

Auto-Calibrated Urban Building Energy Models as Continuous Planning Tools for Greenhouse Gas Emissions Management

by

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Abstract

To reduce greenhouse gas emissions associated with their buildings' energy use, owners frequently rely on building energy models that are calibrated to existing conditions for evaluation of potential energy efficiency retrofits. Development of such calibrated models requires the estimation of a series of building characteristics, a process which is extremely effort-intensive even for a single building and, therefore, almost prohibitive for large campus projects which often include hundreds of diverse-use buildings. There is a need for a framework that combines established urban energy model generation techniques with data-driven methods to reduce the manual and computational cost of developing calibrated baseline campus energy models, allow for real time evaluation of future building upgrades, and display their consequences to decision makers on an ongoing basis.

This dissertation addresses this need by proposing new workflows for different development stages of models designed to evaluate future energy scenarios for large institutional campuses. First, the strengths and limitations of different urban modeling methodologies are assessed (modeling approach). Next, a methodology to employ statistical surrogate models is proposed for rapid estimation of unknown building properties (auto-calibration). Finally, a continuous energy performance tracking framework is presented to enable university campuses to manage their building related greenhouse gas emissions over time (continuous planning). As a proof of concept, the complete method has been implemented and tested at the author's home institution.

Auto-calibration and continuous planning can be implemented independently or combined, and the dissertation includes a discussion about their possible impact if applied across the building stock.

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I. INTRODUCTION

It is widely acknowledged that building energy use is a significant contributor to global greenhouse gas (GHG) emissions (US-EIA, 2018). Energy efficiency upgrades to existing buildings, accordingly, offer a significant opportunity to reduce these emissions. This is especially relevant for established institutional, cultural, industrial or commercial campuses, that have a portfolio of aging buildings that were not designed, and have never been upgraded, to meet present-day energy-performance standards. With energy policies at federal, state and municipal level aiming to realize aggressive GHG reduction targets (e.g., City of New York 2014; City of Boston 2014), owners of large building portfolios from retail chains to institutional campuses are looking to implement a range of energy efficiency retrofits to their existing building stock.

To assess the cost-benefit of implementing building energy efficiency upgrades, decision makers frequently rely on a computer-simulation based evaluation of potential retrofit strategies. Well-established whole-building energy modeling (BEM) programs (ASHRAE 140-2011), which simulate heat and mass flows in and around buildings, are employed to calculate energy use for different end-uses required to meet a building's programmatic requirements. First, a baseline model is developed that takes the existing building energy-performance characteristics as inputs. Once the simulated energy-use matches the actual, historic energy use for a building, it is considered a reasonable virtual representation of existing physical conditions which can then be utilized to simulate the energy effects of potential retrofit scenarios by modifying the relevant model input parameters.

1. Motivation

Established university campuses typically consist of a portfolio of aging buildings with a significant opportunity for energy efficiency retrofits. However, they also have a limited budget to implement upgrades. To reduce building energy use in the most cost-effective manner, university administrations therefore require a prioritization plan (e.g., MIT 2017) which offers a degree of certainty in energy cost or greenhouse gas emission reductions while also allowing them to weigh other concerns such as safety, programmatic needs, changing building uses, campus evolution, etc.

The traditional energy modeling approach, which requires a large effort to build and calibrate an energy model for even a single building, in principle, can be utilized by smaller campuses to study retrofit scenarios. This option, however, is not feasible for larger campuses, which may include hundreds of buildings, such as the campus of the Massachusetts Institute of Technology (MIT) in Cambridge, MA shown in **Figure 1-1**.



Figure 1-1: The MIT campus in Cambridge, MA located on 168 acres (68 ha) of land that spans approximately one mile (1.6 km) along the north side of Charles River basin (image source: <https://betterworld.mit.edu>).

This dissertation sets out to develop methods that allow universities and other institutional administrators to effectively analyze the energy saving potential of all buildings within their portfolio and support the ranking of buildings in order of energy savings potential. The remainder of this chapter further discusses the motivation for this research, presents previous efforts to analyze the energy saving potential of large university campuses, and identifies the needs and opportunities to develop new workflows that are described in the following chapters.

1.1. Large university campus characteristics

Large university campuses exhibit unique qualities: they are long-term owner-occupied, have a wide variety of programmatic uses ranging from classrooms and laboratories to student dorms, and ancillary facilities; and typically have access to current and historic energy use data for most individual buildings. For instance, **Figure 1-2** illustrates the extent of available information: metered utility use and program area distributions, for a stock of one-hundred buildings that represent over 85% of MIT's overall building portfolio of approximately 1.2 million square meters.

