ABSTRACT

Title of Thesis: **A METHODOLOGY TO ESTIMATE RETROFIT ENERGY SAVINGS USING A REDUCED-ORDER ENERGY MODELING APPROACH**

Harshil Uttam Nagda
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Thesis Directed By: Professor Jelena Srebric
Department of Mechanical Engineering

Building energy retrofits help to reduce energy use and improve energy efficiency of the buildings, however, most building owners typically consider retrofit implementation as a financial decision rather than an environmental one. Thus, to upgrade the existing buildings, it is extremely important to make accurate predictions of energy and cost savings which can help the building owners and facility managers to make capital budgeting decisions. The study proposes a methodology using reduced-order energy modeling approach to make rapid and accurate estimations of energy savings from retrofit installations in a building portfolio. A case study of 7 campus buildings undergoing several lighting, envelope and HVAC retrofits, and costing $3.6M to the university, is demonstrated in this thesis. The actual energy savings from the retrofits are compared with the modeled energy savings estimated using the proposed methodology.

A METHODOLOGY TO ESTIMATE RETROFIT ENERGY SAVINGS USING A REDUCED-ORDER ENERGY MODELING APPROACH

by

Harshil Uttam Nagda

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Advisory Committee:
Professor Jelena Srebric, Chair
Assistant Professor Siddhartha Das
Assistant Research Professor Jiazhen Ling

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Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Commercial buildings in the United States account for 19% of primary energy consumption (U.S Energy Information Administration, 2012). Commercial buildings make up 8% of total energy consumption globally, and residential and commercial buildings combined contribute to 33% of the total CO_2 emissions related to energy consumption (Ürge-Vorsatz, et al., 2012). Globally, buildings consume substantial amount of energy and waste an astounding 31% of the energy they consume (Energy Star, 2014). As governments and localities respond to the threat of the climate change, they are turning towards the built environment as an area for gaining sizeable and cost-effective reductions in greenhouse gas emissions. Many cities in the U.S., including Seattle, New York, Austin, San Francisco, Philadelphia and Washington, D.C. have introduced energy benchmarking and stringent environmental laws for commercial buildings, some requiring that low-cost or no-cost improvements be made. In European Union, governments are considering a step-by-step policy approach to periodically lower the threshold of allowable building emissions to reach climate goals (Pehnt and Sieberg 2011).

While approximately two percent of commercial floorspace is constructed new every year, and a considerable amount renovated, the majority of opportunities to advance efficiency over the next several decades will be in existing building stock, most of which are limited by old equipment, aging infrastructure, and inadequate operations resources (Building Efficiency Initiative, 2014). According to the U.S. Energy Information Administration, existing buildings 20 years or older make up nearly 72 percent of the total square footage in the United States. In developed economies, at least half of the buildings that will be in use in 2050 have already been built. Thus, improved efficiency of existing building stock — through building retrofitting and other measures — represents a high-volume, low-cost approach to substantially reducing energy use and greenhouse gas emissions.

1.1: Motivation

While energy efficiency retrofits help reduce energy use, building owners typically consider retrofit implementation as a financial decision rather than an environmental one. Thus, to upgrade the existing buildings, it is extremely important to make accurate predictions of energy and cost savings which can help the building owners and facility managers to make capital budgeting decisions. However, deciding the priority of the retrofit execution and calculating their anticipated energy and cost savings can be an expensive and a complicated effort with a lot of uncertainty.

Several methods have been developed to predict energy savings in buildings, which include elaborate and simplified physics-based engineering methods, artificial intelligence methods and statistical methods. While existing methods for predicting retrofit savings are useful in some contexts, they have their faults. Uncalibrated physics-based models are often inaccurate, and approaches that calibrate physical models are often subjective and overly dependent on engineering judgement. Often, the cost and expertise needed to construct and use a detailed physics-based simulation is considerable when compared to the expected cost savings due to implementing a retrofit. Usually, it is not until after a detailed model is built that a building owner will know if the expected savings justified the cost of the model. Also, complex building energy models require collecting detailed pieces of information from the building which increases the overall simulation time.

Recent technology and policy drivers for the built environment have resulted in widespread collection of large sets of measured data of building characteristics and energy use. The U.S. Department of Energy's Building Performance Database (BPD) and Commercial Reference Building Models are examples of such datasets. These datasets provide opportunities for development of models that use empirical data to estimate building retrofit energy savings from actual buildings. These data points can be used as inputs for energy models, thus substituting data which is not easily available or accessible for collection (eg. lighting and plug load densities, window/wall U-values, infiltration rates etc.) and increases the overall simulation time. Thus, there is a need to establish an energy modeling approach which integrates the use of published building characteristic databases with additional data collected on site. Combining this approach with reduced order energy modeling workflow can dramatically reduce the overall simulation time, and hence enable the estimation of energy and cost savings from retrofits of entire building portfolios like campuses and cities.

1.2: Thesis Outline

The effect of buildings on the environment and the motivation of this thesis have been discussed in the previous sections. Chapter 2: Literature Review provides background information and related research about energy savings methods and tools. Chapter 3: Research Objective and Hypothesis presents the objective and hypothesis of the thesis. Chapter 4: Facility Manager Survey presents an overview of case-study buildings and deployment of the survey Chapter 5: Research Methodology discusses the workflow, and calculations of actual energy savings and modeled energy savings using reduced order modeling. Chapter 6: Results and Discussions presents comparison between actual and modeled energy savings Chapter 7: Conclusion and Future Work rehashes the key findings and research contribution of this thesis and offers future research work.

Chapter 2: Literature Review

2.1: Methods for Predicting Retrofit Energy Savings

Building energy consumption is influenced by several complex and interactive effects, ranging from weather and building envelope design to HVAC systems and occupant behavior. Understanding the influence of these effects on energy use is typically done using building energy models. These modeling methods generally fall into three computational categories: (1) physical models (e.g., DOE-2, EnergyPlus), (2) statistical models, and (3) hybrid models.

Physical models are typically constructed by summing the heat and energy flow into and out of a building and determining analytical relationships between various building components. Statistical models identify correlations between building properties and environmental conditions and historical energy use data. While they typically do not require detailed understanding of building physics, they do require collection of data to train the statistical model. Hybrid approaches attempt to leverage the benefits of both physical and statistical models by modeling the physical interaction between building components but using data to train models of individual components and systems (S. Wang, Yan, and Xiao 2012) (Zhao and Magoulès 2012).

Significant research has been done on predicting the effects of building characteristics and equipment on energy use using physics-based models. A discussion of energy simulation techniques and tradeoffs is provided by (Siddharth et al. 2011). Many such methods simulate energy use for case studies of specific building types and climates. For example, (Al-Ragom 2003) models a house in a hot and arid climate using DOE-2, ("Energy Retrofit of Historical Buildings: Theoretical and Experimental Investigations for the Modelling of Reliable Performance Scenarios - ScienceDirect" n.d.) model a historical building in Italy using EnergyPlus, (Rahman, Rasul, and Khan 2010) model an office building in Australia using a front-end to EnergyPlus, and other authors take similar approaches ("Passive Retrofitting of Office Buildings to Improve Their Energy Performance and Indoor Environment: The OFFICE Project - ScienceDirect" n.d.) ("Energy Retrofit of Historical Buildings: Theoretical and Experimental Investigations for the Modelling of Reliable Performance Scenarios - ScienceDirect" n.d.). Rather than particular buildings, some methods analyze archetypal buildings and environments (Lam, Hui, and Chan 1997). For example, (Chidiac et al. 2011) classify buildings as one of three types based on construction year and building characteristics. Other researchers treat energy retrofits as a multi-objective optimization of energy savings, retrofit costs, and other factors, and use physics-based models to predict energy use (Rysanek and Choudhary 2013) (Asadi et al. 2012).

There is also prevalent research using statistical models with building characteristics and equipment as predictors of energy use. Some methods focus on predicting energy use, but do not thoroughly discuss prediction of retrofit savings(Katipamula, Reddy, and Claridge 1998) (Guerra Santin, Itard, and Visscher 2009). Other methods focus on only specific building types and environments. For example, Beusker et al. (“Estimation Model and Benchmarks for Heating Energy Consumption of Schools and Sport Facilities in Germany - ScienceDirect” n.d.)focus on heating energy in sports facilities and schools, Kolter and Ferreira (Kolter and Ferreira 2011) focus on residential buildings in Massachusetts, and Hsu focuses on buildings in New York City in both (Hsu 2014). A variety of different types of statistical models are used in the literature. (Kavousian, Rajagopal, and Fischer 2013) use stepwise selection to choose predictors in a multiple linear regression model, and use factor analysis to remove collinearity between predictors. (Baker and Rylatt 2008) use clustering, simple regression, and multiple regression. Hsu uses a Bayesian multilevel regression model in (Hsu 2014) to analyze the value of different measurements for predicting energy use, and finds that benchmarking data alone explains energy use as well as benchmarking and auditing data together. In (Hsu 2015), Hsu discusses selection of predictors, develops a hierarchical penalized regression model, and uses cross validation to compare it to other models.

Literature on hybrid approaches to energy savings modeling is also common. For (“Calibration of Building Energy Models for Retrofit Analysis under Uncertainty -

ScienceDirect" n.d.) calibrate parameters in physics-based normative energy models using Bayesian methods.

Some techniques for predicting retrofit savings do not use physical, statistical, or hybrid models. Both ("Evaluation of Economically Optimal Retrofit Investment Options for Energy Savings in Buildings - ScienceDirect" n.d.) and (Menassa 2011) approach energy retrofits from an economic and financial perspective. While significant, they do not thoroughly discuss methods for predicting energy savings. Other researchers predict energy savings using pre- and post-retrofit measurements of energy use, both for small case studies (Ardente et al. 2011) and for large groups of buildings taking place in retrofit programs (Cohen and Goldman, n.d.).

While existing methods for predicting retrofit savings are useful in some contexts, they have their faults. Uncalibrated physical models are often inaccurate, and hybrid approaches that calibrate physical models are often subjective and overly dependent on engineering judgement (Raftery, Keane, and O'Donnell 2011). Often, the time, cost, and expertise needed to construct and use a detailed physics-based simulation model is considerable when compared to the expected cost savings due to implementing a retrofit. Typically, it is not until after a detailed model is built that a building owner will know if the expected savings justified the cost of the model.

