times E_{D,j} + \sum_{k=1}^{n} P_{E,k} \times E_{E,k} \tag{7.1}$$

where P_B is the basic price for every month; $P_{D,j}$ is the unit price of the peak power and

$E_{D,j}$ is the peak power load in every month; $P_{E,k}$ is the unit price of electricity consumption for time period k. $E_{E,k}$ is electricity consumption during time period k. The P_B,$P_{D,j}$, $P_{E,k}$, and k are different under different electricity pricing programs. For instance, in a static electricity pricing program, $P_B = 0$, $P_{D,j} = 0$, and $n = 0$ so that $C_{electricity} = P_E \times E_E$.

Annual natural gas cost C_{gas} is:

$$C_{gas} = P_G \times E_G \tag{7.2}$$

where P_G is the unit price of natural gas; E_G is the annual natural gas consumption.

Therefore, annual energy cost C_{energy} is:

$$C_{energy} = C_{electricity} + C_{gas} \tag{7.3}$$

7.2.3.3 Annual Cost Saving

Energy cost saving R_i by applying EEM i is:

$$R_i = C_{energy,base} - C_{energy,upgr,i} \tag{7.4}$$

where $C_{energy,base}$ is the annual energy cost before the retrofit; $C_{energy,upgr,i}$ is the annual energy cost after applying EEM i.

7.2.4 Selection of EEMs

The initial investment of an EEM is returned by annual cost saving. The ratio of annual cost saving and initial investment is termed as ROI, which reflects the economic efficiency of EEMs. The ROI of EEM i (ROI_i) is:

$$ROI_i = \frac{R_i}{I_i} \tag{7.5}$$

where R_i is annual energy cost saving by adopting EEM i, which can be calculated by using Equations 7.1, 7.2, 7.3, and 7.4; I_i is initial investment of EEM i, which can be calculated by using the method introduced in Section 7.2.3.1.

The higher ROI means the shorter payback period, which building owners tend to select for existing building retrofit projects [69, 113, 168]. In this study, the higher the EEM's ROI is, the higher priority it will be selected. The goal of this selection approach is not to maximize energy saving or cost saving, but to value more profitable EEMs.

7.3 Case Study: U.S. Medium Office Buildings

To evaluate the impact of pricing programs on ROIs, a case study is performed using the U.S. medium office buildings in four typical cities (Honolulu, Buffalo, Denver, and Fairbanks) under the five pricing programs (static, general, critical peak, time of use, and high renewable penetration). The study is conducted in three steps as introduced in Section 7.2: *energy prediction*, *cost estimation*, and *selection of EEMs*.

7.3.1 Energy Prediction

Figure 7.2 shows the status of state energy code adoption for U.S. commercial buildings [43]. Based on the status of state energy code adoption, this study selected the medium office building models for Standard 90.1-2007 from DOE Commercial Prototype Building Models as baseline models [45]. The geometry and thermal zones have been shown in Figure 6.4. The description of the models have been listed in Table 6.2. Four typical cities in different climates were selected. Honolulu in the Climate Zone 1A is hot and humid while Fairbanks in the Climate Zone 8 is extremely cold. Buffalo (5A) and Denver (5B) are in cold climates, which is relatively warmer compared with Fairbanks, but cooler than Honolulu. Buffalo is relatively humid while Denver is dry. Thus, these four studied cities can represent the major climate features in the U.S.

Table 7.1 lists eight selected EEMs based on the literature [75, 77, 185]. To make it convenient, this chapter provides the abbreviation for each EEM.

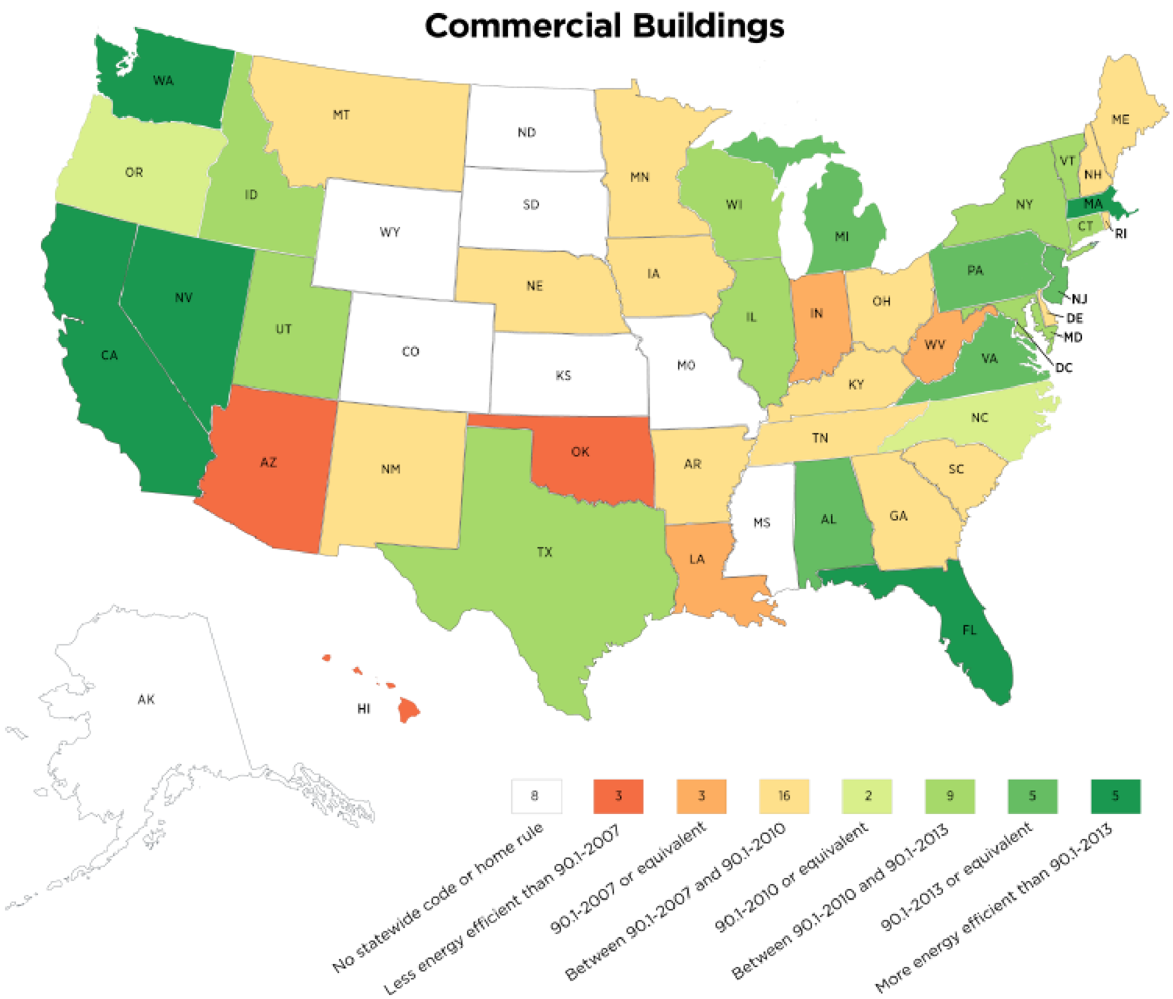


Figure 7.2: Status of state energy code adoption (U.S. commercial buildings) [43]

The baseline values of the selected EEMs are the values in the baseline models. The upgraded values are the values of the EEMs after the retrofits based on the Advanced Energy Retrofit Guide [111]. Table 7.2 lists the baseline and upgraded values of the EEMs in the four studied cities.

The EEMs impact building's monthly maximum power and annual energy consumption. Figure 7.3 shows the impact of varying a single EEM on average monthly peak power for buildings. The first six EEMs reduce the average monthly peak power. Since the heating system and hot water system consume natural gas, HEATING and DHW do not change the average monthly peak power.

Table 7.1: Description of EEMs

EEM	EEM Code	Variable
Add wall insulation	WALL	Wall insulation R-value
Add roof insulation	ROOF	Roof insulation R-value
Replace windows	WINDOW	U-factor, SHGC
Replace interior fixtures with higher-efficiency fixtures	LPD	Lighting Power Density
Replace office equipment with higher-efficiency equipment	PLD	Plug Load Density
Replace cooling system with higher-efficiency system	COOLING	COP
Replace heating system with higher-efficiency system	HEATING	Heating Efficiency
Replace service hot water system with higher-efficiency system	SWH	Hot Water Efficiency

Moreover, the greatest reduction is by replacing office equipment with higher-efficiency equipment (EQUIP) in all four cities. The first four EEMs have moderate impacts on the changes of average monthly peak power. These four EEMs retrofit the envelopes and lighting fixtures. Because the efficiency of the cooling system is not significantly improved, the COOLING only has a low impact on the changes of average monthly peak power. Furthermore, EEM's impacts on reducing average monthly peak power varies depending on the climates. For example, improving insulation of envelopes (WALL, ROOF, and WINDOW) can reduce more peak power in the extremely cold/cold climate (Denver, Buffalo, and Fairbanks) than the hot climate (Honolulu). Another example shows that the EQUIP reduces more peak power in the hot climate (Honolulu).