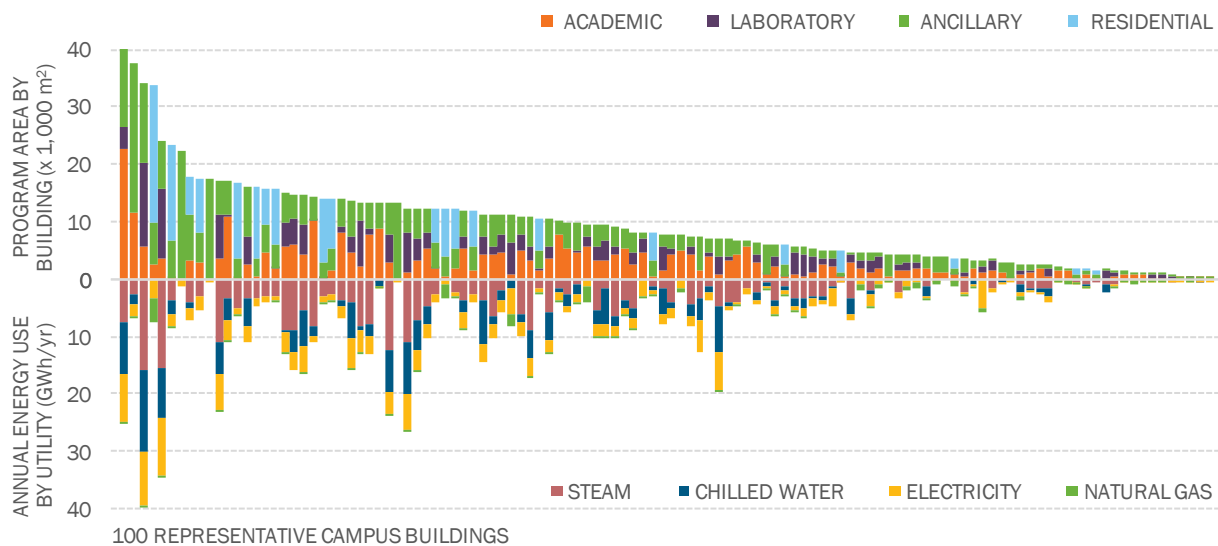


Figure 1-2: Illustration of information available for a stock of one hundred buildings on MIT campus, including program area distribution (left), and annual energy use distribution by utility type (right).

Time and budget constraints typically necessitate that owners of such campuses look to develop prioritization plans that phase the upgrade of their entire portfolio over several years by implementing a few efficiency measures in a few buildings at a time. Such large university campuses include high diversity use buildings that need to be studied individually, cannot be easily classified into predominant archetypes and the literature review ahead will show that traditional statistical approaches that analyze large building stocks do not offer suitable resolution to formulate cost-effective carbon emissions reduction strategies at the individual building level.

Assessment models for deeper investigation into potential savings from specific measures, in specific buildings, require information about individual building energy use data as well as most building performance related parameters. Some of these parameters such as building geometry and envelope constructions are typically known or relatively easy to determine, whereas mechanical and electrical system parameters are complicated to determine and thus have high uncertainties attached to them.

1.2. Calibrated building energy models

When all the physical and operational characteristics of a building cannot be determined by available evidence because the data collection process would be too costly or building access is restricted, the calibrated model development involves inverse approximation of several inputs to reconcile the model output with observed energy use. Overall, model input parameters include the building location and climate, building geometry and envelope constructions, lighting and electrical equipment characteristics, mechanical system configuration and controls, as well as usage and operational profiles for all systems. Climate data is readily available in hourly format for many locations worldwide through the US Department of Energy (US-DOE) and other sources. Building form and envelope characteristics can typically be determined from building audits or existing design documents. The assessment of electrical and mechanical system parameters, however, takes considerable time and effort, and constitutes one of the main sources of discrepancies between simulated and measured energy use (Reddy et al. 2006).

Given several input variables are inter-dependent, the above laid out calibration process is usually over-parameterized (Coakley et al. 2015; Heo et al. 2012). For example, internal electric loads could either stem from electric lighting or other electric equipment, or high conditioning loads could result from envelope conduction or infiltration losses. Traditionally, the definition of such parameters in an energy model relies on modeler experience and judgement, manual iterations, and trial and error; making the calibrated model development process considerably time and effort intensive.

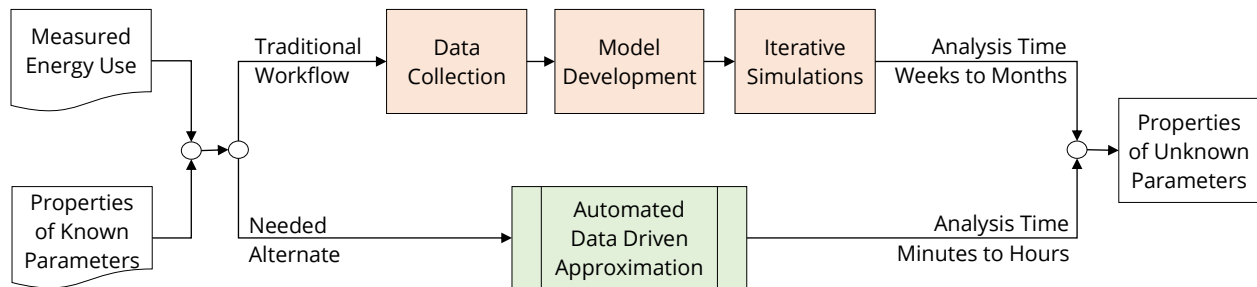


Figure 1-3: Needed alternate framework to estimate properties of unknown building characteristics that reduces the model calibration time from the traditional weeks or months of manual effort to a matter of minutes

There is a need for an automated and flexible rapid-response methodology (**Figure 1-3**) that, based on measured energy use data and a few known performance characteristics, can estimate the properties of several unknown parameters for buildings with diverse programmatic uses, and thus generate calibrated baseline energy models with minimal manual expense.

1.3. Continuous planning framework

The development of campus-wide building energy models currently requires substantial effort and expertise for detailed geometric model building, and considerable amounts of information and time for setup and calibration of individual building models. Once developed, however, campus energy models' use is typically limited to a single moment in time and the analysis of results is limited to evaluating static proposals. These models help university administrations to evaluate potential future scenarios for the unique set of existing conditions, and to ground aspirational greenhouse-gas emission reduction targets on technical realities. Due to the considerable effort involved, however, they are not updated regularly as retrofit programs are implemented, new buildings are added, or building use or occupancy change over time.