2.2: Overview of Current Retrofit Tools

A number of software tools exist to measure the energy efficiency of buildings and identify energy efficiency measures. These tools can be differentiated in many ways, depending on the information sought, the depth of analysis desired, and the methods for comparison. They can be broadly classified into energy benchmarking tools and asset rating tools

Pacific Northwest National Laboratory conducted a review of energy benchmarking and rating systems as part of the market research for the development of the Energy Asset Score for commercial buildings (McCabe and Wang 2012). Tools can be differentiated by those that offer operational ratings, which measure the building performance as operated, and asset ratings, which measure buildings performance distinct from occupancy and operational characteristics. Ratings can also be split by those based on technical feasibility, the minimum consumption possible if the building used best-available technology, or a statistical rating, comparing the building against a set of similar buildings. The methods for comparison include pre-simulation comparisons, time-series comparisons, normative calculations, and energy simulation with entered inputs. Pre-simulation comparison involves comparing a building to a similar reference building that has been modeled in energy simulation software, with a set of suggested energy efficiency measures. This method quickly becomes cumbersome for the rating agency, as an exponentially expanding database is required to incorporate variability in the building stock. The comparison cannot account for operational and maintenance characteristics.

The time-series method uses utility data to draw inferences about performance and potential energy efficiency measures. This method can be powerful, especially with sub-hourly data, but cannot easily distinguish energy performance between building systems and operational efficiency. Lastly, the energy simulation method involves a simplified energy model, using a subset of building data to infer the rest of the parameters for the model simulation (McCabe and Wang 2012).

Most operational rating tools, most notably EnergyStar Portfolio Manager, use a statistical rating referenced to the Energy Information Agency's 2003 Commercial Building Energy Consumption Survey (CBECS) ("Energy Information Administration (EIA)- Commercial Buildings Energy Consumption Survey (CBECS) Data" n.d.) or the 2006 California Commercial End-Use Survey (CEUS) ("California Commercial End-Use Survey - CEUS" n.d.). Some come into more detail, include ASHRAE Building Energy Quotient ("ASHRAE Building Energy Quotient (bEQ)" n.d.).

Several green building rating programs, including Green Globes ("Building Environmental Assessments - Welcome" n.d.), Leadership in Energy and Environmental Design (LEED) (U.S. Green Building Council, 2013), and BREEAM("BREEAM" n.d.), use an asset-based method to measure performance.

Several studies have compared energy benchmarking and rating tools. A summary of several rating tools including LEED and BREEAM can be found in ASHRAE 1286-TRP “Evaluation of Building Energy Performance Rating Protocols” (Glazer 2018). An important finding from this study was that all of the rating protocols rated the majority of a random set of buildings as above average, suggesting the energy performance standards could be made more rigorous. Several of the tools analyzed in the study are no longer maintained, and many more have been created since the report was completed.

Lawrence Berkeley National Lab conducted a survey of benchmarking tool preferences and divided tools into three levels: whole-building energy benchmarking, which screen for energy efficiency potential at the building level, action-oriented energy benchmarking tools which identify and prioritize energy efficiency opportunities, and investment-grade energy audits that estimate cost and savings for specific energy efficiency measures(Mills et al. 2008).

Overview of the tools

Energy Star Portfolio Manager (ESPM). ESPM is the most popular energy benchmarking tool, provided by the EPA’s Energy Star Program. It relies on a simple set of inputs including monthly utility bills, basic building specifications, and some type-specific reference units to weight buildings. The ratings are provided on a 1-100 scale, reflecting the corresponding percentile of buildings in CBECS 2003 ("ENERGY STAR Buildings and Plants" n.d.). A more detailed overview is available in (Glazer 2018).

FirstFuel. FirstFuel is a proprietary times-series disaggregation tool from a private software company of the same name. It performs an analysis on hourly utility data to evaluate performance and recommend energy efficiency measures. The energy performance reference is also proprietary (FirstFuel, 2012)

FirstView. FirstView is a regression analysis developed by the New Buildings Institute (NBI). The goal of the tool is to target audit resources for potential retrofit opportunities, and provide feedback on building performance referenced to several energy use drivers. It references performance to CBECS 2003 and CEUS 2006 ("FirstView®" n.d.).

LEAN. LEAN is a formalized five-point regression utility bill disaggregation tool developed by Johnson Controls, based on linear relation of energy use to heating and cooling degree days. It is used to identify the savings potential of basic building systems and suggest energy efficiency measures for further investigation (Johnson Controls, 2012).

Energy Scorecards. Energy Scorecards is a proprietary monthly utility bill disaggregation tool, targeted to be an interface for ESPM to provide an easy benchmarking solution for buildings in cities that require energy reporting ("EnergyScoreCards - The Energy Benchmarking Service" n.d.).

Virtual Energy Assessment (VEA). VEA is a proprietary time-series disaggregation tool developed by Retroficiency. The tool uses sub-hourly data to provide a high resolution break-down of energy use to target areas for energy efficiency improvement, and to determine strategies for reducing peak demand energy use. It compares a building to a proprietary database of peer buildings.

Federal Energy Decision System (FEDS). FEDS was developed by PNNL as a tool to assist energy managers and contractors in retrofitting federal buildings, especially defense installations. It is a forward-model, using collected parameters about the building – no utility bills – to build an energy model and identify a package of energy efficiency measures for a building or across a building set. It uses a data set to prepopulate building parameters based on building age. The software optimizes a collection of energy efficiency measures based on the net present value of the life-cycle cost of energy efficiency measures, using NIST's assumptions for fuel price escalation.

Energy Asset Score. PNNL is developing Energy Asset Score to assess relative building efficiency due to building systems as separate from operational performance. It has a simple, advanced and beyond advanced mode that require increasing levels of data input from the user. There are increasing levels of complexity, going from a subset of inputs for the simple version, trending to significant user input in the beyond advanced version for energy modelers and engineers. The parameters are used to create a simplified building energy model in EnergyPlus via OpenStudio. Other parameters are inferred on a statistical basis from a set of similar buildings. Operational parameters, including plug loads and occupant schedules, are inferred from COMNET standards(“Guidelines and Quality Standards for Building Energy Modeling” n.d.). The tool then uses FEDS to recommend a set of energy efficiency measures based on the net present value of life-cycle cost. The tool, like ESPM, uses source energy as the basis for comparison. It is meant to be paired with ESPM to help building owners determine whether to focus on the operational or building asset characteristics of their buildings(N. Wang and Gorrissen 2013).

Chapter 3: Research Objectives and Hypothesis

Building energy modeling has been more used than ever at various phases of the building life cycle to improve energy efficiency and reduce energy use. However, detailed and comprehensive energy simulation of existing buildings may not always be feasible; especially when there is very limited information available about the building or if a large portfolio of building needs to be simulated to make retrofit decisions.

3.1: Research Objectives

The goal of this work is to develop a framework to estimate energy savings achieved by retrofit measures in commercial building portfolios using existing building energy databases and a simplified energy modeling approach based on the principles of reduced-order energy modeling. This knowledge would, (1) allow rapid and accurate projections of building energy and cost savings from retrofit installations, (2) help to enable energy simulations of large building portfolios like campuses or cities to plan sustainability strategies and reduce energy use, and (3) simplify the process of energy modeling so that it can be easily accessible and incorporated into the decision-making process by the building owners and facility managers. The approach is demonstrated by modeling 7 case study buildings on campus and comparing the modeled energy savings with the energy savings achieved by the actual retrofit projects undertaken in these case study buildings.

3.2: Research Hypothesis

The hypothesis of this research work is that (1) simplified energy models based on reduced-order energy modeling principles and (2) available building characteristic datasets can be effectively combined to develop an approach which can enable rapid and accurate estimation of energy savings in the commercial building portfolios.

Chapter 4: Facility Manager Survey

The main purpose of this survey is to collect information about the building and its equipment from a facility manager or a building operator, which would then be used to create a building energy model. An important aspect of modeling the buildings using this methodology is to create simple models using information that is easily available and accessible. Thus, the survey seeks information from the building operators or facility managers, which might be available off the top of their head or can be easily accessed and retrieved. The questions in this survey are intended to be as simple and user-friendly as possible while also providing all the high-level inputs necessary for creating an energy model.

This survey is different than a virtual audit in that, the intention of the survey is not in identifying the energy efficiency measures for the building, but in collecting high-level information about the building and its equipment which can be used as inputs for reduced-order energy models. For example, each building might have a unique HVAC system design and capacities; the survey seeks information about the type of heating and cooling equipment in the building and its quantities among other information, however, detailed parameters like the design capacities of these equipment are auto-sized in the energy modeling tool. Thus, instead of following the tedious process of collecting and analyzing the information from an HVAC floor plan of each building in the portfolio, the information was collected by asking questions to the facility manager.

4.1: Case-Study Buildings

Based on the information available from the campus facilities management team, seven buildings were identified as case study buildings. These buildings were chosen because they satisfied two important conditions: (1) retrofit projects were implemented at these buildings in the last five years and (2) energy use data was available for all the utilities of the building. Table 1 shows the list of seven case study buildings along with their type, area and 2017 energy use intensity. The total floor area of these buildings is a little less than one million sq.ft. For comparison, University of Maryland buildings make up a total of 15 million sq.ft. of floor area. The building type was identified by analyzing the room inventory list of each building available on the UMD Facilities Management website and is discussed in detail in Chapter 5.

Table 1: List of Case Study Buildings

Sr. No.	Bldng No.	Buildings	Building Type	Gross Floor Area (sq.ft.)	Acronym
1	976	IBBR CARB 1	Lab	77,305	CRB-1
2	977	IBBR CARB 2	Lab	126,323	CRB-2
3	809	Police Training Centre	Office	9,763	PTC
4	46	Marie Mount Hall	Lab	113,268	MMH
5	806	Technology Ventures	Office	53,928	TVB
6	35	McKeldin Library	Library	365,865	MLB
7	68	Eppley Recreation Center	Gym	233,421	ERC

4.2: Deployment

The survey was put together on Google Forms and was emailed individually to the facility managers of the respective case study buildings. Most facility personnel are very busy and have very limited time available for additional activities like taking tours of the building with auditors for data collection. Thus, rather than spending hours walking around the building, an online survey or telephone survey provides a quick and easy method to convey information about the building.

The survey initially had 15 questions and was revised to 19 questions after initial responses. It took respondents on an average 20 minutes to complete the survey. The survey had 7 responses, one for each case study building, and of the 5 respondents 3 were building technicians and 2 were facility managers. The survey questionnaire can be found in the Appendix A.

4.3: Retrofit and Audit Reports

A brief secondary survey was done to collect information about the energy retrofit projects that were implemented in the case study buildings in the past five years. This was an email survey and collected three important pieces of information about the retrofit projects:

1. A brief description of the retrofit(s) performed
2. Start and end month/year of the project (to define the pre-retrofit and post-retrofit period of energy-use) and

3. The cost of the retrofits (breakdown of each retrofit in case of multiple projects)

This information was critical in modeling the energy savings achieved by the retrofit projects and comparing with the actual energy savings.