Figure 7.4 shows the changes in annual electricity consumption and natural gas consumption by applying individual EEMs. The EQUIP leads to the greatest reduction of annual electricity consumption in all four cities. By using WALL or ROOF, the annual electricity consumption is reduced while there is also a minor change for the annual natural gas consumption. The COOLING only impacts the annual electricity use while the HEATING and DHW only change the annual natural gas consumption. Furthermore, the rest three EEMs (WINDOW, LPD, and EQUIP) reduce the annual electricity use while they increase the annual natural gas use. For example, the

Table 7.2: Values of variables

Variable	Unit	1A: Honolulu		5A: Buffalo		5B: Denver		8: Fairbanks	
		Base[1]	**Upgr**[2]	**Base**[1]	**Upgr**[2]	**Base**[1]	**Upgr**[2]	**Base**[1]	**Upgr**[2]
Wall insulation R-value	m^2-K/W	1.04	4.38	2.37	5.71	2.37	5.71	2.37	5.71
Roof insulation R-value	m^2-K/W	2.60	3.95	3.47	5.50	3.47	5.50	3.47	6.18
U-factor	W/m^2-K	5.78	3.69	2.65	2.21	2.65	2.21	2.49	1.93
SHGC	-	0.31	0.25	0.43	0.25	0.43	0.25	0.43	0.25
Lighting Power Density	W/m^2	10.76	8.07	10.76	8.07	10.76	8.07	10.76	8.07
Plug Load Density	W/m^2	8.07	5.92	8.07	5.92	8.07	5.92	8.07	5.92
COP	-	3.23	3.37	3.23	3.37	3.23	3.37	3.23	3.37
Heating Efficiency	-	0.80	0.90	0.80	0.90	0.80	0.90	0.79	0.90
Hot Water Efficiency	-	0.81	0.90	0.81	0.90	0.81	0.90	0.81	0.90

[1] Base: Baseline model.
[2] Upgr: Upgrade model.

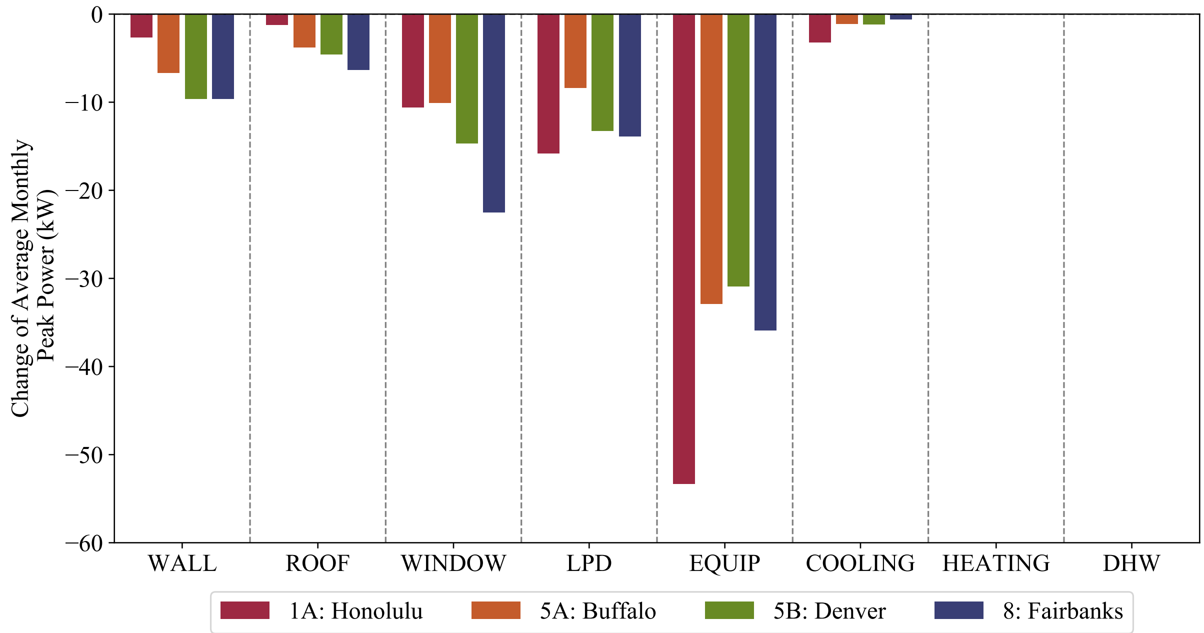


Figure 7.3: Changes in average monthly peak power by applying EEMs for buildings

EQUIP reduces the annual electricity use in all four cities while it increases the annual natural gas use in cold and extremely cold climates (Buffalo, Denver, and Fairbanks). The high-efficiency office equipment consumes less electricity for internal load. Furthermore, these models use electricity for cooling and natural gas for heating. By using the EQUIP, the cooling load is decreased and heating load is increased. In hot climate (Honolulu), the heating load is almost zero. The EQUIP reduces the annual electricity use for both internal load and cooling, and only has a small impact on the annual natural gas use. In the cold and extremely cold climates (Buffalo, Denver, and Fairbanks), the high-efficiency office equipment reduces both internal load and cooling load, but increases energy consumption for heating. Thus, the electricity consumption is reduced and natural gas consumption is increased. It is noticeable that the natural gas consumption is increased in cold and extremely cold climates (Buffalo, Denver, and Fairbanks) after replacing windows (WINDOW). It is because the Solar Heat Gain Coefficient (SHGC) of the new windows is lower than the windows in the baseline models, which causes less solar radiation enters into the building.

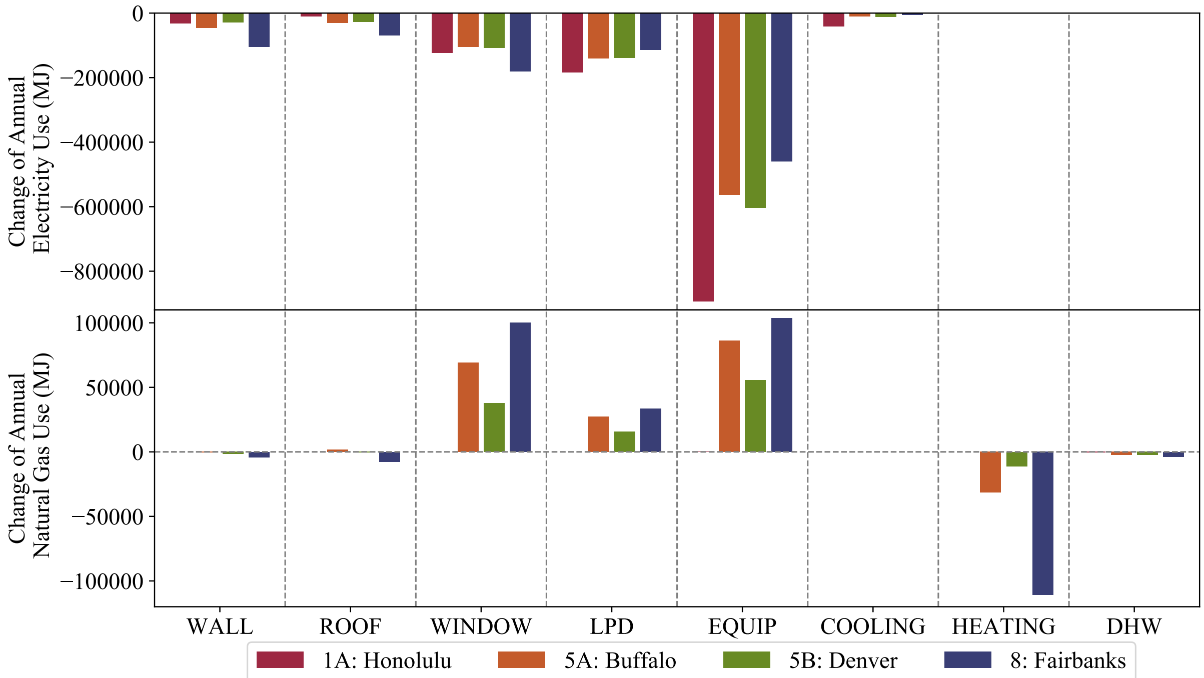


Figure 7.4: Changes in annual electricity and natural gas consumption by applying EEMs

7.3.2 Cost Estimation Under Different Electricity Pricing Programs

This section considers five types of electricity pricing programs: static, general, critical peak, time of use, and high renewable penetration. First, the initial investments of eight EEMs introduced in Table 7.1 will be estimated in this section. Secondly, energy costing saving contributed by individual EEMs will be calculated under the five types of pricing programs.