Campus level transformations typically stretch over decades, from retrofitting programs for buildings to façade renewal efforts. Campus conditions are also in constant flux as building uses change and student populations fluctuate. In principle, energy models, which incorporate performance parameters in extensive detail, can be easily updated by simply modifying the relevant inputs as condition change. A data-flow infrastructure, such as the one illustrated in **Figure 1-4**, which tracks energy use and campus developments over time to automatically update the underlying building energy models, has the potential to serve as a facility planning platform on an ongoing basis.

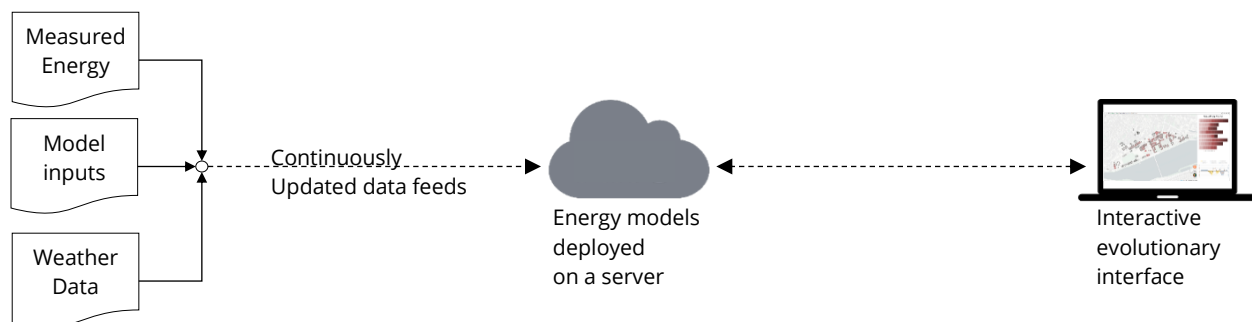


Figure 1-4: An example of the needed data flow infrastructure that tracks energy use and campus developments over time, automatically updates models, and allows facility planners to remotely evaluate scenarios at any time.

University campuses can benefit from a framework that allows for continuous energy performance tracking and expands the point-in-time analysis capabilities of conventional energy modeling platforms. This would enable the management of building energy-use over time by automatically tracking actual performance against earlier defined targets, updating individual building energy models following the implementation of any upgrades, and evaluating future retrofit strategies. This dissertation proposes, and validates, workflows to meet this need.

2. State of the Art

Large university campuses typically rely on spreadsheet tools (e.g., Brown 2012; Bricca et al. 2017; Escobedo et al. 2014), or on-site surveys [e.g., Chung et al. 2014; Vasquez et al. 2015] to estimate the current energy use for individual buildings. Other universities have employed cluster analysis to determine load features of different building groups (Guan et al. 2016), normalized energy use based on site weather information, and developed reduced order models defined by only a few influential input variables (Heidarinejad et al. 2017), to provide data for evaluating potential strategies. Finally, recent studies have presented web-based platforms (Chen et al. 2017), and software (Robinson et al. 2009) designed to allow users to quickly set up and run urban energy models with case studies (e.g., Cocolo et al. 2015) that analyze energy demand of buildings and evaluate alternate scenarios.

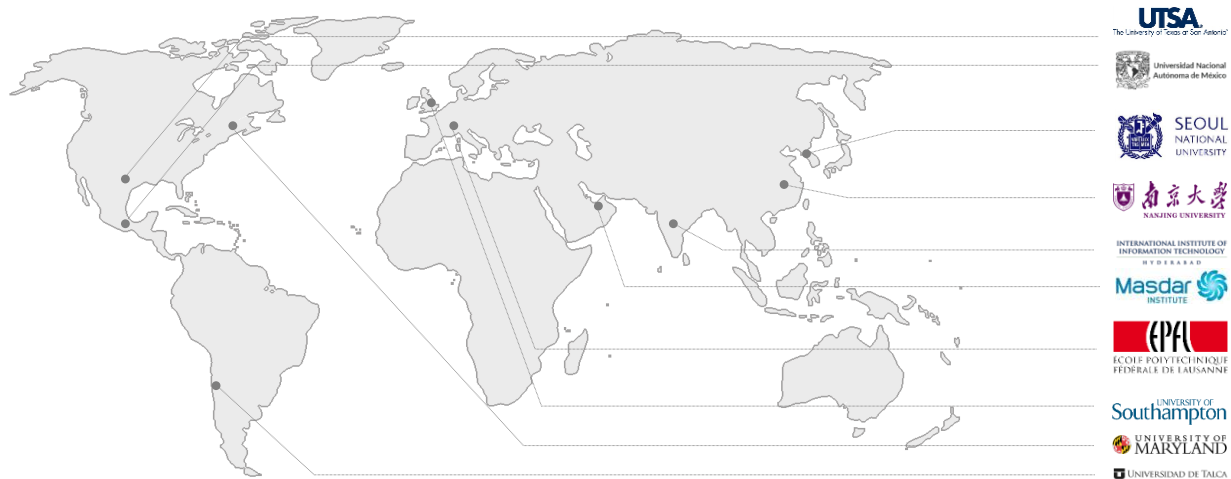


Figure 2-1: University campuses across the world that have been researching the development of building energy models for their campuses to understand existing conditions, and plan for future scenarios.