Table 2: Retrofit Projects of the Case Study Buildings

Building	Retrofits	Timeline	Cost (USD)
IBBR CARB 1	• Lighting Upgrade	Oct'13 – Feb'14	$ 142,000
IBBR CARB 2	• Lighting Upgrade • Chiller Plant Optimization • Demand Controlled Ventilation	Oct'13 – Dec'14	$ 1,370,000
Police Training Facility	• Lighting Upgrade • HVAC Scheduling • Weatherization • Optimizing AHU Discharge	Jul'13 – Dec'15	$ 50,000
Marie Mount Hall	• HVAC Scheduling • Outdoor Air Economizers • Optimizing AHU Discharge • Automation of VAV units	Nov'15 – Jun'16	$ 1,100,000
Technology Ventures Building	• HVAC Scheduling using Volttron	Proposed	$ 38,400
McKeldin Library	• Lighting Upgrade • Improving lighting controls with sensors	Proposed	$ 795,000
Eppley Recreation Center	• Lighting Upgrade • Pool Heat Recovery	Dec'15 – Sep'16	$ 622,000

Chapter 5: Research Methodology

Building energy simulations are essentially thermal load simulation programs which calculate heating and cooling loads necessary to maintain thermal control setpoints, coil loads, and the energy consumption of primary plant equipment as well as many other details. This research uses EnergyPlus Version 8.9.0 (“EnergyPlus | Lawrence Berkley National Laboratory, UIUC Building Systems Laboratory” n.d.)as a means of quantifying cost and energy savings from retrofits. EnergyPlus simulations are fundamental to the methodology which involves four mains steps viz. data collection, baseline model development, calibration and energy savings estimations.

5.1: EnergyPlus Simulation Overview

EnergyPlus is an energy analysis and thermal load simulation program that solves the overall heat balance equation shown below to determine the air required from the HVAC systems to address the building thermal loads.

$$C_z \frac{dT_z}{dt} = \sum_{i=1}^{Nc} \dot{Q}_i + \sum_{i=1}^{Nf} h_i A_i (T_{si} - T_z) + \sum_{i=1}^{Nz} \dot{m}_i \, C_p (T_{zi} - T_z) + \dot{m}_{inf} C_p \, (T_\infty - T_z) + \dot{Q}_{sys}$$

Where,

$\sum_{i=1}^{Nc} \dot{Q}_i$ = sum of convective internal loads

$\sum_{i=1}^{Nf} h_i A_i (T_{si} - T_z)$ = convective heat transfer from zone surfaces

$\dot{m}_{inf} C_p \, (T_\infty - T_z)$ = heat transfer due to infiltration of outside air

$\sum_{i=1}^{Nz} \dot{m}_i \, C_p (T_{zi} - T_z)$ = heat transfer due to interzone air mixing

$\dot{Q}_{sys}$ = air systems output

$C_z \frac{dT_z}{dt}$ = energy stored in zone air

$C_z = \rho_{air} C_p C_T$

ρ_{air} = air zone density

C_p= zone air specific heat

C_T = sensible heat capacity multiplier

Energy balance equations for room air and surface heat transfer are two essential equations solved by many energy simulation programs, including EnergyPlus.

The energy balance equation for room air is

$$\sum_{i=1}^{N} q_{i,c} A_i + Q_{other} - Q_{heat\_extraction} = \frac{\rho V_{room} C_p \Delta T}{\Delta t} \quad (1)$$

Where,

$\sum_{i=1}^{N} q_{i,c} A_i$ = convective heat transfer from enclosure surfaces to room air

$q_{i,c}$ = convective flux from surface i

N = number of enclosure surfaces, A_i = area of surface i

Q_{other} = heat gains from lights, people, appliances, infiltration, etc.

$Q_{heat\_extraction}$ = heat extraction rate of the room

$\rho V_{room} C_p \Delta T / \Delta t$ = energy change in room air

ρ = air density, V_{room} = room volume, C_p = specific heat of air

ΔT = temperature change of room air

Δt = sampling time interval, normally 1 (Zhai et al. 2001).

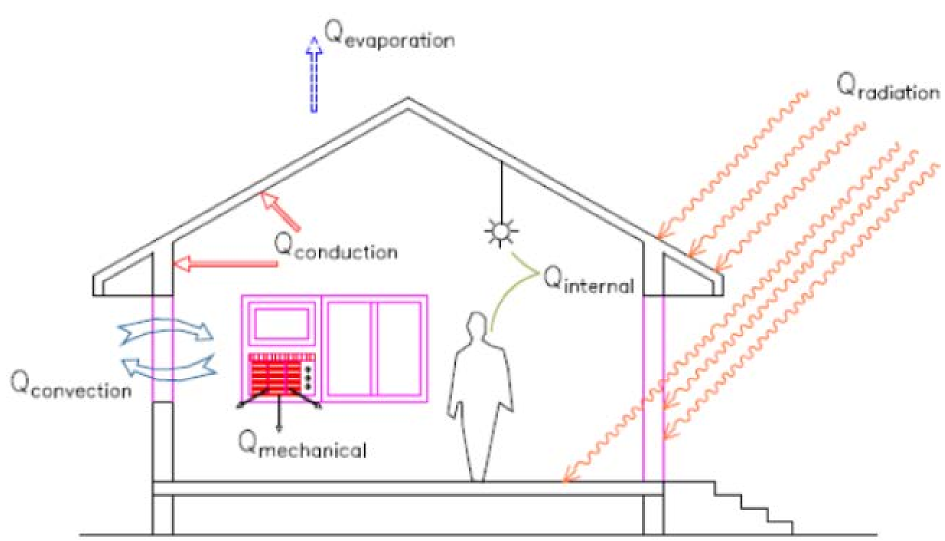

Figure 1: Heat Flows in a Room/Zone

The heat extraction rate is the same as the cooling/heating load when the room air temperature is maintained as constant (ΔT=0). The energy balance equation for a surface (wall/window) can be written as

$$q_i + q_{ir} = \sum_{k=1}^{N} q_{ik} + q_{i,c} \qquad (2)$$

where,

q_i = conductive heat flux on surface i

q_{ir} = radiative heat flux from internal heat sources and solar radiation

q_{ik} = radiative heat flux from surface i to k.

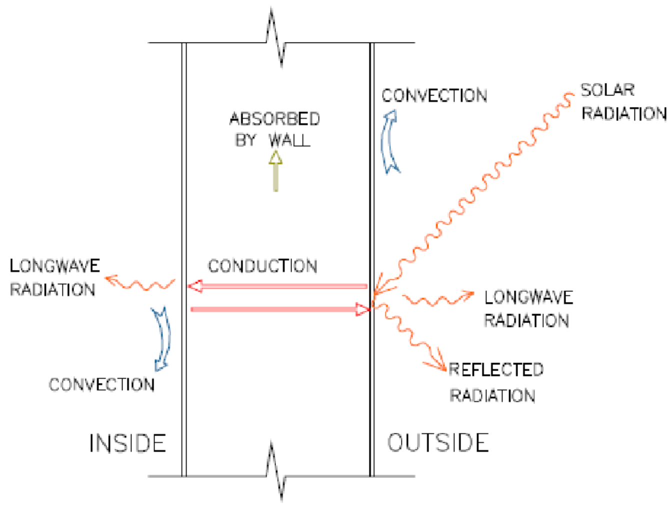

Figure 2: Heat Transfer Through Building Envelope

The q_i can be determined by transfer functions, by weighting factors, or by solutions of the discretized heat conduction equation for the enclosure surface using the finite-difference method.

The radiative heat flux is

$$q_{ik} = h_{ik,r}(T_i - T_k) \tag{3}$$

where,

$h_{ik,r}$ = linearized radiative heat transfer coefficient between surfaces i and k

T_i = temperature of interior surface i

T_k = temperature of interior surface k

$$q_{i,c} = h_c(T_i - T_{room}) \tag{4}$$

where,

h_c = convective heat transfer coefficient

T_{room} = room air temperature

The convective heat transfer coefficient, h_c, is unknown. Most energy programs estimate h_c by empirical equations or as a constant. If the room air temperature, T_{room}, is assumed to be uniform and known, the interior surface temperatures, T_i, can be determined by simultaneously solving Eq. (5). Space cooling or heating load can then be determined from Eq.(4). Thereafter, the coil load is determined from the heat extraction rate and the corresponding air handling processes and HVAC system selected. With a plant model and hour-by-hour calculation of the coil load, the energy consumption of the HVAC system for a building can be determined.

Figure 1 shows the work flow of the simulation process which is explained in detail in various sections of this chapter.

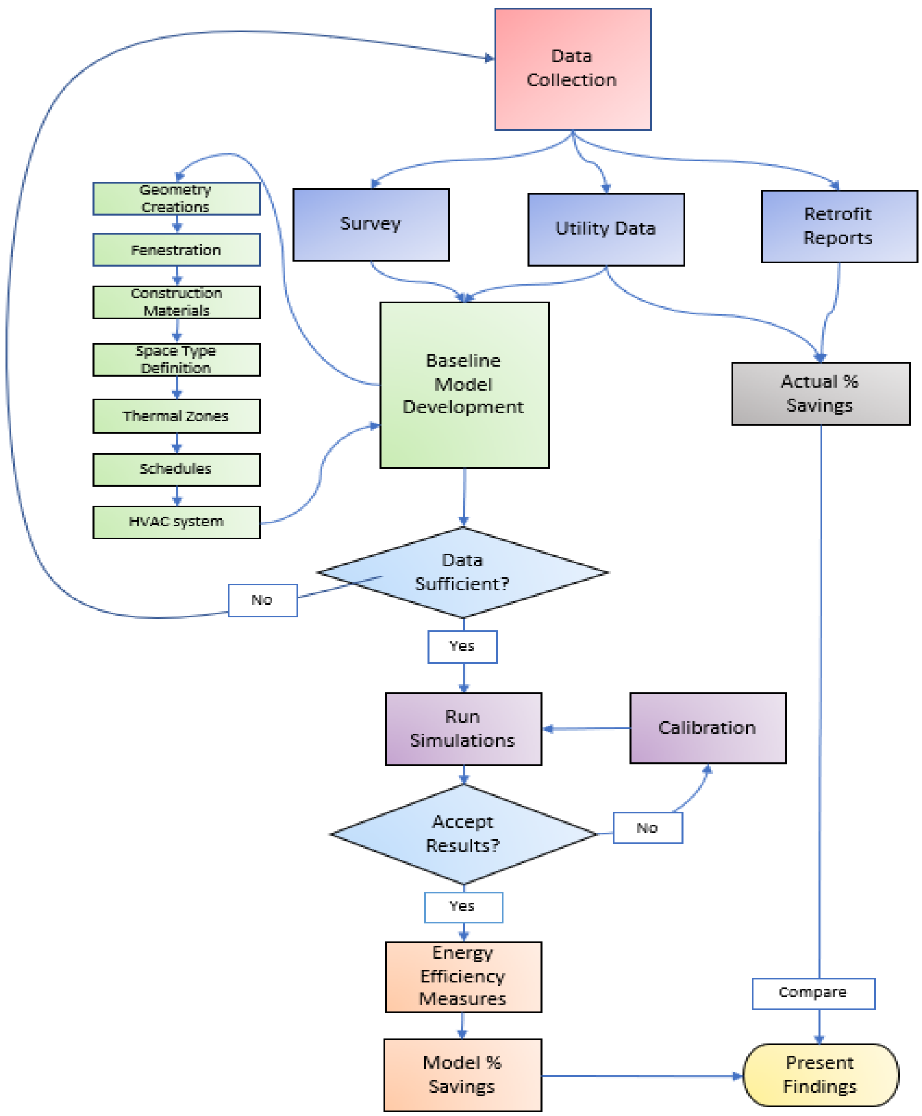

Figure 3: Workflow of the Simulation Process

5.2: Utility Data

The first step to developing a building energy model is to collect the energy/utility data. Utility data analysis is an important part of the energy modeling workflow for building energy retrofit analysis and particularly for this study mainly because of two reasons (1) calibration of the model is done against the actual energy use obtained from the utility meters and (2) actual energy savings achieved from the retrofits are calculated based on the utility meter data collected from the pre-retrofit and post-retrofit period. Thus, it is necessary to clean and analyze the utility data for each of the case study building. Most of the buildings had energy consumption data available for all or some of the utilities namely electricity, natural gas, steam and chilled water in the units of kWh, therms, lbs and ton-hr respectively.