7.3.2.1 Initial Investment Estimation

Using the methodology described in Section 7.2.3.1, the initial investment of each individual EEM (I_i) in the four studied cities was estimated, as shown in Table 7.3.

This section considers five types of electricity pricing programs: static, general, critical peak, time of use, and high renewable penetration. First, the initial investments of eight EEMs introduced in Table 2 will be estimated in this section. Secondly, energy costing saving contributed by individual EEM will be calculated under the five types of pricing programs.

Table 7.3: Initial investment (I_i) for the EEMs in building retrofits

EEM	1A: Honolulu	5A: Buffalo	5B: Denver	8: Fairbanks
WALL	$11,267	$9,556	$8,272	$12,408
ROOF	$17,875	$20,557	$19,305	$35,214
WINDOW	$155,202	$131,678	$143,634	$166,441
LPD	$33,496	$27,658	$25,942	$35,868
EQUIP	$64,725	$58,640	$57,352	$66,302
COOLING	$11,063	$10,516	$9,776	$11,008
HEATING	$2,968	$2,780	$2,678	$2,961
DHW	$1,910	$1,864	$1,824	$1,908

It can be seen from Table 7.3 that the initial investment of WINDOW is significantly higher than the other EEMs in all four studied cities. It is costly to replace all exterior windows into the new windows with lower U-factor and SHGC. Then EQUIP and LPD are the second and third expensive EEMs for the initial investment. By compared with these EEMs, it is relatively cheaper to add insulation for the envelopes (WALL and ROOF) and replace systems (COOLING, HEATING, and DHW).

Generally, the initial investments of EEMs are similar among four cities, while they are a little higher in Fairbanks than in the other three cities. But, the initial investment of ROOF in Fairbanks is significantly higher than that in the other three cities. One reason is that the difference of roof insulation R-value between baseline and upgraded in Fairbanks is larger than that in other cities. As shown in Table 7.2, the difference of roof insulation R-value between baseline and upgraded in Fairbanks is 2.71 m^2-K/W, while the difference value in Honolulu, Buffalo, and Denver are 1.36 m^2-K/W, 2.03 m^2-K/W, and 2.03 m^2-K/W, respectively.

7.3.2.2 Energy Cost Saving Estimation

In reference to existing electricity pricing programs [191, 47, 48, 68, 98], this study designed five electricity pricing programs using Equation 7.1. The parameters of each program are given in Table 7.4.

Table 7.4: Electricity pricing programs designed to case cities

Electricity Pricing Programs	**City**	**Basic (\$/Mon)** P_B	**Demand (\$/kW Peak Load Every Month)** P_D	**Energy (\$/kWh)** P_E		
				Peak		**Off Peak**
				Critical Peak	**On Peak**	
Static	Honolulu	0	0	0.2917		
	Buffalo	0	0	0.1527		
	Denver	0	0	0.1080		
	Fairbanks	0	0	0.2007		
General	Honolulu	144.0	79.60	0.01245		
	Buffalo	75.4	41.67	0.00652		
	Denver	53.0	29.47	0.00461		
	Fairbanks	99.0	54.77	0.00857		
Critical Peak [1]	Honolulu	92.9	53.07	4.1	-	0.01245
	Buffalo	48.6	27.78	2.1		0.00652
	Denver	34.4	19.65	1.5		0.00461
	Fairbanks	63.9	36.52	2.8		0.00857
Time of Use [2]	Honolulu	92.9	15.21	-	0.24441	0.06047
	Buffalo	48.6	7.96		0.12794	0.03166
	Denver	34.4	5.63		0.09049	0.02239
	Fairbanks	63.9	10.46		0.16816	0.04161
High Renewable Penetration [3]	Honolulu	92.9	15.21	4.1	0.24441	0.06047
	Buffalo	48.6	7.96	2.1	0.12794	0.03166
	Denver	34.4	5.63	1.5	0.09049	0.02239
	Fairbanks	63.9	10.46	2.8	0.16816	0.04161

[1] This study selects 15 days, which are assumed to appear critical-peak for the power grid. The critical-peak time period is from 12:00 pm to 17:00 pm in these 15 days.

[2] The on-peak time appears on workdays in Jun, Jul, Aug and Sept. The on-peak time period is from 12:00 pm to 20:00 pm. The other time period is off-peak.

[3] The days are divided into three categories based on the one day's radiation level: low, moderate, high radiation days. In the low radiation day, the critical-peak time period is from 13:00 pm to 17:00 pm, the on-peak time period is from 12:00 pm to 13:00 pm and from 17:00 pm to 20:00 pm, and the other time period is off-peak. In the moderate radiation day, the on-peak time period is from 12:00 pm to 20:00 pm, and the other time period is off-peak. In the high radiation day, the on-peak time period is from 17:00 pm to 20:00 pm, and the other time period is the off-peak.

Static: There is no basic charge or demand charge in this program. The unit price of electricity consumption P_E is same during the year. The electricity cost $C_{electricity}$ is the product of P_E and electricity consumption. Static pricing program provides building users price signal to reduce energy consumption [47, 48]. In this study, P_E is designed by referring the average price of electricity in the studied cities [62].

General: The electricity prices (P_B, P_D, and P_E) in this program are same during the year ([190]. The electricity cost ($C_{electricity}$) is the sum of basic charge, demand charge, and energy charge. Basic charge is fixed. Demand charge is the product of P_D and monthly peak power. Energy charge is the product of P_E and electricity consumption. Therefore, general pricing program provides building users price signals to reduce peak power and electricity consumption.

Critical Peak: P_B and P_D in this program are same during the year. But P_E is different during different time period. P_E is high during a few critical-peak hours of the day and discounted during the rest of the day [47, 48]. The critical-peak hours are only designed for a certain number of days (e.g. 15 days in this study) during a year. Critical peak pricing program gives building users strong price signals and encourages them to reduce their electricity use during critical-peak periods.

Time of Use: P_B and P_D in this program are same during the year. But P_E in this program varies during different times of the day, that is, high during on-peak hours and low during off-peak hours [47, 48, 177]. The on-peak hours are designed in summer (e.g. from 12:00 pm to 20:00 pm in this study). This program provides building users price signals to reduce their electricity consumption during on-peak hours and shift electricity consumption to off-peak hours.

High Renewable Penetration: This chapter designs this electricity pricing program for the scenario of future high renewable energy penetration. Many studies show that Photovoltaic (PV) power systems will have an important role in electricity generation in the future [38, 199]. Most buildings will have PV power systems and thus, the peak power load demanded from the power grid will change in the future. Based on this assumption, a dynamic pricing program is designed, which is named high renewable penetration. The schematic diagram of this future program is shown in

Figure 7.5. Based on the one day's radiation level, the days are divided into three categories: low, moderate, and high radiation days.

The low radiation days are the 15 days with the lowest radiation levels over a year. In these days, the PV only generates a small amount of electricity due to the low radiation, and the critical-peak time period appears in these days (Figure 7.5a). To simplify the process of this study, it is assumed that the critical-peak time period is from 13:00 pm to 17:00 pm, the on-peak time period is from 12:00 pm to 13:00 pm and from 17:00 pm to 20:00 pm, and the other time period is the off-peak. The moderate radiation days (Figure 7.5b) are the 15 days with the $16^th \sim 30^th$ lowest radiation levels. The PV generates more electricity than it does during the low radiation days. As a result, the peak powers in moderate radiation days are all lower than the critical-peak threshold. Here, it is assumed that the on-peak time period is from 12:00 pm to 20:00 pm, and the other time period is the off-peak. The high radiation days are the rest days (Figure 7.5c). The PV generate a lot of electricity during the daytime, which can significantly reduce the peak power. It is assumed that the on-peak time period is from 17:00 pm to 20:00 pm, and the other time period is the off-peak.

The natural gas price (P_G) is designed by referring the natural gas prices released by U.S. Energy Information Administration [61]. The natural gas prices in Honolulu, Buffalo, Denver, and Fairbanks are \$27.41/kft^3, \$6.87/kft^3, \$7.17/kft^3, and \$9.79/kft^3, respectively.

Based on the five electricity pricing programs in Table 7.4, and applying Equations 7.1, 7.2, 7.3, and 7.4, annual energy cost saving (R_i) resulted by each EEM is calculated, as shown in Figure 7.6. Generally, EEMs have the highest R_i under static pricing program, followed by general, critical peak, time of use, and high renewable penetration. The EQUIP has the highest R_i under all pricing programs.