All of the above models developed for different universities highlighted in **Figure 2-1** are based on the premise that the complex nature of building energy use renders the calibration of numerous building energy models time and effort intensive, and do not fully capture the unique architectural features, programmatic requirements, or the electrical and mechanical systems configurations of individual campus buildings. As a result, without access to individual building performance characteristics, these cluster or archetype level urban energy models are able to provide general guidance across multiple buildings but are unable to assess future scenarios for individual buildings.

This chapter presents existing work in the field of building energy analysis for large building stocks, identifies and discusses recent developments in computational techniques that are significant for this research, and illustrates the gaps that this dissertation attempts to close.

2.1. Urban building energy modeling

Over the past few years, a genre of urban building energy models or UBEM (Reinhart & Cerezo 2015) has been developed. These bottom-up engineering methods apply building energy modeling concepts to a large number of buildings at a neighborhood, or even a city scale (**Figure 2-2**) (Sokol et al. 2017). UBEMs divide a given building stock into archetypes, and assign the same construction standards, usage patterns, and mechanical and electrical system parameters to all buildings within an archetype. Once calibrated to measured energy use of a subset of buildings, UBEMs have been shown to successfully project total energy use of residential neighborhoods (Cerezo et al. 2016).



Figure 2-2: 3D view of the urban building energy model for the city of Cambridge (Sokol et al. 2017). The outlined building subset was used to train models that could then effectively simulate all neighborhoods.

When upgrades are to be implemented across a large number of buildings, Bayesian calibration based UBEMs have been shown to simulate the diversity of monthly energy uses of buildings within an archetype and predict neighborhood level savings (Howard et al. 2012). Such UBEMs have been utilized by municipalities for developing suitable energy policy measures and to assess broad scope greenhouse gas emission reductions for residential neighborhoods (Cerezo et al. 2015).

Large university campuses, in contrast to residential neighborhoods, include buildings with high diversity uses which cannot be easily classified into a single predominant archetype. For projects where each building needs to be evaluated individually, UBEM approaches need to be complemented with calibrated individual building models to formulate effective carbon reduction strategies.

2.2. Automated calibration techniques

Automatic building level energy model calibration, with the goal of computationally estimating the unknown characteristics of a building based on some known building properties and measured energy use information, has been a focus of research in recent years (e.g. Fabrizio & Monetti 2015; Robertson et al. 2013). Most of these techniques utilize an optimization function (**Figure 2-3**) to reduce the difference between measured and simulated data by iteratively adjusting the values of unknown parameters. Studies have proposed employing brute-force sampling (New et al. 2012), graphical pattern recognition (Sun et al. 2016), and global optimization algorithms (Lee & Claridge 2002) to iteratively adjust the values of unknown parameters until the difference between measured and simulated data is minimized. These techniques essentially replace the manual trial-and-error based iterative parameter adjustment by mathematically informing the input assumptions for a simulation run based on results from earlier iterations.

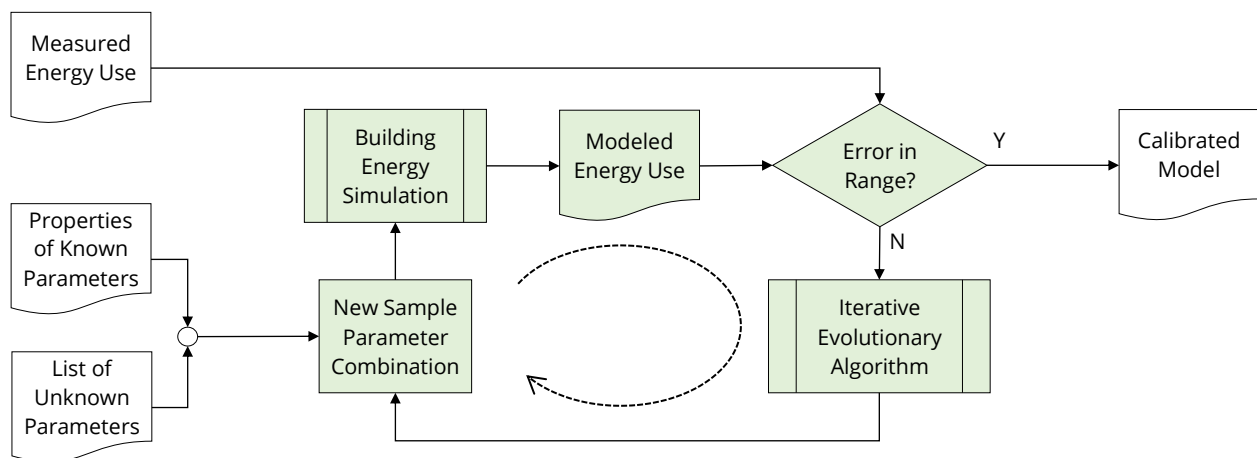


Figure 2-3: Most auto-calibration techniques require numerous energy simulations that iteratively adjust values of unknown parameters until the difference between measured and simulated energy use is within desired range.

While these techniques can significantly reduce the high time and cost expense associated with experienced auditors and modelers working through the calibration process, they still result in a considerable computational expense required to generate and run hundreds of thousands of energy simulations, making these techniques inaccessible in most scenarios.

This computational cost can, in principle, be significantly reduced if these auto-calibration methods, which currently rely on detailed engineering models to simulate each iteration, could instead incorporate data-driven approximation techniques that employ statistical models. In combination with established model generation techniques from UBEM, these hybrid methods could potentially develop calibrated models considerably faster than traditional approaches.