In terms of the time resolution, energy data can be available in monthly, daily, hourly or sub-hourly intervals. Although, interval level data (daily, hourly or sub-hourly) is preferred as it enables better understanding of the building energy profile, monthly data is much more accessible. Monthly utility data was used for this study instead of interval level data for two reasons (1) the interval level data was not

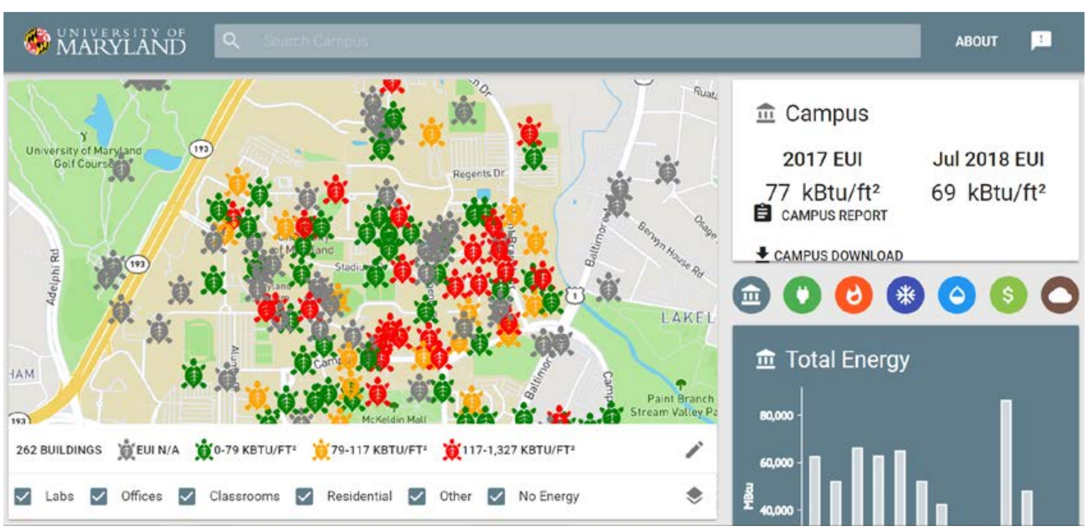

Figure 4: Screenshot of the Terpfootprints Dashboard available online

available for most of the buildings for both post and pre-retrofit periods, and (2) calibration of the reduced order energy models even with monthly utility data as per ASHRAE Guideline 14 can result in an accurate model. The utility data for all the campus buildings is available on a dashboard called TerpFootprints ("CITY@UMD TerpFootprints" n.d.) created by the CITY@UMD group at the University of Maryland. The data was downloaded in CSV format for each of the building and parsed to remove any erroneous values. For off-campus buildings like IBBR CARB-1 and CARB-2, data is not integrated in the Terpfoorptints dashboard and hence was downloaded directly from the UMD's Enterprise Energy Management (EEM) suite.

5.1.1: Analyses

Based on the type of energy source, the case study buildings can be divided into 3 cases: (1) electricity for both heating and cooling; (2) electricity for cooling and natural gas for heating; and (3) electricity for cooling and district steam for heating. The energy data was collected for a maximum of two years before and after the retrofit installation period which was anywhere between 2 months to 8 months for the case study buildings. The electricity, steam and natural gas data was converted to the units of kBtu using the conversion factors available from ENERGY STAR Portfolio Manager of Environmental Protection Agency (EPA) as shown in Table 3.

Table 3: Conversion Factors and Utility Rates

Utility	Unit	Cost per Unit	Conversion Factor to kBtu
Electricity	kWh	$0.11	3.412
Steam	lbs	$0.24	1.194
Natural Gas	Therm	$1.03	100
Chilled Water	ton-hr	$0.17	12

Figure 2 shows the monthly consumption of each commodity namely electricity and steam of Marie Mount Hall (MMH) for the year 2015 which is the pre-retrofit period of the building. The utility data for this building was obtained from a third source different that the two sources mentioned earlier in this section. The data was obtained from the building's WebCTRL building automation system, access to which was provided by the Facilities Management. It can be seen in the graph that the electricity consumption is higher during the summer months, indicating that the building is using electricity for cooling during those months. The facility manager survey of this building confirmed that the building houses a chiller plant which produces chilled water that is supplied to the 7 surrounding buildings other that itself.

Since the chilled water was sub-metered, it was possible to calculate the electricity required to produce chilled water for just the MMH building.

Another key insight from the MMH utility data is in the steam consumption; which is although higher in the winter months, it's still significant during the summer months as well. This could possibly indicate a simultaneous heating and cooling

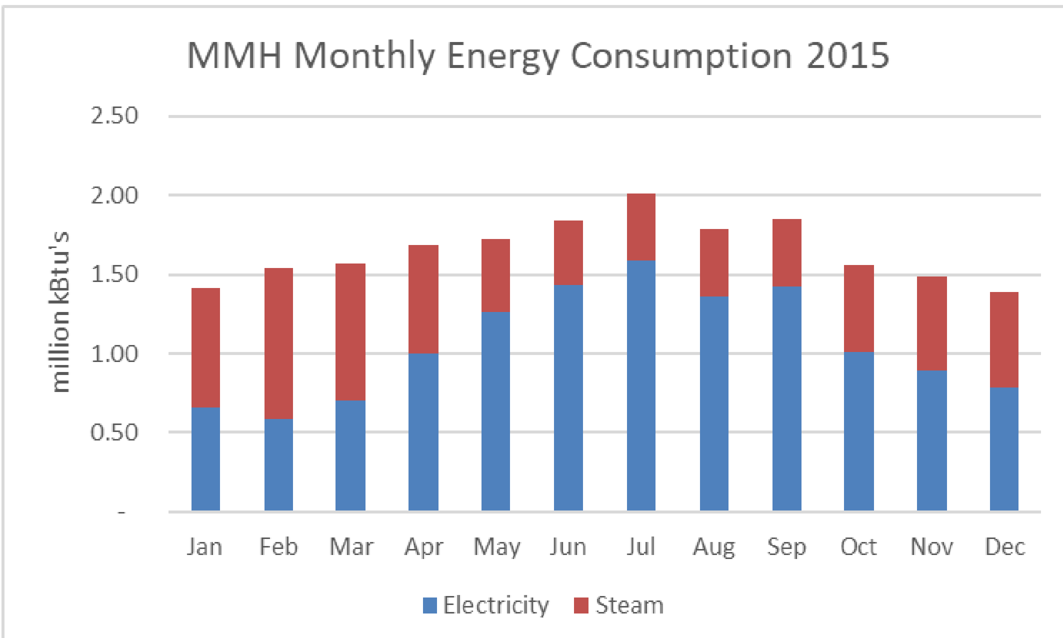

Figure 5: Marie Mount Hall (MMH) 2015 Monthly Energy Consumption

problem during the summer months. Dehumidification necessities might require the air to be cooled below the room temperature, thus requiring reheating at the terminals to raise the temperature back to the required levels.

Another example would be the Police Training Center (PTC) Building which uses electricity for both heating and cooling. Figure 3 shows PTC monthly electricity

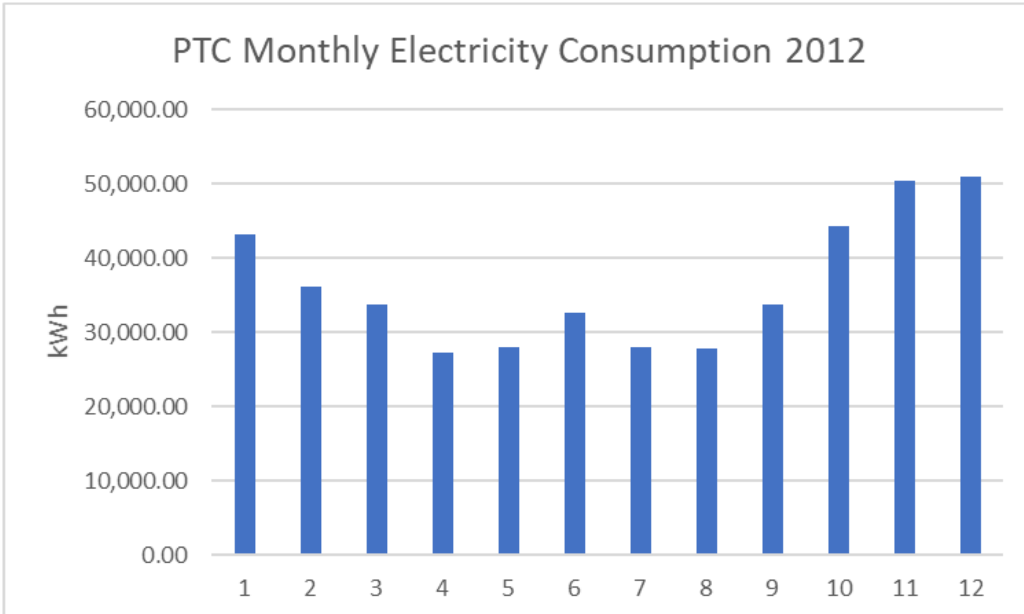

Figure 6: Police Training Center (PTC) Monthly Electricity Consumption 2012

consumption for the pre-retrofit year of 2012. It can be seen that the building energy use is heating dominated and that the electricity consumption is relatively higher in the transition seasons.