The annual cost savings are generated by the combined effects of power changes, energy changes, and price (P_B, P_D, P_E and P_G). For example, the annual cost savings for using more efficient office electric equipment (EQUIP) is significantly higher in Honolulu than the other three studied cities. The reason is that the EQUIP in Honolulu has the greatest reductions for average

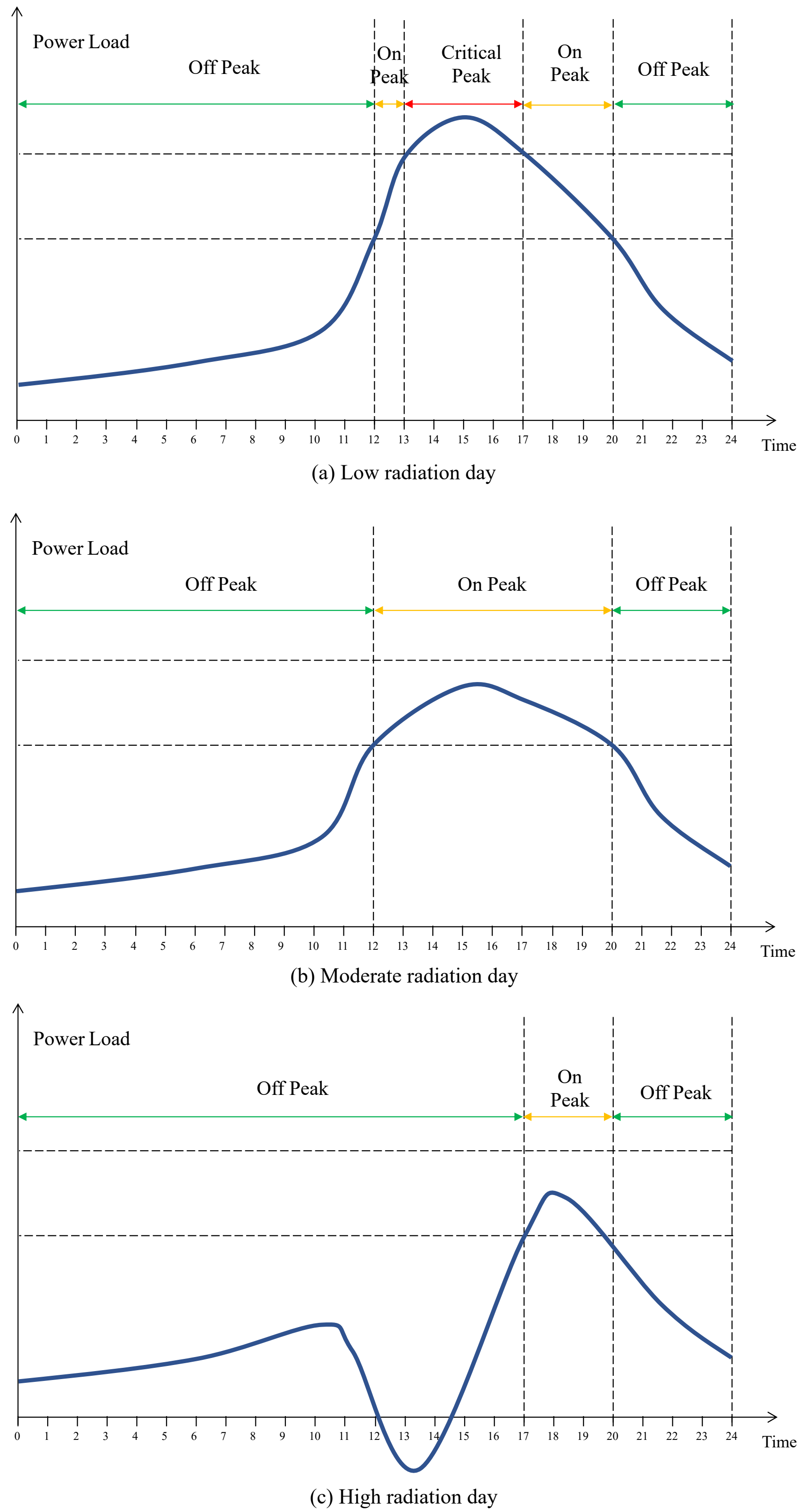


Figure 7.5: Schematic diagram of high renewable penetration

monthly peak power and annual electricity consumption, and Honolulu has the highest energy price among all four cities. The aggregated effect leads to a significant difference in the annual cost saving for the EQUIP between Honolulu and the other three studied cities. Another example is that adding roof insulation (ROOF) in Fairbanks reduces a significantly more annual cost than the other three studied cities. The ROOF in Fairbanks reduces the most average monthly peak power, and annual electricity and natural gas consumption. Furthermore, Fairbanks has the second highest price among the four studied cities. Thus, the highest annual cost saving is the aggregated effect of these two reasons.

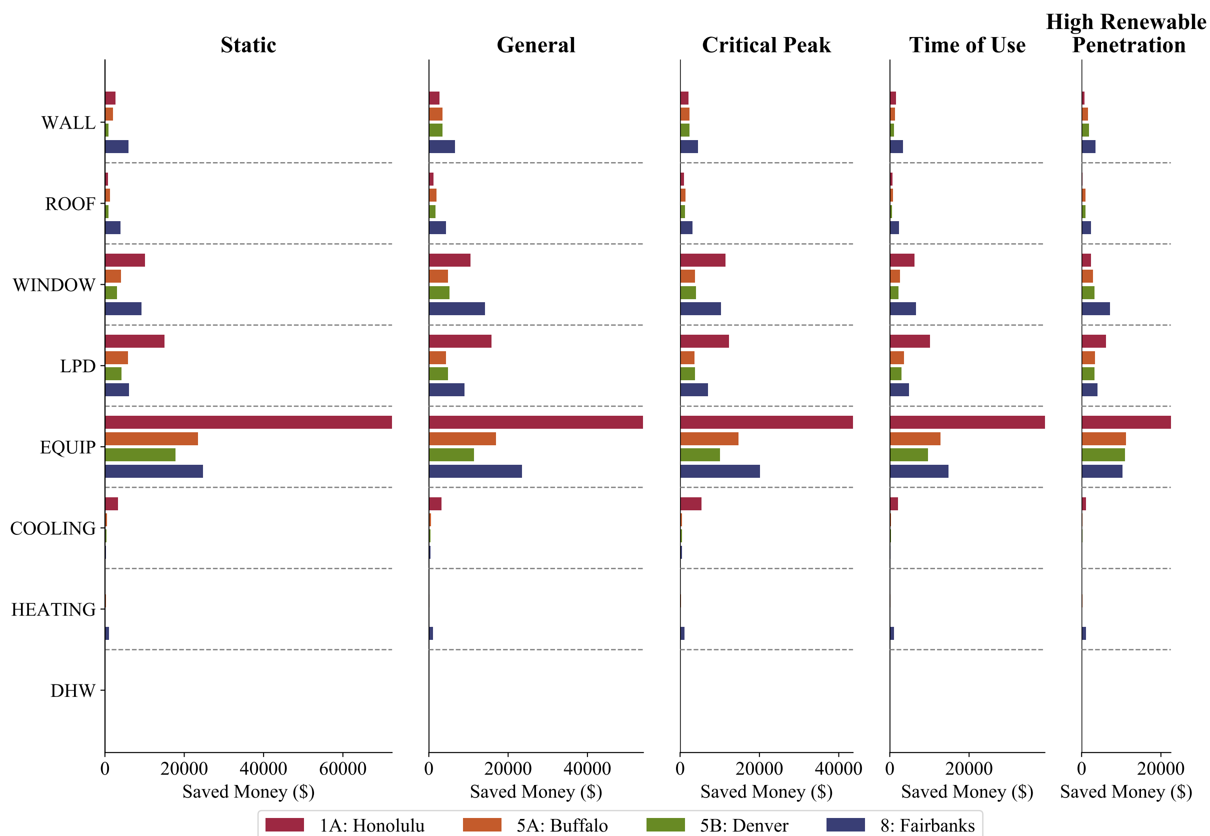


Figure 7.6: Annual cost saving (R_i) under the five electricity pricing programs

7.3.3 Selection of EEMs

After obtaining the initial investment of each EEM i and yearly energy cost saving (R_i) in Sections 7.3.1 and 7.3.2.1, and by using Equation 7.5, the ROI of the each EEM in the four studied cities under five electricity pricing programs can be calculated. The results are shown in Figures 7.7 $\sim$ 7.10.