2.3. Surrogate modeling strategies

Surrogate models constitute a class of machine learning algorithms designed to make computation faster and enable more productive exploration and optimization of design variables (Forrester et al. 2008; Mueller 2014). These algorithms attempt to create mathematical models of the physical behavior of systems based only on available data, using statistical techniques such as regression. **Figure 2-4** illustrates how a few computer-generated samples are created and then fit to an approximation model, which can then directly generate new representative data samples without the need for computationally expensive engineering simulations. Once trained using a small simulation-generated sample set, the surrogate models can provide instant feedback associated with changing individual building characteristics and can vastly reduce the computation time required by optimization routines to find the best solutions.

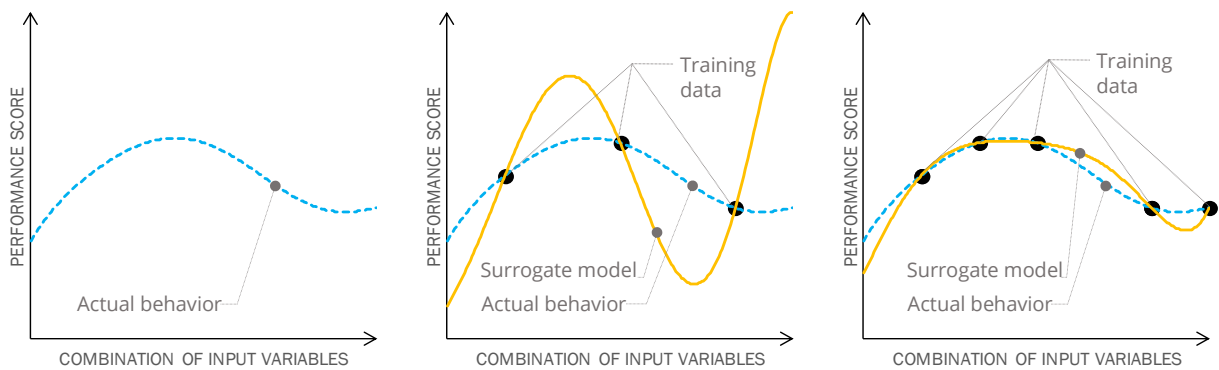


Figure 2-4: A surrogate regression model is trained to replicate a physical behavior (left) based on a collection of pre-computed data points (middle). With enough training data (right), the resulting model can be used to predict performance for other points in the design space with some degree of error (Redrawn, Mueller 2014).

There are several approximation algorithms that are designed to fit detailed simulation results to a statistical function, a few of which have been studied for their effectiveness in reducing the computational expense associated with detailed building energy simulations (Aijazi & Glicksman 2016; Tsanas & Xifara 2012). Utilizing these trained surrogate models, an optimization algorithm (e.g. Brown 2016, Tseranidis et al. 2016) can be used to search for the combination of unknown parameters that results in the highest performance score. While both gradient-based and stochastic optimization algorithms can be used with surrogate models, the typical optimization process starts with random samples in the design space, and then use stochastic operators to direct the process of finding the highest score. While employing surrogate models in lieu of detailed engineering models can, in principle, significantly expedite this process, it has not been researched specifically for incorporation in auto-calibration routines for developing building energy models.

3. Challenges and Opportunities

The previous two chapters present the significant work that has been done in the field of building energy modeling, especially as it relates to evaluations of large building stocks, and highlight the critical areas that need to be addressed before the current tools can be utilized by university campuses to plan for future energy scenarios. Large campuses include several diverse-use buildings that need to be evaluated individually to manage their greenhouse gas emissions targets. These buildings cannot be easily classified into programmatic archetypes rendering the traditional urban building energy modeling approaches insufficient. In addition, the complex nature of institutional building characteristics makes the development of calibrated energy models for individual buildings prohibitively time and effort intensive. Finally, even when substantial time and effort is invested, the models are typically designed to be only used once, to evaluate static proposals relevant for the unique set of existing conditions, at a single point in time.

3.1. Research goal

To address some of the above limitations, the goal of this research is to develop new workflows for the generation of calibrated campus energy models, that are designed to evaluate future building level upgrades, present their consequences to decision makers on an ongoing basis, and enable administrators to manage their building related greenhouse gas emissions over time.

3.2. Hypotheses

This research is based on the premise that it is *important* and *possible* to generate such models, and is founded on the following hypotheses which are revisited in the concluding chapter:

- *Feasibility*: surrogate modeling techniques can considerably reduce the required time and effort to generate calibrated bottom-up energy models for large university campuses that enable building-by-building evaluation of potential retrofits and future energy scenarios.
- *Reliability*: the resulting auto-calibrated energy models can identify the areas of maximum potential savings within reasonable limits of uncertainty and allow campus owners to systematically study only the high priority areas in further detail for more accurate assessments.
- *Significance*: bottom-up campus energy models yield accurate simulation results for building level assessments and have the potential to evolve continuously over time allowing them to be utilized as continuous planning tools as university campuses implement their retrofit plans.

3.3. Organization of dissertation

This dissertation is divided into three parts: Introduction, Workflows, and Conclusions.

Part I: Introduction, includes the first three chapters, and addresses the need for study and background work for research questions considered in this dissertation.

Chapter 1: Motivation, presents the motivation for this research, critiques existing methods for their strengths and limitations, and identifies the needs to develop new workflows.