Similarly, the utility data analysis was done for all the case study buildings prior to the development of baseline energy model. This section shows how a preliminary analysis of utility data can reveal important insights about the building energy use which can be used to further build the retrofit recommendations. However, the objective of the analysis for this particular study was not to identify the energy efficiency opportunities, but to calculate the energy savings achieved by the already executed energy efficiency measures (EEMs). The next section shows how the actual percent energy savings were calculated for the performed retrofits from the utility data.

5.1.2: Actual Energy Savings from Retrofits

Previous section described how the utility data was collected and analysed for all the case study buildings. In this section, it is shown how the energy savings were calculated from the actual retrofits executed in the buildings. The actual energy savings were compared with the modeled energy savings which are calculated in the following sections. The type of retrofits and the retrofit period were defined in Table 2 in Section 4.3: Retrofit and Audit Reports.

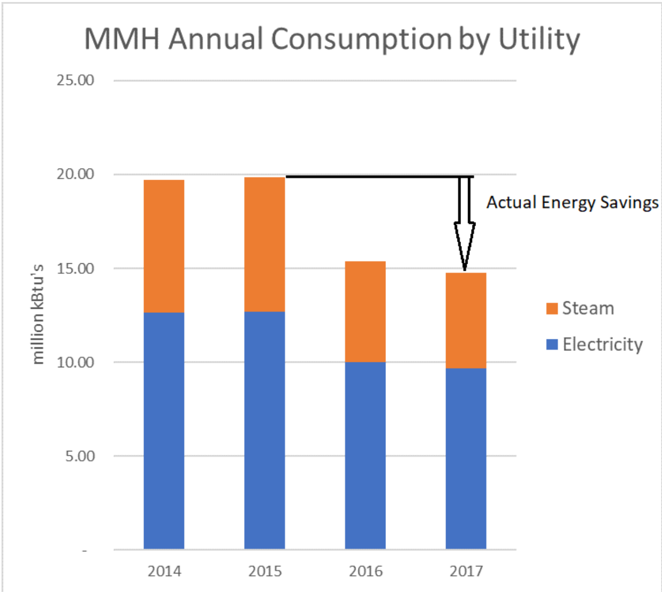

Figure 7: MMH Annual Consumption by Utility

The annual electricity and steam consumption of the MMH building can be seen in the Figure 4. The building was retrofitted with four EEMs namely: (1) HVAC Scheduling, (2) Outdoor Air Economizers, and (3) Optimizing AHU discharge temperature, and (4) Automation of VAV units with installation of a Building Automation System (BAS), over a period of 8 months from November 2015 to June 2016. The project cost the university close to $1.1M. The year 2015 was considered as pre-retrofit period and 2017 was considered as post-retrofit period and the Energy Use Intensity (EUI) were calculated to be 175.4 kBtu/sq.ft. and 131.7 kBtu/sq.ft. respectively. This resulted in energy savings of 24.9% due to the retrofit as calculated from the equation given below. The energy savings before the project implementation were proposed to be 28.1% by the Facility Performance Group of the UMD Facilities Management.

$$Actual\ \%\ Energy\ Savings = \frac{(PreRetrofit\ EUI - PostRetrofit\ EUI)}{Pre - Retrofit\ EUI} \times\ 100$$

Similarly, energy savings were calculated for all the case study buildings. These energy savings were not weather normalized as the objective was to compare them with the energy model savings which were generated using Actual Meteorological Year (AMY) files. Table 4 shows the energy savings achieved from the retrofits implemented in the case study buildings. Actual energy savings were available for only

5 case study-buildings. McKeldin Library building (MLB) had not completed the lighting retrofit when the thesis was written, but a proposed energy saving number was available from a retrofit report generated by a consultant. Eppley Recreation Center (ERC) data available from the dashboard was found to be incomplete as discussed in the previous section and hence it was not possible to calculate annual

Table 4: Actual Energy Savings of Case Study Buildnigs

Sr. No.	Buildings	Actual Energy Savings
1	IBBR CARB 1	15.2%
2	IBBR CARB 2	4.3%
3	Police Training Centre	42.7%
4	Marie Mount Hall	24.9%
5	Technology Ventures	8.6%*
6	McKeldin Library	14.5%*
7	Eppley Recreation Center	NA

*proposed savings

energy savings for above two buildings.

For Technology Ventures Building (TVB) case study the energy savings calculations were slightly different since the retrofit project implemented was only for one month. This was because the retrofit of HVAC scheduling was implemented by a graduate student as a part of a thesis. Thus, the measurements were scaled up to reflect savings which could be achieved if the retrofit was implemented throughout the year.

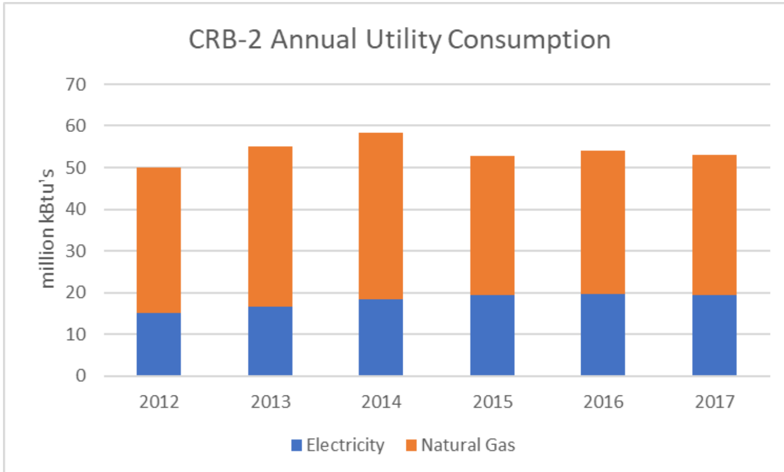

Figure 8: CRB-2 Annual Consumption by Utility

IBBR CRB-2 building had executed three retrofits including (1) Lighting Upgrade, (2) Chiller Plant Optimization, and (3) Demand Controlled Ventilation. The retrofit period was from October 2013 to December 2014, hence, 2013 was considered as the pre-retrofit year and 2015 as post-retrofit year. As seen in Figure 5 there is only a slight drop in the energy use between 2013 and 2014. Despite a massive investment of $1.37M, only 4.3% energy savings were achieved. The facility manager later confirmed that the energy savings were not as good as expected because the building got many new tenants in 2014. Eventually, the actual energy savings calculated in this section would be used to compare to the model energy savings in the following chapter.

5.3: Baseline Energy Model Creation

Energy modeling of buildings has traditionally been exceptionally time consuming and cumbersome. Often, it takes an experienced designer many days or even weeks to develop a reliable energy model. Buildings are complex, and software

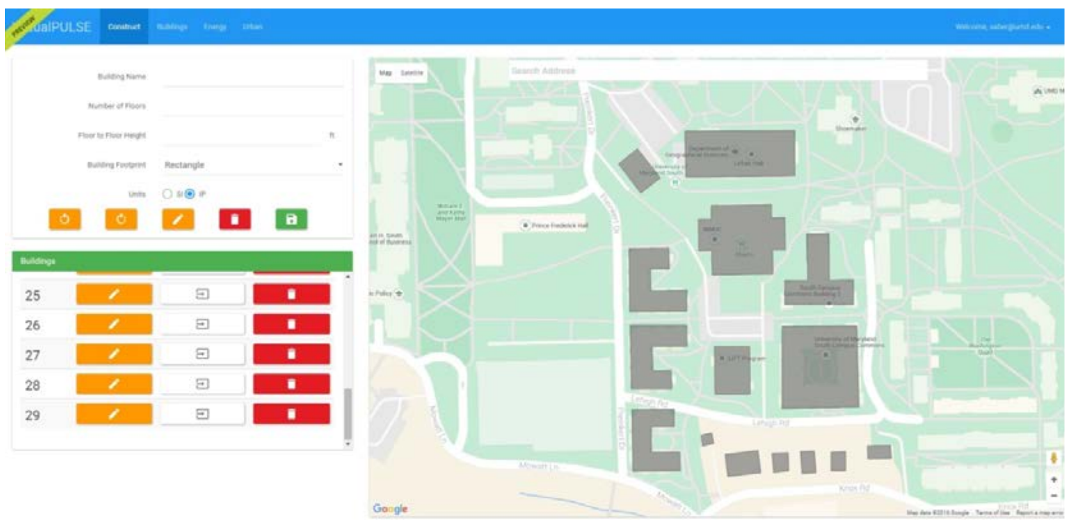

Figure 6: Screenshot of the VirtualPulse Web Application

to model its geometry and energy demands is limited. Current software solutions lack either a user-friendly front-end interface or a proven back end engine. By simplifying the building input process, the user interface, and the access to such software, energy simulations reach a wider audience and empower modelers to capture even the combined effect of multiple buildings. Virtual PULSE (“Virtual PULSE: Building Simulations” n.d.) is a web application that allows users to simulate buildings energy consumption (Heidarinejad et al. 2015). The tool encapsulates an online web interface with building specification fields, geometry importing, 3D visualization, EnergyPlus simulation engine and outputs. In Virtual PULSE, user draws a simple footprint of the building on the Google Maps either using standard shapes such as rectangles and T-shape footprints or creating a custom footprint. Then the user enters number of floors and floor to floor height and Virtual PULSE creates a 3D simplified geometry. Based on the type of the building, Virtual PULSE creates an EnergyPlus model that has all the features such as construction, mechanical systems, schedules, and temperature setpoints many of which are obtained from the Commercial Reference Building Models published by the US DOE ("Commercial Reference Buildings | Department of Energy" n.d.). These input parameters which are taken from the reference building models have many values that are tracked back to the original data source (standards, etc) wherever possible. Without getting into a lot of details, Virtual PULSE creates a simplified model that simulates your target building energy use. The user can modify the default parameters in Virtual PULSE or download an OpenStudio model (OSM) or EnergyPlus IDF file and work extensively on the model.

This study has used the energy modeling section of the Virtual PULSE for creating the baseline energy models of the target buildings. Then the model has gone through multiple modifications and data calibration to make sure that it meets the accuracy suggested by ASHRAE Guideline 14 ("ASHRAE Guideline 14 - 2014" n.d.). However, in many cases the models don't meet the guideline standards but are still useful in estimating energy savings.

5.3.1: Simplifications in Model Input Parameters

The approach in this thesis is to reduce the details in the baseline energy model as much as possible. These simplified models can then go through the sensitivity analysis to see the magnitude of the influence from main parameters and revisit and modify the most influential ones in the model. Through this process of tweaking the main parameters, the simplified models can reach to calibration. In the end, we have simplified models representing the reality to a good extent which have details for just some specific parameters. Here are the main simplifications in my case study building models.