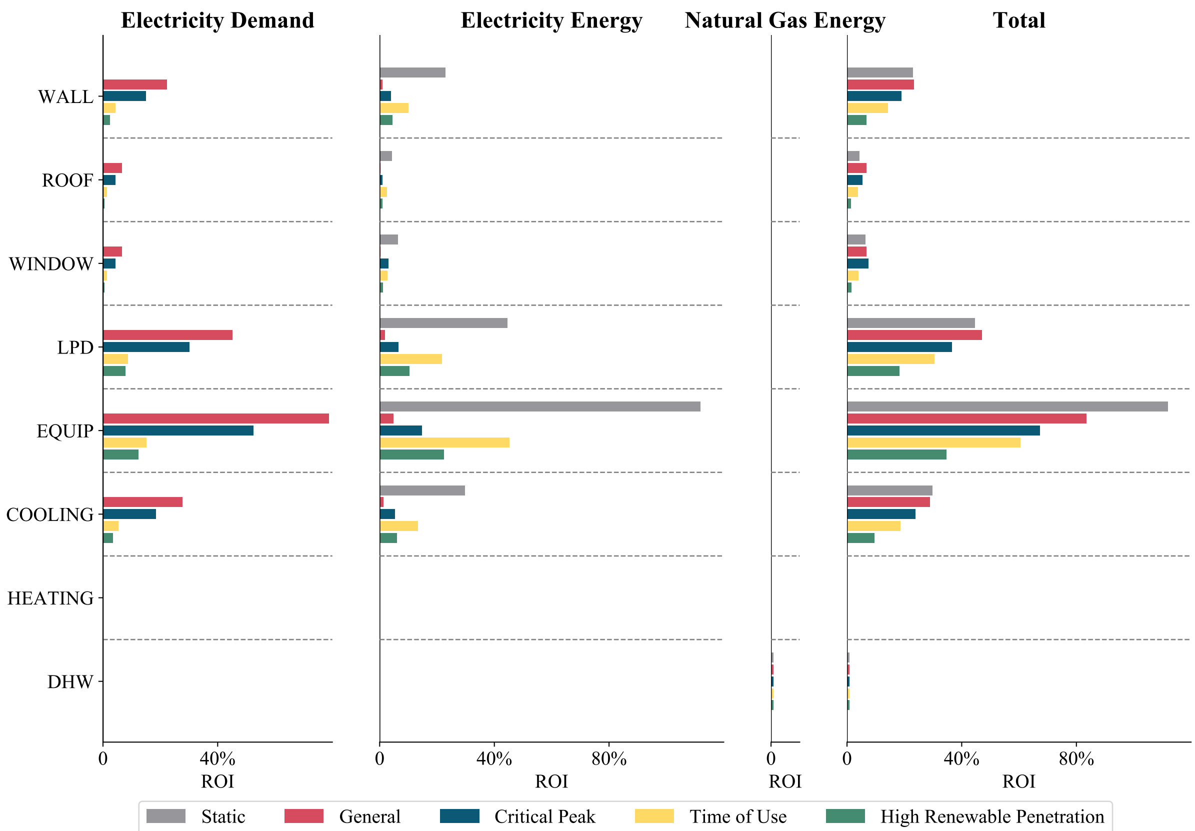


Figure 7.7: ROIs of EEMs under five electricity pricing programs for Honolulu (1A)

As shown in Figure 7.7, EQUIP can result in the highest ROI (70%) in Honolulu. This is largely due to the factors: On one hand, EQUIP has significantly higher annual cost saving (R_i) than the other EEMs under all pricing programs as previously shown in Figure 7.6. On the other hand, the initial investment (I_i) of EQUIP is not the highest one as shown in Table 7.3.

The EEM ranking by ROI is the same under five different pricing programs. EEM with the highest ROI is EQUIP, followed by LPD, COOLING, and WALL. But the ROIs of these EEMs has considerable variation. For example, the ROI of EQUIP varies from 35% to 112% under different pricing programs. And the ROI of LPD varies from 18% to 47%.

For a specific EEM, the pricing program, which can generate higher ROI, is different because the total ROI is a combined result of electricity demand and electricity energy when the initial investment is the same. The EQUIP and COOLING can generate the highest ROI under the static electricity pricing program. The LPD and WALL can generate the highest ROI under the general pricing program. The total ROI under static pricing program is mainly contributed by electricity energy, while the total ROI under general pricing program is mainly contributed by electricity demand.

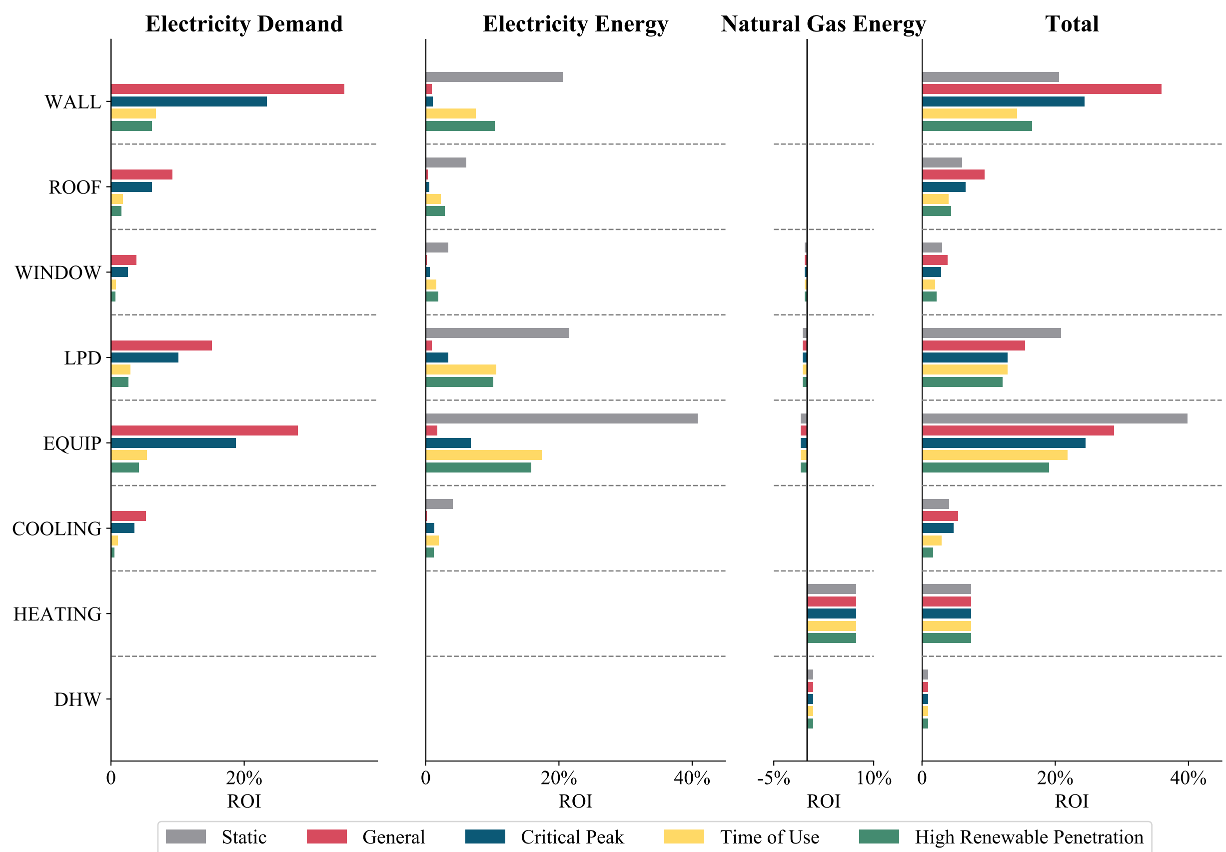


Figure 7.8: ROIs of EEMs by using the four electricity pricing programs for Buffalo (5A)

As shown in Figure 7.8, EQUIP and WALL have the highest ROIs in Buffalo, which is about 27% and 23%, respectively. The EQUIP can achieve high ROI because it can significantly reduce peak power and energy consumption, as shown in Figures 7.3 and 7.4. Although WALL's impact on reducing power load and energy consumption is less significantly than EQUIP, its initial investment is significantly lower than EQUIP. As a result, WALL also has a high ROI.