Chapter 2: State of the Art, presents an overview of existing work, discusses developments in relevant computational techniques, and identifies the areas for further research.

Chapter 3: Challenges and Opportunities, discusses the challenges with current tools to illustrate the opportunities for further research, and lays out specific objectives of this research.

Part II: Workflows, is broken down into four chapters, each of which will describe a proposed new workflow for a different development stage of university campus energy models.

Chapter 4: Modeling Approach, assesses the strengths and limitations of two recent urban modeling methodologies and suggests best practice procedures for large university campuses.

Chapter 5: Automated Calibration, evaluates a methodology to develop baseline campus models by employing surrogate models for rapid estimation of unknown building parameters.

Chapter 6: Energy Supply Systems, presents a planning tool that translates simulation results from calibrated models for building energy use to associated greenhouse gas emissions.

Chapter 7: Continuous Planning Framework, proposes an energy performance planning system that enables campuses to assess and manage building related greenhouse gas emissions over time.

Part III: Conclusions, discusses how these workflows could be employed in practice and concludes the dissertation with a summary of contributions in the final two chapters.

Chapter 8: Summary and Discussion, summarizes the specific contributions of this dissertation and discusses the possibilities of integrating these workflows as a single unified approach.

Chapter 9: Research Outlook, discusses the potential impact of this thesis, envisioned applications, and important directions for future research.

References are included in the appendix.

II. WORKFLOWS

This section first presents, in Chapter 4, two previously developed calibrated energy models for the MIT campus – one based on a spreadsheet approach with select BEMs in the background, and the second an archetype-based UBEM – and establishes the minimum model requirements needed to develop campus retrofit plans for assessment of upgrade strategies for individual buildings.

To work towards an ideal campus model that meets the above requirements, while significantly reducing the computational cost of developing hundreds of calibrated building energy models, Chapter 5 proposes a hybrid auto-calibration methodology that combines model generation techniques from UBEM with rapid-response data-driven approximation techniques.

Chapter 6 presents a planning tool developed to evaluate district energy system configurations in combination with campus building energy models. This tool identifies opportunities to reduce campus greenhouse gas emissions from an optimal selection of campus electricity and thermal energy supply systems, including the incorporation of renewable energy sources.

Finally in this section, Chapter 7 presents a framework to expand the point-in-time analysis capabilities of conventional urban energy modeling platforms and presents a tool for the development and implementation of campus-level continuous energy-performance tracking and planning system. The system archives historic data, enables exploration of potential upgrade scenarios, and allows for the documentation of energy retrofits to individual buildings.

4. Modeling Approach¹

The Office of Sustainability at MIT, in response to the City of Cambridge's Net Zero Action Plan (2015), recently completed a feasibility study for potential upgrades to existing campus buildings (MIT 2017). To work towards the ideal urban model for a campus that provides the fidelity of information that a collection of individual calibrated building energy models would yield while requiring the same effort as to build an urban building energy model, two models were recently developed for the campus of the Massachusetts Institute of Technology. The first approach utilizes a combination of statistical techniques that attribute energy use to the primary programmatic uses on campus before evaluating the effect of energy efficiency measures for those specific program types; and the second (**Figure 4-1**) bottom-up engineering approach develops an urban building energy model for the campus designed to forecast the impact of building-by-building retrofit scenarios.

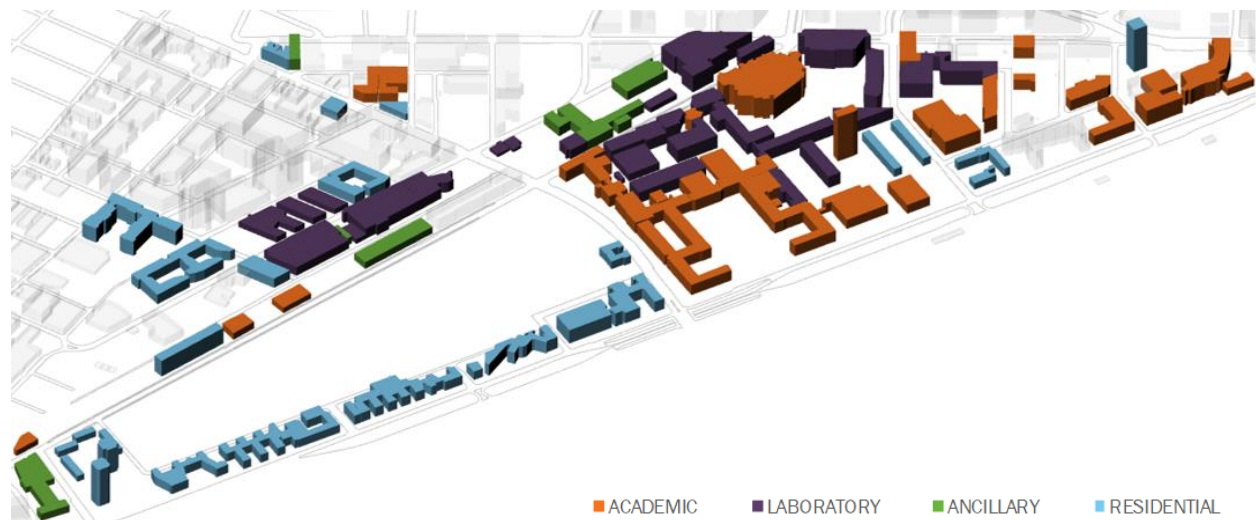


Figure 4-1: Graphic rendering of the urban building energy model for MIT campus showing distribution of programmatic archetypes. This is one of the two models developed to study the feasibility of potential energy efficiency upgrades to existing buildings in response to the City of Cambridge's Net Zero Action Plan (2015).