A. Geometry Creation

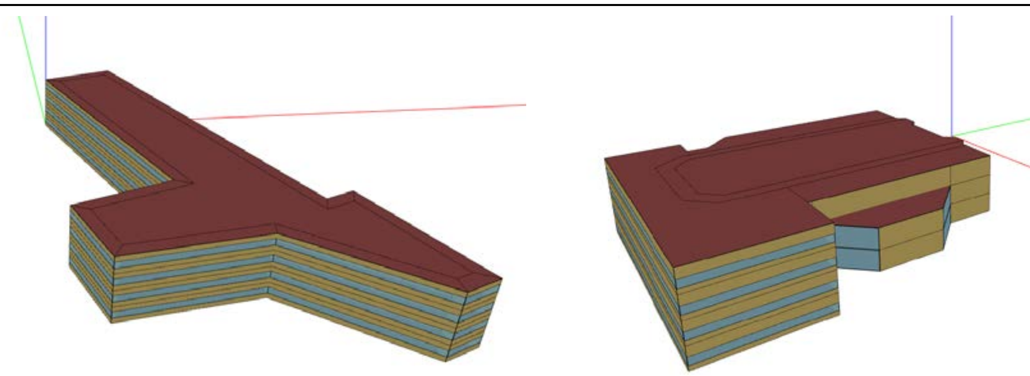

Figure 9: Building Geometries of CRB-2 and MMH

Footprint of the buildings was created on Virtual Pulse application using embedded Google Maps tool. MMH was a slightly complex building and SketchUp was used to edit the geometry after creation in Virtual Pulse. However, these geometries can also be quickly represented by standard shapes like rectangle or T-shape. Based on a recent study on the shapes of the building, typical shapes allow representations of more than 80% of the building using reduced-order modeling (Heidarinejad et al. 2017). The PTC building was smallest at 10,000 sq.ft. while the MLB was largest at 365,000 sq.ft. gross floor area.

Construction materials of the building vary with type of buildings and climate. DOE Reference buildings have been specified for 16 different climate zones and the one used in this study are for the Baltimore, MD climate zone. Virtual Pulse lets you choose the construction sets based on the age of the building which can be either (1) Pre-1980, (2) 1980 – 2004 or (3) post 2004.

B. Fenestration

According to the same approach simplifying the shape of the buildings and see them in standard shapes, there are other architectural simplifications. One important architectural element is the fenestration that is simplified. Windows are seen as strips around the building facade. Each strip represents the windows of one floor. The size of the strip of windows is calculated based on the Window-to-Wall Ratio (WWR). This value was approximately calculated using the Google Street View and the photos of the building.

C. Thermal Zoning

The interior details and complexities are not usually seen in the reduced-order energy models because the it requires detailed analysis of HVAC floorplans which is timeintensive. Instead, interior spaces are modeled into perimeter and core zones. The size of the perimeter and core spaces is estimated based on a perimeter zone depth

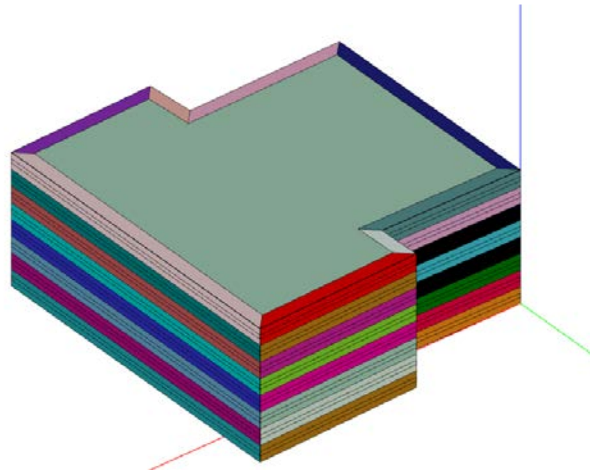

Figure 10: Perimeter and Core Thermal Zones of McKeldin Library Building

value. Although the perimeter spaces are the only spaces directly get the solar radiation, the inter-zone heat transfer and airflow are seen in the EnergyPlus. In the figure below, you can see the perimeter and core zones of the energy model of the McKeldin Library rendered by thermal zones.

D. Space-Type Identification

In order to build a reduced order model with default values pulled from the Commercial Reference Building Models, it is extremely important to first understand the type of the building usage, which can be identified from the space types of the building. Currently, there are 16 commercial reference building models available as shown in Table 5.

Table 5: Commercial Reference Building Models

1	Large Office	9	Supermarket
2	Medium Office	10	Quick Service Restaurant
3	Small Office	11	Full Service Restaurant
4	Warehouse	12	Hospital
5	Stand-alone Retail	13	Outpatient Health Care
6	Strip Mall	14	Small Hotel
7	Primary School	15	Large Hotel
8	Secondary School	16	Midrise Apartment

The space types of the campus buildings was calculated from the room inventory data available on the UMD Facilities Management website ("Room Inventory - UMD FM" n.d.). The data was available in CSV format and included the room number, room area and a room code. A mapping file was also available on the website which described the room codes and the activity the room was used for. The data was downloaded and analyzed for all case study buildings using a python script. The code analyzed the data for each room of the building and

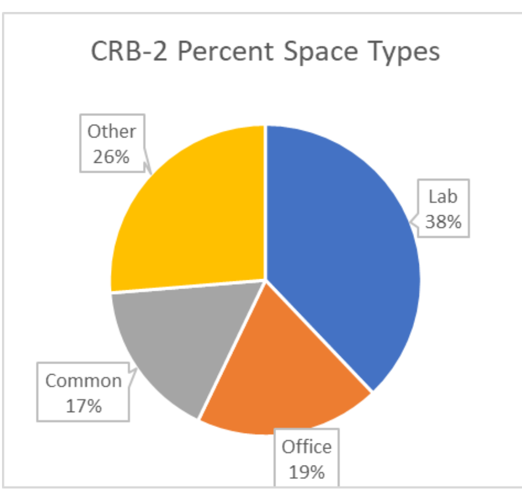

Figure 12: CRB-2 Percent Space Types

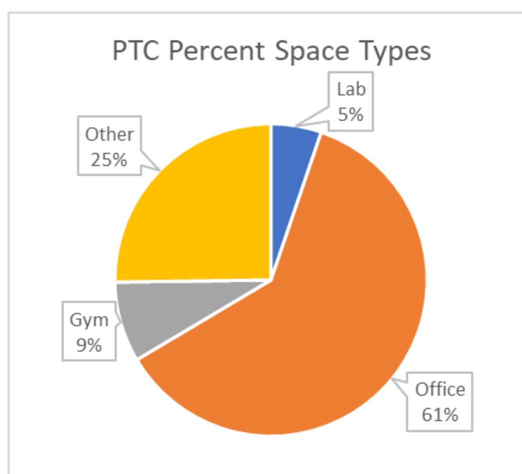

Figure 11: PTC Percent Space Types

calculated percent floor area of each of the following space types in a building viz. lab, classroom, office, common area, gym, library and other. Labs are considered to be energy-intensive and a building with lab area above 15% was considered to be a lab type building. Thus, MMH, CARB-1, CARB-2 were defined as lab buildings with lab areas as 19%, 29% and 38% respectively as seen in Figure 8. PTC and TVB were considered as office buildings with office space more than 30%, and MLB and ERC were defined as library and gym buildings respectively. This space type information was also confirmed with the facility managers in the survey.

Due to lack of available prototype models of campus building types like lab, classroom and library buildings, all case study buildings were modeled as small, medium or large office buildings for the baseline models. Models were later refined during the calibration process, based on the survey inputs and the type of buildings. As such, this study can also be used in the future to create reference building models of campus building types like lab, library and mixed-use type buildings.

E. HVAC System

Modeling HVAC systems is one of the most complicated and time-consuming tasks while developing a building energy model. However, it is also very important to model the systems accurately as space heating and cooling are two of the most energy-intensive operations in a building. In this study, the HVAC system modeling was simplified in the following manner. First the survey provided insights into the type and quantity of the plant equipment as well as the air distribution equipment. Secondly, the HVAC systems for the baseline models were selected from the ASHRAE

Table 6: ASHRAE 90.1 Appendix G - Baseline HVAC Systems

Sr No	System Code	System Type	Fan Control	Cooling Type	Heating Type
1	PTAF	Packaged Terminal Air Conditioner	Constant Volume	Direct Expansion	HotpWater Fossil Fuel Boiler
2	PTHP	Packaged Terminal Heat Pump	Constant Volume	Direct Expansion	Electric Heat Pump
3	PSZ-HP	Packaged Rooftop Air Conditioner	Constant Volume	Direct Expansion	Fossil Fuel Furnace
4	PSZ-HP	Packaged Rooftop Heat Pump	Constant Volume	Direct Expansion	Electric Heat Pump
5	Packaged VAV with Reheat	Packaged Rooftop Units, VAVs with Reheat	VAV	Direct Expansion	Hot-water Fossil Fuel Boiler
6	Packaged VAV with PFP Boxes	Packaged rooftop VAV with parallel fan power poxes and reheat	VAV	Direct Expansion	Electric Resistance
7	VAV with Reheat	VAV with Reheat	VAV	Chilled Water	Hot-Water Fossil Fuel Boiler
8	VAV with PFP Boxes	VAV with Reheat	VAV	Chilled Water	Electric Resistance

90.1 Appendix G Baseline HVAC Systems. Virtual Pulse has HVAC systems setup based on the above standard. Once the system type is identified from the survey, the baseline model is created using the ASHRAE Baseline systems. The systems cannot be edited further in the Virtual Pulse interface and the OSM model was downloaded to refine the systems. The HVAC system is refined in the model calibration phase based on the type of the building and calibration statistics.

Information about the temperature setpoints, HVAC system schedules, temperature setbacks and typical occupancy schedules for the building were collected by the survey of the facility managers. This information is easier to collect via an online survey as it's available off the top of the head of facility managers. Likewise, the type of HVAC systems and quantities of major equipment is easily available from the facility managers. However, design capacities and equipment sizes are not readily accessible information and although these questions were present in the survey, most facility managers ignored those questions.