The EEM ranking by ROI is different under five pricing programs. Under the static pricing program, EQUIP, LPD, and WALL have higher ROIs than others. Under the general pricing program, WALL, EQUIP, and LPD have higher ROIs than others. Under the critical peak pricing program, EQUIP, WALL, and LPD have higher ROIs than others. Under time of use pricing program, EQUIP, WALL, and LPD have higher ROIs. Under high renewable penetration pricing program, EQUIP, WALL, and LPD have higher ROIs than others. The EEM with the highest ROI is WALL under the general pricing program, while it is EQUIP under the other four pricing programs. It means that the top priority EEM varies under different pricing programs. It is because the ROI of WALL is mainly contributed by electricity demand, while the ROI of EQUIP is mainly contributed by electricity energy. The general pricing program has highest demand price compared with the other four programs. Therefore, the EEM which can reduce peak power significantly has higher ROI under the general pricing program.

As shown in Figure 7.9, generally, WALL and EQUIP can result in highest ROI in Denver, which is approximately 23% and 21%, respectively. This result is similar with Buffalo. However, the ROI of EQUIP in Denver is lower than that Buffalo.

The EEM ranking by ROI is also different under five different pricing programs. The EEMs with high ROI in Denver is the same with that in Buffalo while the ranking of these EEMs is slightly different. Under static pricing program, EQUIP, LPD, and WALL have higher ROIs than others. Under general pricing program, WALL, EQUIP, and LPD have higher ROIs than others. Under critical peak pricing program, WALL, EQUIP, and LPD have higher ROIs than others. Under time of use pricing program, EQUIP, WALL, and LPD have higher ROIs than others. Under high renewable penetration pricing program, WALL, EQUIP, and LPD have higher ROIs than others.

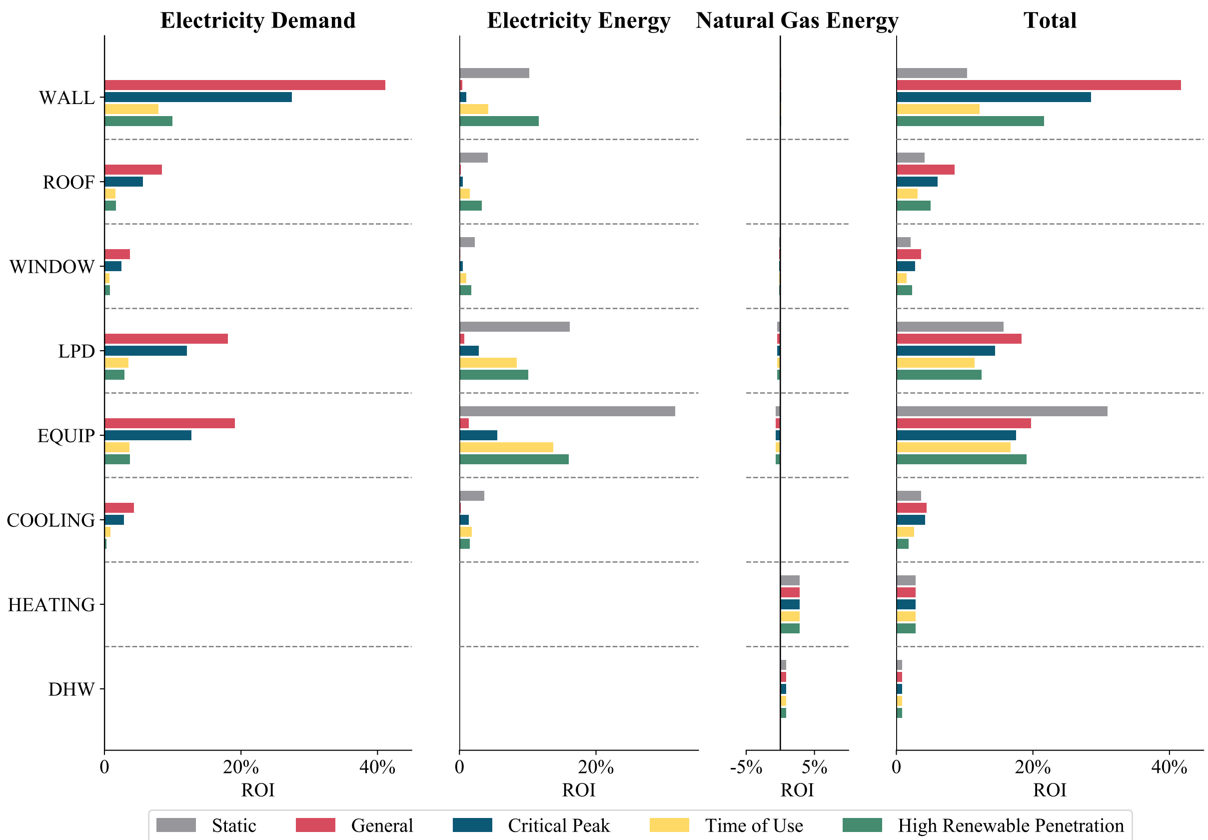


Figure 7.9: ROIs of EEMs by using the four electricity pricing programs for Denver (5B)

As shown in Figure 7.10, generally, WALL and HEATING can result in the highest ROIs in Fairbanks, which is approximately 38% and 35%, respectively. Although the annual saved money (R_i) of WALL and HEATING is not high, the initial investments (I_i) of them are lower than the other EEMs. Therefore, they have higher ROIs.

Same as Buffalo and Denver, the EEM ranking by ROI in Fairbanks is also different under five different pricing programs. Under static pricing program, WALL, EQUIP, HEATING, and LPD have higher ROIs than others. Under general pricing program, WALL, EQUIP, HEATING, LPD and ROOF have higher ROIs than others. Under critical peak pricing program, WALL, HEATING, EQUIP, and LPD have higher ROIs than others. Under time of use pricing program, HEATING, WALL, EQUIP, and LPD have higher ROIs than others. Under high renewable penetration pricing

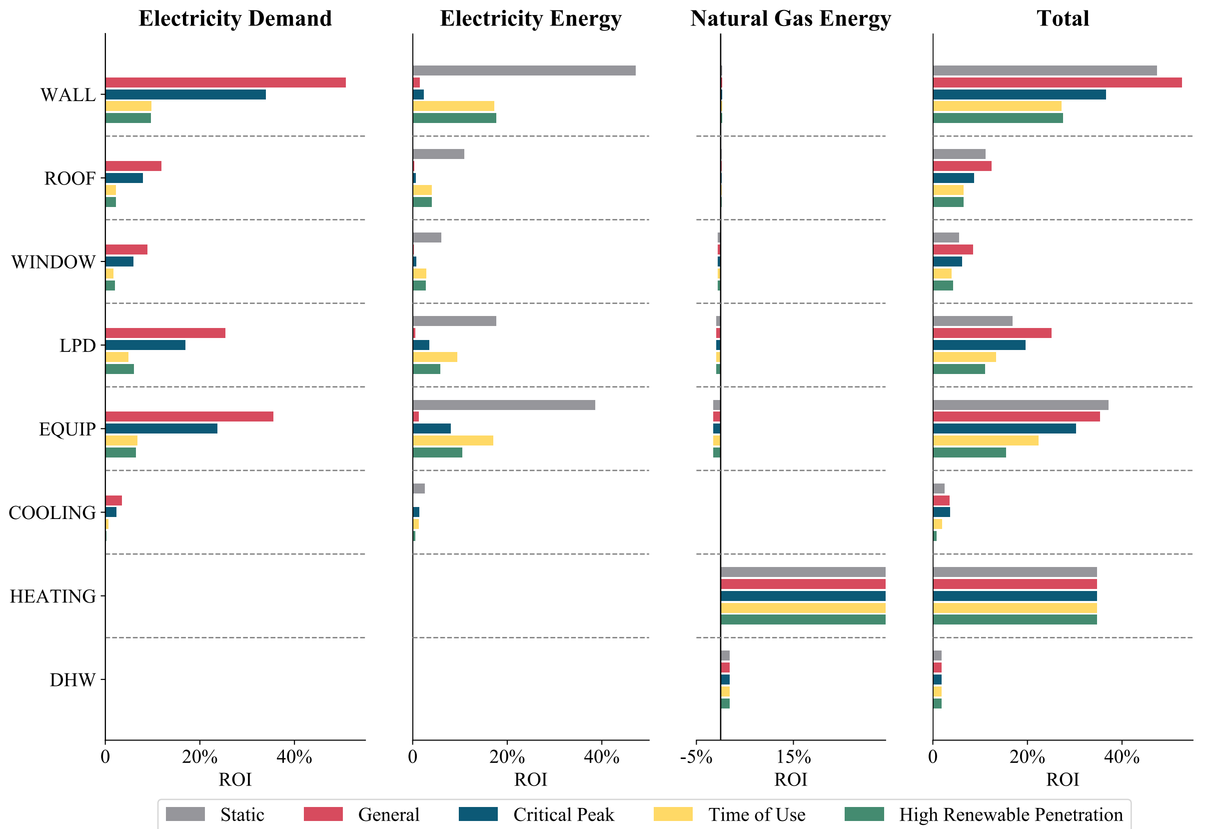


Figure 7.10: ROIs of EEMs by using the four electricity pricing programs for Fairbanks (8)

program, HEATING, WALL, EQUIP, and LPD have higher ROIs than others. The EEM with the highest ROI is WALL under static, general, and critical peak pricing programs, while it is HEATING under time of use and high renewable penetration pricing programs. The top priority EEM varies because the ROI of WALL changes under different pricing programs. The ROI of HEATING is not changed. It is because HEATING reduces natural gas consumption, but HEATING has no impact on electricity consumption. So, electricity pricing programs has no impact on the ROI of HEATING.