This chapter reviews these two models with regards to their setup and calibration effort, ability to model current individual building energy use vis-à-vis measured data as well as predicted savings from implementing a variety of retrofitting measures. Sections in this chapter will describe the two approaches in detail with regards to the model inputs and the underlying development procedures, and compare and contrast the results from these two models for baseline conditions as well as potential retrofit scenarios at campus and individual building levels. The objectives are to identify both models' strengths and weaknesses and to suggest best practice procedures for administrators of other campuses interested in undergoing a similar exercise.

¹ A version of this chapter has been published: S. Nagpal, C. Reinhart, A comparison of two modeling approaches for establishing and implementing energy use reduction targets for a university campus, *Energy and Buildings*, 2018.

4.1. Studied workflows

Each building on the MIT campus is broadly classified as academic, laboratory, ancillary or residential, based on the predominant programmatic use. In addition, detailed floor area compositions with fifteen functional uses have also been compiled for most buildings. As an example, **Table 4-1** presents a sample of the available information for three representative campus buildings.

Table 4-1: Level of available information: known program area distribution and utility consumption for three representative campus buildings.

Building Type	Laboratory	Academic	Residential
Total Area (m ²)	30,233	8,851	14,044
<i>Area Distribution (%)</i>			
Academic Spaces			
1 Offices	11%	24%	-
2 General Use I	2%	2%	12%
3 General Use II	-	-	-
4 Classrooms	-	27%	-
5 Study	-	-	-
Laboratory Spaces			
6 Lab Type I	43%	-	-
7 Lab Type II	-	-	-
8 Special Use	3%	-	-
9 Athletic	-	-	-
Ancillary Spaces			
10 Circulation	19%	24%	26%
11 Mechanical	17%	19%	3%
12 Garage	-	-	-
13 Support	3%	1%	-
14 Services	2%	3%	6%
Residential Spaces			
15 Dormitories	-	-	53%
<i>Utility use (GWh/yr)</i>			
Steam/Natural Gas	19.44	2.53	3.15
Chilled Water	8.04	0.93	-
Electricity	9.97	0.90	2.43

Figure 4-2 presents this program area distribution across the campus as a tree-map, where colors represent four predominant space categories that are broken down by detailed program uses within each category. The maps illustrate that ancillary uses such as circulation, support and mechanical spaces occupy almost 35% of overall campus floor area, followed by academic spaces at about 30%. Labs occupy less than 20% and residential spaces constitute 15% of the floor area.

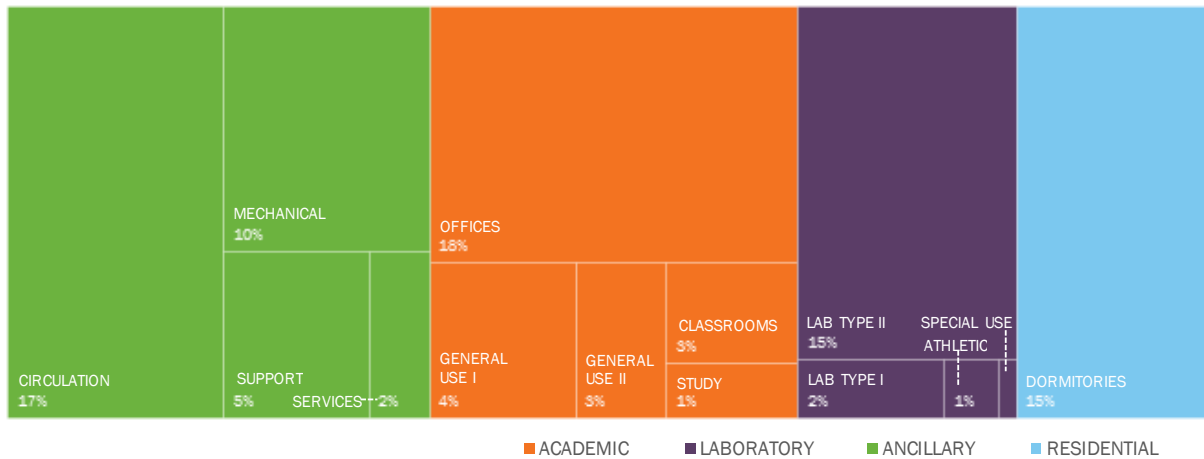


Figure 4-2: Campus floor area distribution by programmatic use.

The annual energy use data for all buildings, broken down by three utility end-uses, is also available for each building. Most campus buildings are served by the campus central co-generation plant and monitored via building utility meters for steam and electricity consumption. The academic and laboratory buildings are served by campus chilled water for space cooling which is also metered at the building level. Most residential buildings, in contrast, incorporate individual electric packaged terminal air conditioners for dormitories, and the energy associated with space cooling is included in the metered electricity consumption. **Figure 4-3** illustrates this information for most MIT campus buildings arranged in order of decreasing energy use intensities, where each column represents an individual building, with known annual utility use breakdown plotted on the y-axis.