5.3.2: Baseline Input Parameters for Example Case Study Buildings

Previous section explained the simplifications that were established for the reduced order energy modeling workflow. In this section, Table 7 shows the input parameters

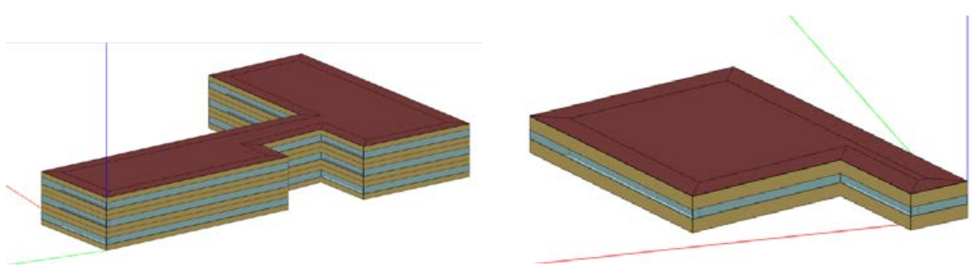

Figure 13: CRB-1 and PTC Models

for the baseline energy model created in Virtual Pulse for two example case study buildings CRB-2 and PTC. Figure 10 shows the geometry creation of both the buildings in Virtual Pulse

Table 7: CRB-2 and PTC - Baseline Model Input Parameters

Data Input	IBBR Carb-1	Police Training Center
No. of floors (12 ft per floor)	3	1
Year constructed	1975	1984
Actual area (sq.ft.)	77305	9763
Building type	Office	Office
Weather file	AMY CP 2016	AMY CP 2012
Window – Wall Ratio (%)	40	25
Thermal zoning setup	Perimeter and core	Perimeter and core
Primary space type	Medium Office	Small Office
Lighting Power Density (W/sq.ft.)	1.9	1.81
Equipment Power Density (W/sq.ft.)	1	1
Occupancy (people/1000 sq.ft.)	5	5
Infiltration (CFM/sq.ft.)	0.2232	0.279
HVAC system type	System 7	System 6
Cooling type	Direct expansion	Direct expansion
Heating type	Hot-water Fossil Fuel Boiler	Electric resistance
Air distribution	VAV	VAV
Construction type	DOE Ref Pre 1980	DOE Ref 1980 - 2004
Fan Efficiency	70%	70%
Boiler Efficiency	90%	-
Heating Fuel	Natural Gas	Electricity
Heating Setpoint Temperature (^{O}F)	70	70
Cooling Setpoint Temperature (^{O}F)	75	75
Schedules	Medium Office - DOE Reference Building	Small Office – DOE Reference Building

5.4: Model Refinement and Calibration

After the online survey and data collection stage, a baseline energy model was setup. Since many input parameters were estimated either based on local energy standards or experience, certain degree of deviation of the model output from actual energy data occurred. Therefore, the initially estimated parameters need to be fine-tuned.

In the current section, a manual calibration procedure is executed. First, the appliance and lighting system power density are adjusted to match the simulation results with actual electricity consumption in transition seasons; second, heating and cooling energy related parameters (building air leakage, heating indoor temperature set-point, window U-value, etc.) are set-based on survey information and building energy standards. A secondary survey was required for IBBR CRB-1 and CRB-2 lab buildings as the baseline models deviated a lot from the actual energy data. This survey revealed insights about the specific equipment like fume-hoods and steam sterilizers which were not considered in the main survey and hence the baseline model.

The models are calibrated using ASHRAE Guideline 14-2002 (ASHRAE, 2002, p. 15) for model uncertainty. To meet these criteria, the discrepancy between simulated energy use and utility data on a monthly basis must have a coefficient of variation of the root mean square error (CVRSME) less than 15%, and a normalized mean bias error (NMBE) of less than 5% as follows:

- Coefficient of variation of the root mean square error (CVRMSE):

  $$\mathrm{CVRMSE} = 100 \times [\Sigma(\mathrm{y_i} - \hat{y})^2/(\mathrm{n} - \mathrm{p})]^{1/2}/\bar{y}$$

- Normalized mean bias error (NMBE):

  $$\mathrm{NMBE} = 100 * |\Sigma(\mathrm{y_i} - \widehat{y_i})|/[(\mathrm{n} - 1) \times \bar{\mathrm{y}}]$$

Table 8: Model Errors

Buildings	CVRMSE (%)	NMBE (%)
IBBR CARB 1	20.58	8.89
IBBR CARB 2	14.1	0.87
Police Training Centre	18.7	0.65
Marie Mount Hall	21.53	1.74
Technology Ventures	25.24	5.86
McKeldin Library	18.75	0.95
Eppley Recreation Center	28	21.38

5.5: Estimating Retrofit Energy Savings

After the manual calibration, energy efficiency measures were executed on the model to calculate the retrofit savings. This was the most important step of the thesis which would enable to eventually compare the modeled savings with actual savings. The model savings were calculated by executing EEMs available from the Building Component Library (BCL). BCL contains energy savings measures as scripts that have been created to apply an EEM to an energy model. All the measures that were used from the BCL to model the corresponding retrofits of the case study buildings are described below.

1. **Retrofit:** Lighting Upgrade to LEDs

   BCL Measure: Reducing lighting loads by percentage

   Description: In this retrofit, the older fluorescent lamps (T8, T5, etc) were replaced with latest LED lamps. The measure models a scenario where the current lighting system of the building is using more power per area than is possible with the latest lighting technologies. This is done by reducing the lighting power consumption on an average by 30% to 50% for the entire building (or specific space types).

2. **Retrofit:** HVAC Scheduling

   BCL Measure: Replace thermostat schedules

   Description: The measure models a scenario where a building has none or limited control over the heating and cooling setpoint temperatures. Basically, the system runs 24x7 with no temperature setbacks because of a lack of programmable thermostats or a BAS. HVAC scheduling retrofit adds these capabilities in the building. This measure can replace current 24x7 temperature schedules with a more efficient but fixed schedules with temperature setbacks of 5-10^{o}C during unoccupied night hours.

3. **Retrofit:** Chiller Plant Optimization

   BCL Measure: NA

   Description: This was done manually as a measure was not available in the BCL. In this retrofit, the chiller plant was recommissioned by executing chilled water temperature resets and improved controls which improved its COP. The measure was run in the model by changing the kW/ton value of the chiller from 0.882 to 0.647 as mentioned in the retrofit reports.

4. **Retrofit:** Weatherization

   BCL Measure: Reduce space infiltration by percentage

   Description: In this retrofit the air leaks and unnecessary opening in the building were sealed, exterior doors were weather-stripped, and exterior door open times were shortened. The measure was modeled by reducing the infiltration rate by 20% from 0.279 to 0.2232 CFM/sq.ft. external area based on the pre-1980 and post-1980 construction sets.

5. **Retrofit:** Demand Controlled Ventilation

   BCL Measure: Enable demand-controlled ventilation

   Description: In this retrofit demand controlled ventilation (DCV) was enabled based on the detection of Total Volatile Organic Compound (TVOC) in the spaces. The measure was modeled by enabling DCV and lowering the air changes in the spaces from 12 ACH pre-retrofit to 8 ACH post-retrofit.

6. **Retrofit:** Optimizing AHU Discharge

   BCL Measure: NA

   Description: In this retrofit the AHU discharge temperature was optimized by automating the dampers and control valves which were previously manually operated. The building had a problem of simultaneous heating and cooling. This EEM was modeled by implementing Warmest Supply Air Temperature (SAT) reset setpoint manager control in the air distribution loop. This resets the SAT based on the warmest zone temperature thus reducing reheat energy.

7. **Retrofit:** Outside Air Economizers

BCL Measure: Enable economizer control

Description: The retrofit automated the manually operated outside air controls. This was modeled by enabling the outside air control for the air distribution loop.

8. **Retrofit:** Lighting Controls Improvement

BCL Measure: Advanced energy design guide (AEDG) interior lighting controls

Description: In this retrofit occupancy sensors were used to control lighting in the building. The measure used in the model reduced the values associated with lighting schedules to simulate reductions due to occupancy sensors throughout the building.

The advantage of using a BCL measure instead of manually editing the model is that the BCL measure can be run individually or as a group of measures on a single model using a tool called Parametric Analysis Tool (PAT). PAT removes the need to hand edit each model to try out different energy efficiency measures. It applies scripts from BCL to your baseline model and lets you quickly compare many alternatives This speeds up the process of analyzing a measure/s on the model to rapidly estimate energy savings.

Most energy efficiency retrofit upgrades can be found as EEMs on the BCL library, ready to be downloaded and executed on the model. However, there are some retrofits which could be more difficult than others to implement in a model like the "Automation of VAV Units" retrofit of the MMH building. This measure was implemented to expand the scheduling and indoor environmental control to the zone-level and integrating the air distribution system with the building automation system. However, in the model this measure was only executed as an HVAC Scheduling measure. The measures described above were implemented in the reduced-order calibrated models of the case study buildings and the savings estimations are shown in the Table 8. These percent savings were calculated using the following equation:

$$Model\ \%\ Energy\ Savings = \frac{(PreRetrofit\ Model\ EUI - PostRetrofit\ Model\ EUI)}{Pre - Retrofit\ Model\ EUI} \times\ 100$$

Table 9: Modeled Retrofit Energy Savings

Sr. No.	Buildings	Actual Energy Savings
1	IBBR CARB 1	16.1%
2	IBBR CARB 2	7.4%
3	Police Training Centre	45.5%
4	Marie Mount Hall	27.6%
5	Technology Ventures	3%
6	McKeldin Library	12.5%
7	Eppley Recreation Center	4.5%

Chapter 6: Results and Discussions

6.1: Actual and Estimated Energy Savings

A comparison between actual and modeled energy savings from retrofitting the 7 case study buildings is presented in this section as seen in Figure 11. The actual energy savings were calculated from the utility bills of the case study buildings from pre-retrofit and post-retrofit period and the calculations are presented in Section 5.1 in the previous chapter. The modeled energy savings were calculated using the reduced-order energy modeling approach and are presented in Section 5.4. The