7.3.4 ROIs of EEMs in the Four Studied Cities

In order to compare the ROIs among the four studied cities, the total ROIs of EEMs in the four cities are compared in Figure 7.11.

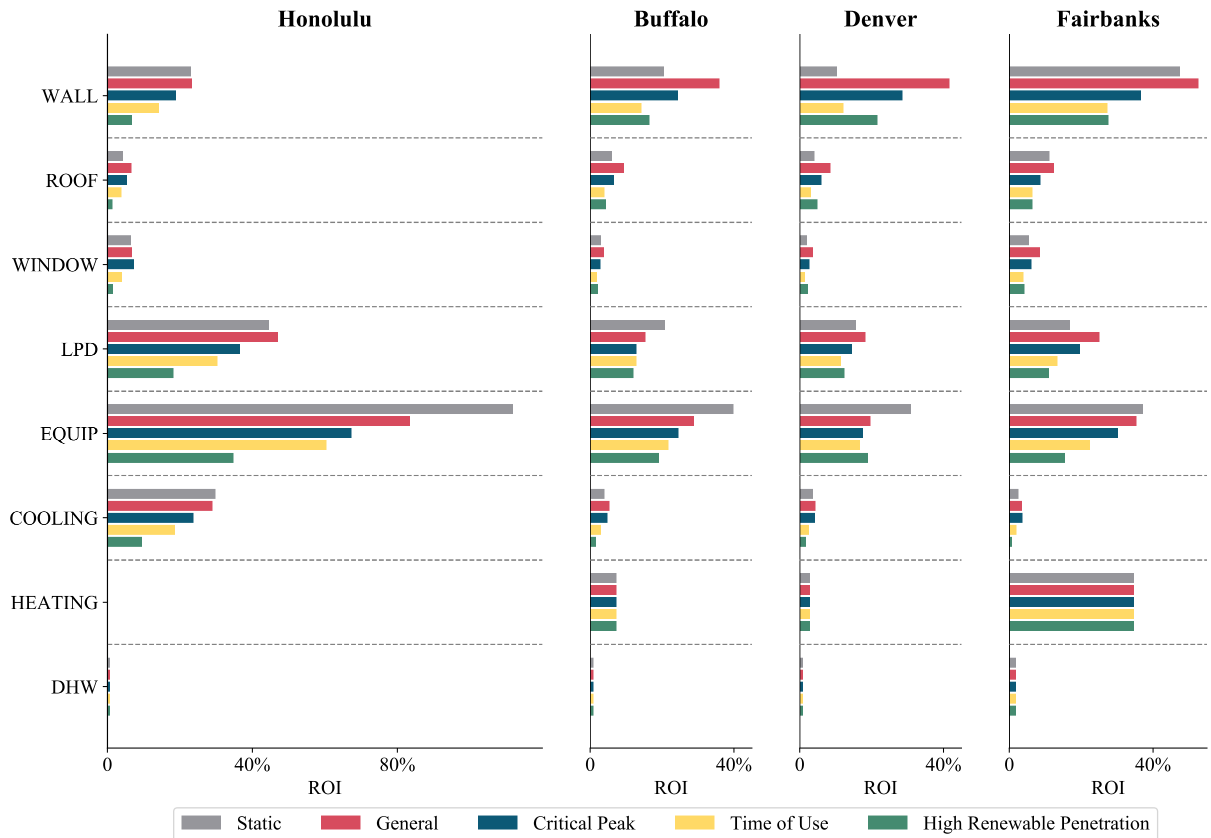


Figure 7.11: Total ROIs of EEMs in four studied cities

In terms of the EEMs with high ROIs, Honolulu has the highest ROIs (up to 112%) among all four cities due to its high energy price. LPD, EQUIP, COOLING in Honolulu almost have doubled ROIs than the other cities. This is because energy used for internal load (equipment operation and lighting) and cooling plays an important role in total energy consumption in hot areas, such as Honolulu. HEATING and WALL applied in Fairbanks has higher ROI than the other cities since heating and insulation plays an important role in total energy consumption in the extremely cold area, such as Fairbanks. Therefore, retrofitting internal load (e.g. LPD, EQUIP) and cooling is more profitable in hot area, while retrofitting heating system and wall insulation is more profitable in extremely cold area.

In terms of variations of ROIs of an EEM under different pricing program, the ROI of EQUIP in Honolulu varies most dramatically under different pricing programs. It is because the EQUIP in Honolulu can generate more energy savings and power reduction. However, the ROI of HEATING and DHW do not vary under different pricing programs. It is because natural gas is used for heating and hot water system. The price of natural gas is stable.

In term of high renewable penetration pricing program, the ROIs of EEM in Buffalo, Denver, and Fairbanks will change slightly while the ROIs of EEM in Honolulu will decrease considerably. This is because the PV panels generate more electricity power in Honolulu than other three studied cities and peak power impact will greatly decrease in Honolulu. However, by using the high renewable penetration pricing programs, the ROI of the EQUIP still has approximately 40% in Honolulu, which is necessary to conduct building energy retrofits.

7.4 Discussion

Section 6.4 shows that different baseline models could cause various results for the analysis about the impact of the energy savings on the EEM selection. This section discusses whether different baseline models are able to change the results about the impact of the electricity pricing programs on the EEM selection. By using the same strategy shown in Section 7.2, this section calculates the ROIs of EEMs for the prototypical building energy models of medium office buildings created in Section 5.2.1 (New Models (Pre- and Post-1980)). To make this discussion, this section compares the results by using the New Models and generated in Section 7.3 (Prototype Model). The Time-of-Use electricity pricing program and Buffalo (climate zone 5A) are used for this study. Figure 7.12 shows the ROIs of EEMs by using New Model and Prototype Model.

The New Models represent the pre- and post-1980 medium office buildings in the U.S. while the Prototype Model is created based on the ASHRAE Standard 90.1-2007 [9]. Figure 7.12 shows that the New Model (Pre-1980) has the highest ROIs for the six EEMs and the Prototype Model

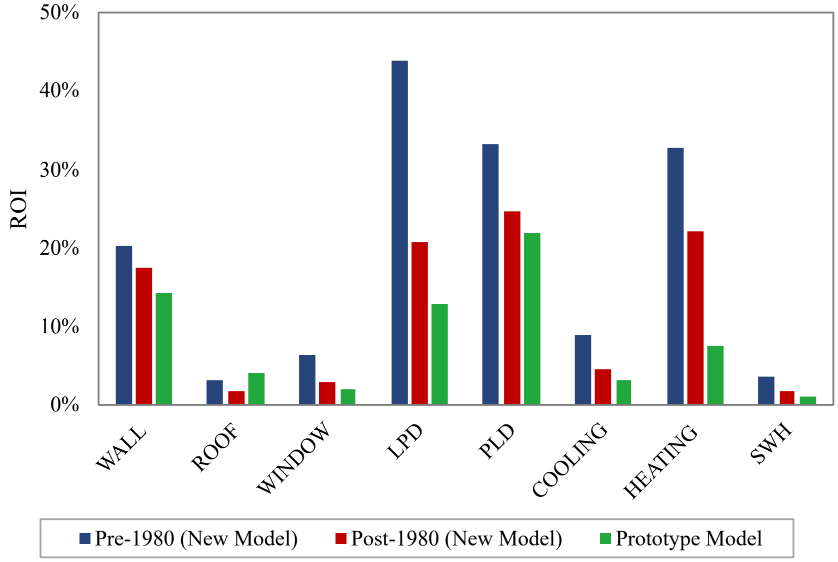


Figure 7.12: ROIs of EEMs by using different medium office models (Time-of-Use; 5A, Buffalo)

has the lowest ROIs: WINDOW, LPD, PLD, COOLING, HEATING, and SWH. The building energy retrofit directly replace the devices by using these six EEMs, which leads to the same initial investment for different baseline models. Furthermore, the Prototype Models have better performance than those in the New Models. Thus, the New Model (Pre-1980) has the greatest improvement and the Prototype Model has the smallest improvement among the three models.