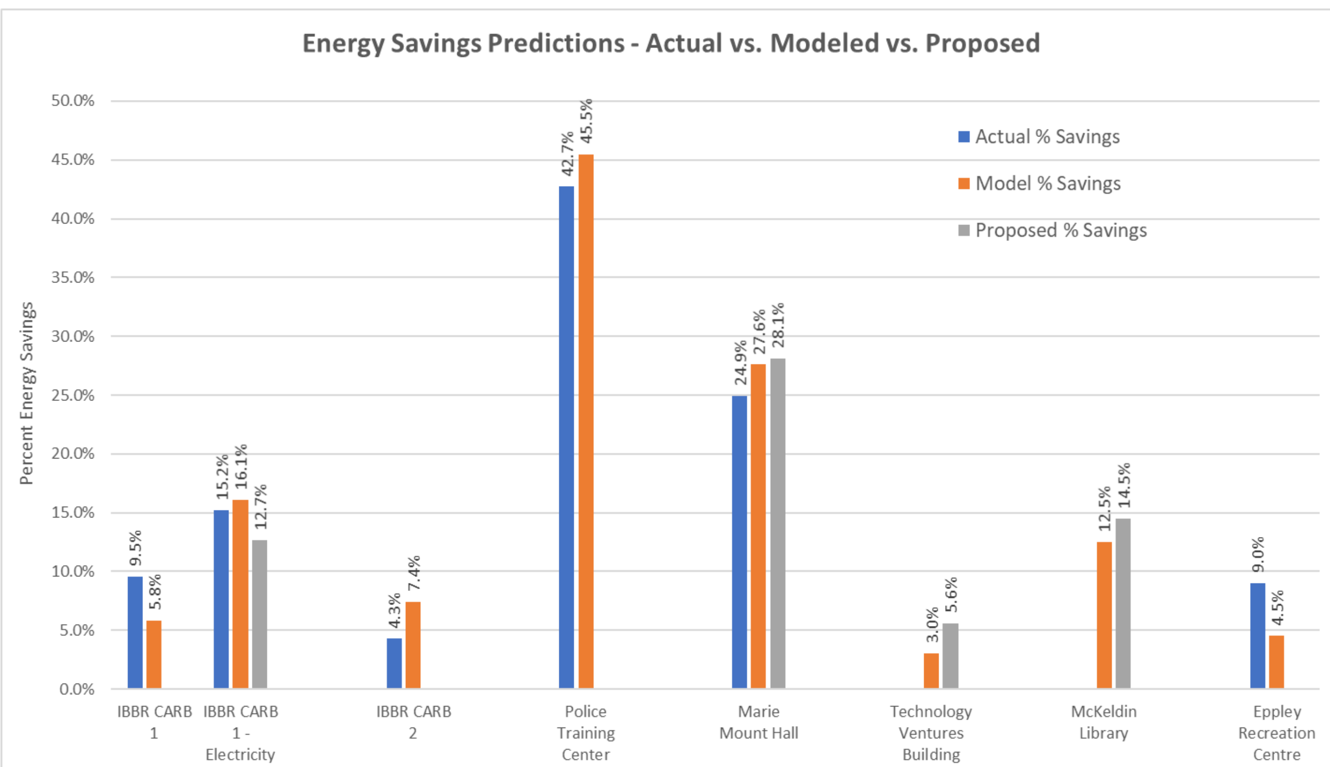

Figure 14: Actual vs Estimated Retrofit Energy Savings

proposed savings in this figure are the energy savings estimated by third parties (consultants, etc) while proposing the project.

Using this methodology, the models were able to predict energy savings within 15% of the actual savings for 4 of the 7 cases. The modeled or proposed savings for most case studies were higher than the actual savings probably because of two reasons (1) proposed savings are kept higher to make the project look financially attractive for selling it to the client and (2) energy models can result into a conservative design approach and ideal scenarios whereas the actual designs in most cases have oversized equipment or deviate from ideal operations.

The IBBR CRB-1 is one of two buildings, other being ERC, for which the modeled savings (5.8%) are lower than the proposed or actual savings (9.5%) achieved. Further investigation into the utility data revealed that the natural gas consumption of the building dropped considerably during the post-retrofit period, whereas in the energy model as well as in an ideal scenario, the space heating energy consumption increases because the LED lamps emit less heat than the traditional lamps. The reason for this drop was unknown and hence just the actual electricity savings (15.6%) data was analyzed which compared well with the model estimated savings (16.1%).

The ERC building model failed to predict the energy savings by 50%. This could be attributed to the uniqueness of the building, in that it is a gym building with lots of huge open spaces and an indoor pool with high dehumidification loads. This level of complexity was not added in the model because of the approach of the study as well as the time limitations. Thus, this approach can result in unpredictable results in modeling unique campus buildings like a gym which would require an additional layer of model complexity.

The IBBR CRB-2 building model overpredicted energy savings by 70%. This was due to the fact that post-retrofit period coincided with new tenants moving into the building which was confirmed by the facility manager. This increased the energy consumption during the post-retrofit period and hence reduced energy savings. Thus, taking into account the building occupant activity in the post-retrofit period is important to make accurate energy savings predictions.

6.2: Evaluation of the Case Studies as a Building Portfolio

Table 10: Payback Period of Retrofits

Buildings	Annual kWh Savings	Annual Steam/NG Savings (kBtu)	Cost Savings ($)	Payback (years)
IBBR CARB 1	380,000	NA	42,000	3.4
IBBR CARB 2	511,000	5,251,000	161,000	5.2
Police Training Centre	186,000	NA	21,000	2.4
Marie Mount Hall	840,000	9,825,000	288,000	3.8
Technology Ventures	124,000	NA	14,000	2.8
McKeldin Library	1,867,000	NA	205,000	3.9
Eppley Recreation Center	1,188,000	NA	131,000	4.8
Total	**5,098,000**	**15,076,000**	**$870,000**	

The proposed methodology can enable use of reduced-order building energy simulations for rapid and accurate estimations of building energy and cost savings for execution of different energy efficiency measures (EEMs). This would allow estimation of savings from multiple EEM packages and retrofit scenarios within a few hours of simulation. Thus, a portfolio of buildings can be simulated, and energy and cost savings can be predicted. Figure 12 shows how the 7 case study buildings have been evaluated as a portfolio. A total of $3.6M were invested by the university for retrofitting the 7 buildings. After implementation of all the retrofits, they will generate an annual cost savings of $870,000 thus resulting in a payback period of 4.1 years. However, since these retrofits were implemented in stages starting from September 2013, the investment was first paid off in July 2015 and for the second time in June

2016. Since the first investment was made in 2013, a total of $8M have been achieved in cost savings as per this analysis.

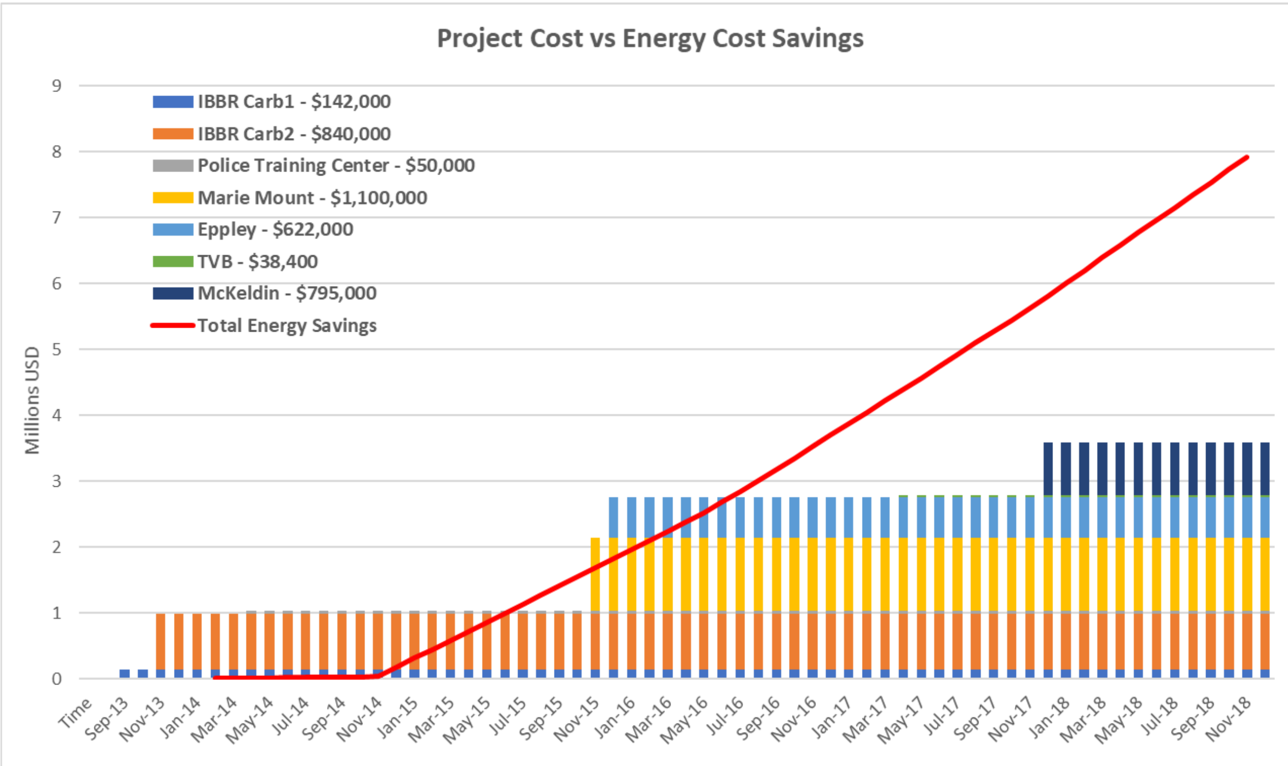

Figure 15: Case Study Buildings Evaluated as a Portfolio

This type of analysis can support large-scale energy efficiency initiatives at university campuses and cities. This methodology can enable development of reduced-order energy models of entire cities and campuses, and multiple retrofit energy efficiency scenarios can be simulated on these models. Energy savings estimations can be made to support sustainability initiatives like the University of Marylands' initiative to reach campus carbon neutrality by 2050.

Chapter 7: Conclusions and Future Work

Literature review revealed that the current methods of predicting energy savings in buildings can be divided into three categories namely physical, statistical and hybrid. The method proposed in this study falls into the first category of physical models, in that a reduced-order energy modeling approach can rapidly and accurately estimate energy savings from retrofit installations. Once a large database of retrofit projects is built using the methodology proposed in this study, statistical models can then be used to predict energy savings from retrofit installations in similar building types and climate zones.

The methodology in this study uses Virtual Pulse for building baseline reduced order models, DOE Reference Building Models for baseline inputs, a facility manager survey for data collection, and OpenStudio for calibration and energy savings predictions. The method accurately predicted retrofit energy savings in 4 of the 7 case-study buildings. The remaining buildings had problems like inaccurate utility data, change in building tenant occupancy in the post-retrofit period and a complex gym building with indoor pool.

Facility manager survey for data collection was useful in gathering easily accessible data like building space type percentages, fixed heating and cooling temperature setpoints, basic HVAC schedules, and type and quantity of HVAC equipment. The respondents, given an option, did not answer questions about the capacities of the equipment like ton-hr of chillers, kBtu/hr of boilers or CFM of fans.

The study relied on the accuracy metrics developed by ASHRAE Guideline 14 for calibration of the models which took bulk of the research time. Although a lot of models did not meet the guideline requirements of CVRMSE<15% and NMBE<5%, the energy savings predictions were comparable to the actual energy savings, which indicates that accuracy of the models did not severely impact savings predictions. However, it should be noted that investment grade predictions would require a higher model complexity as well as sub-metered data for heating and cooling energy use. Calibration took most time for the lab buildings where it became necessary to conduct a secondary phone survey of the manager which revealed information about the fume-hoods and steam sterilizer equipment.

The methodology also heavily relies on the reference building models for accuracy and speed of the process. However, lack of available prototype models for campus buildings like labs, libraries and gym type buildings was a limitation. A future study could develop prototype models for multiple campus building types, especially lab buildings, which could further improve the speed of the workflow and accuracy of predictions. Further, automating the methodology to a point where a facility manager, after providing building energy model inputs, can analyze multiple retrofit scenarios in real-time could be highly valuable to the campus facilities management team. Overall, the developed methodology allows rapid and accurate building energy model creation. The methodology can be used to make quick energy savings estimations which could help in the decision-making process of the building energy retrofits.

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