For the EEMs, WALL and ROOF, this section adds the same insulation based on the existing exterior walls and roof. Thus, the initial investments are also the same for the three models. However, many factors affect the improvement of the energy performance in the three models, such as the values of baseline and upgraded models, and the geometry of models. Based on the results shown in Figure 7.12, the WALL has the greatest improvement in the New Model (Pre-1980) while the lowest improvement in the Prototype Model. However, the ROOF has the greatest improvement in the Prototype Model while the lowest improvement in the New Model (Post-1980), which is different from the results of WALL.

Furthermore, there are some differences for the rankings of the ROIs. For example, the PLD has the highest ROIs for the New Model (Post-1980) and the Prototype Model while the LPD has the highest ROIs for the New Model (Pre-1980). Another example is that the HEATING has the second highest ROI in the New Models (Post-1980) while WALL is the EEM with the second highest ROI in the Prototype Model. Thus, it is necessary to determine which models are suitable for specific analyses before conducting building energy analyses. The best baseline models for the analysis in this chapter are the Prototype Models, which have been analyzed in Section 7.2.2.

7.5 Summary

To understand how electricity pricing programs impact the selection of EEMs, this chapter conducts an analysis of the ROIs of EEMs under the five electricity pricing programs: static, general, critical peak, time of use, and high renewable penetration. The results reveal that:

(1) The ROIs of EEMs are changed under different pricing programs.

(2) The EEM with higher ROI in hot areas are replacing office equipment with higher-efficiency equipment, replacing interior fixtures with higher-efficiency fixtures, and replacing cooling system with higher-efficiency system. But the EEM with higher ROI in cold areas are adding wall insulation and replacing heating system with higher-efficiency system.

(3) The ROI of EQUIP in Honolulu is affected by electricity pricing programs most significantly, which varies from 35% to 112%.

(4) Different baseline models are possible to generate different results and thus, it is necessary to determine which models are suitable for specific analyses before conducting building energy analyses.

The innovation and contribution of this study mainly lie in the following aspects. Firstly, it designs a reasonable electricity pricing program for the scenario of high renewable penetration. Secondly, it reveals the importance of electricity pricing programs on EEMs selection. Finally, it can help building owners to select optimal EEMs under different electricity pricing programs.

This study is intended to show the potential impact of electricity pricing programs on the selection of EEMs. To apply this research to real world practice, one will need to use real pricing data.

Chapter 8

Conclusion and Future Research

8.1 Conclusion

Current research has three limitations: (1) a standardized computational framework to conduct building energy analyses does not exist; (2) current prototypical building energy models only represent limited types of buildings in certain countries; and (3) the impacts of dynamic electricity pricing programs for high penetration of renewable energy on the selection of EEMs have not been fully established. To address these limitations, this dissertation created a standardized computational framework, applied it to create new prototypical models, and analyzed the impact of dynamic electricity pricing on these models.

First, this dissertation conducted an extensive review on energy-related data for U.S. commercial buildings. These sources include nine building energy databases total; three from surveys and six from simulations. This dissertation also detailed their applications for building energy analyses. This work is the most current and comprehensive review up in the field. The results also serve the basis for the standardized computational framework.

Next, this dissertation created a standardized computational framework, which can select the best data sources and methods to create prototypical building energy models and conduct building energy analyses. This framework regulates the analysis process and automatizes the whole procedure, which supports users for different analyses. This work allows users to conduct building energy analyses with a short computational time and accurate results. For example, by using this framework, the computational time is reduced from 1.9 years to 30 minutes. During this time, millions of building energy simulations are run to identify the neutral values for thousands of model inputs.

Then, by using the framework, this dissertation proposed a new methodology for prototypical building energy model creation. This methodology standardizes the rules to identify the values and uncertainties of the model inputs and provides the rule-based links for the models in different climate zones. Furthermore, the improved genetic algorithm (GA) calibrates the models, which enables the selection of the best values among the uncertainties of model inputs under the limited reference energy data. By using this new methodology, this dissertation created prototypical building energy models for four types of U.S. commercial buildings: (1) medium office buildings, (2) religious worship buildings, (3) college/university buildings, and (4) mechanical shops. These models represent over 20% of the 5.6 million commercial buildings in the U.S. and can be used in a standard for industry applications. This dissertation used medium office buildings and religious worship buildings as two case studies.

In the first case for medium office buildings, over 300 qualified building samples were provided by the *2003 Commercial Buildings Energy Consumption Survey* (CBECS). The regression models based on these building samples were used to validate the performance of these new prototypical building energy models. In order to be considered valid starting points for building energy analyses, the *coefficient of variation of the root-mean-square deviation (CV(RMSD))* between the prototypical building energy models and regression models had to be less than 0.05. The *CV(RMSD)* of these new models is only approximately 0.012. Based on the evaluation results, they are accurate starting points. Furthermore, the *CV(RMSD)* of existing models provided by the U.S. Department of Energy (DOE) is approximately 0.15. The models created in the dissertation are a better representation of U.S. medium office buildings.

In the second case for religious worship buildings, the qualified building samples were insufficient to create the regression models for the model validation. Thus, this dissertation designed the rule-based criteria to validate the performance of these new models. All models for religious worship buildings met these criteria, and thus, they are accurate stating points. Furthermore, these models complement the existing models for missing building types provided by the DOE.

Finally, this dissertation used the framework to analyze the impacts of building energy savings and electricity pricing programs on the selection of energy efficiency measures (EEMs). The DOE Commercial Prototype Building Energy Models for medium office buildings were the baseline models in these analyses. Three global sensitivity analysis methods were used: *Standardized Regression Coefficients (SRC)*, *Morris*, and *Sobol*. The results of the EEM selection are similar to those of other studies.

Moving on to the cost analysis, this dissertation studied the impacts of the five electricity pricing programs on the selection of EEMs. They are *static*, *general*, *critical peak*, *time-of-use*, and *high renewable penetration* electricity pricing programs. Except for the static electricity pricing programs, the other four programs are dynamic. The results indicated that the return on investment (ROIs) of EEMs greatly change under different electricity pricing programs. For example, in Honolulu, Hawaii, the ROI of improving the efficiency of office equipment ranges from 35% to 112% for different pricing programs. This result shows that, if different electricity pricing programs were available to commercial buildings, building owners would be more likely to conduct energy retrofits to take advantage of these savings. This research provides a new perspective about the selection of EEMs in building energy retrofits and would enable policymakers to design electricity pricing programs for our future buildings. Furthermore, this dissertation discussed how different baseline models impact the energy and cost savings in relationship to the EEM selections. By using different baseline models, both rankings of the sensitivity levels of the selected EEMs and ROIs of the selected EEMs are varied. Thus, it is important to identify which prototypical building energy models are suitable for the studied baseline model. The standardized computational framework developed in the dissertation provides a solution to systematically select prototypical building energy models.

8.2 Future Research

Based on this dissertation, there are some potential future research, which is listed as follows:

(1) *Extend the scope of the standardized computational framework.* First, the database in the standardized computational framework will be complemented. The existing framework focuses on the research related to the energy consumption of U.S. commercial buildings. In the future, the data for buildings in other countries and other building types will be included into the framework. Second, it is necessary to conduct large-scale building energy simulations for the urban-scale building energy modeling and building-to-grid integration. Furthermore, these two studies require to process a rich set of data sources automatically. The framework is able to conduct large-scale building energy simulation and automatically process data. Thus, based on existing framework, it is possible to extend the scope of the research and conduct more types of building energy analyses, such as the urban-scale building energy modeling and building-to-grid integration.

(2) *Improve the existing prototypical building energy models and create models for other missing building types.* First, it is necessary to improve the linkage of the existing prototypical building models to real systems, which needs to be considered in the future research. Second, based on the literature review, there are still some missing building types, which need prototype building energy models as starting points for various building energy analyses. Since this standardized computational framework is able to create prototypical building energy models, it is worth creating prototypical building energy models for the missing building types.

(3) *Conduct a comprehensive analysis about the impact of dynamic electricity pricing programs on the EEM selection.* The analysis in the dissertation was conducted based on EnergyPlus models. It is necessary to further clarify if current tool is sufficient for this analysis (e.g. calculate peak power in a building). Moreover, this dissertation studied the impact of dynamic electricity pricing programs on the EEM selection. The results indicate that there is a great influence on the EEM selection. It is necessary to provide the prediction about the impact of various possible dynamic electricity pricing programs for the policymakers.

Then the policymakers can design new dynamic electricity pricing programs, which can encourage building owners to continue retrofitting their buildings. Furthermore, the new programs have potential impact on the strategies of power grid. It could be a preparation work for the building-to-grid integration.

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