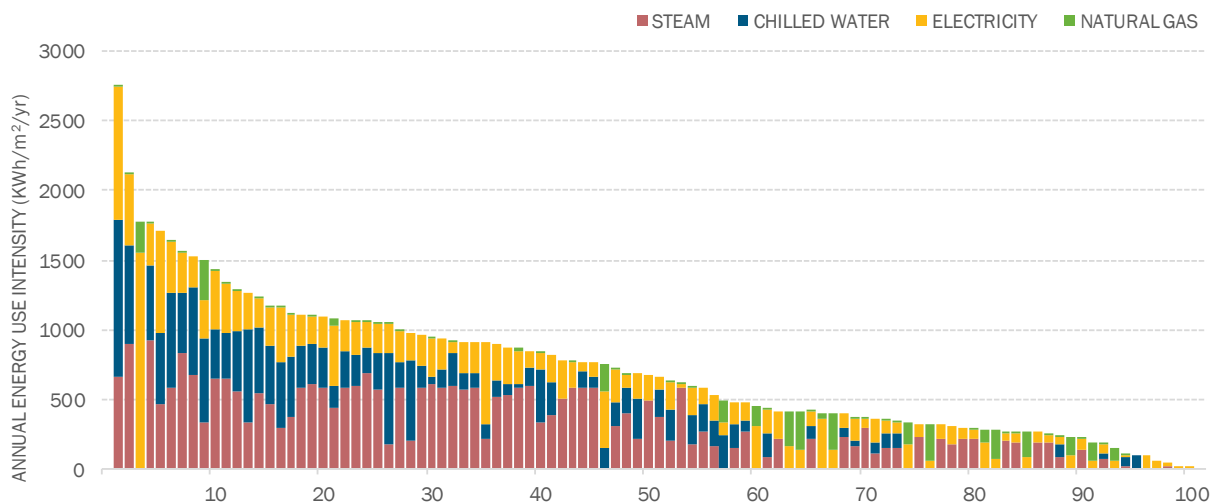


Figure 4-3: Information available for 100 MIT main campus buildings for 2016 (Source: MIT Office of Sustainability).

4.1.1. Model 1: Spreadsheet Approach

This method, developed for MIT by the environmental design consulting firm Atelier Ten, utilizes a simple statistical technique to calculate energy use intensities (EUI) that can be attributed to the 15 programmatic uses from Table 1. The approach assumes that the EUI for each program use (EUI_{PU}) depends primarily on the internal load and operating parameters, and is not significantly affected by variations in envelope configuration, age of the building, or other design parameters. In other words, for the purpose of this model, the 15 EUI_{PU} are assumed identical across all campus buildings.

The total annual campus energy use, E_C , can then be expressed as a linear function of the floor area of the different programmatic uses within each building, A_{PU} (Building), and the average energy use intensity for each programmatic use and energy end use, EUI_{PU} (End Use). For the 100 campus buildings, 15 different programmatic uses and three energy end uses (electricity, steam and chilled water) and the model can be expressed as:

$$E_C = \sum_{B=1}^{100} E_B, \text{ and } E_B = \sum_{PU=1}^{15} A_{PU}(\text{Building}) \times \sum_{U=1}^3 EUI_{PU}(\text{End Use}) \quad \dots (1)$$

where,

- E_C : known total annual energy use for studied building stock
- E_B : known annual energy of a specific building
- B : 1 of 100 studied campus buildings
- P : 1 of 15 campus programmatic uses
- U : 1 of 3 campus utility end-uses
- A_{PU} : known floor area of specific program type in a specific building
- EUI_{PU} : campus average energy use intensity for a specific end-use and program type

Given that the annual utility consumption for 3 end-uses for chilled water, steam/natural gas, and electricity as well as floor areas of 15 program types were known for all campus buildings, all 45 (3x15) EUI_{PU} (Energy Use) values could be regressed from Equation 1. The resulting values are listed in **Table 4-2**.

Table 4-2: Regressed energy use intensity for 15 campus program uses.

#	Program Use	Energy Use Intensity (EUI _{PU} - kWh/m ² -yr)			
		Chilled water	Steam /Natural Gas	Electricity	Total
Academic Spaces					
1	Offices	173	231	290	694
2	General Use I	66	213	83	362
3	General Use II	132	201	83	416
4	Classrooms	115	204	83	402
5	Study	99	207	83	389
Laboratory Spaces					
6	Lab Type I	123	259	103	486
7	Lab Type II	444	878	432	1,755
8	Special Use	1,728	3,100	2,028	6,856
9	Athletic	432	854	420	1,706
Ancillary Spaces					
10	Circulation	202	357	145	704
11	Mechanical	230	352	145	727
12	Garage	4	8	4	16
13	Support	49	96	50	195
14	Services	16	222	83	321
Residential Spaces					
15	Dormitories	12	144	87	243

As explained in the introduction, the primary purpose of this campus energy model is to provide a mechanism for predicting the change in energy use for future retrofit and evolution scenarios. However, the data from **Table 4-2** can only be used to calculate energy use impact of scenarios if a known program type is added or converted into another known program type. In addition, this spreadsheet model can only extrapolate from current performance, and cannot evaluate energy savings associated with future high-performance retrofits.

To expand the capabilities of the spreadsheet model to evaluate potential future scenarios, simple transient block energy models were developed for each of the four predominant space categories using the eQuest interface for DOE2.2 (Hirsch, 1998) simulation engine. **Figure 4-4** illustrates these block energy models that consist of a five-floor, five-zone per floor, 10,000 m² thermal model with a central core and four perimeter zones facing into the four cardinal directions.

Table 4-3 presents the envelope, internal load and mechanical system parameters that were manually adjusted based on a combination of modeler experience and campus knowledge, and numerous iterative simulations of the baseline eQuest models until the results fit the energy use intensities in **Table 4-2**.

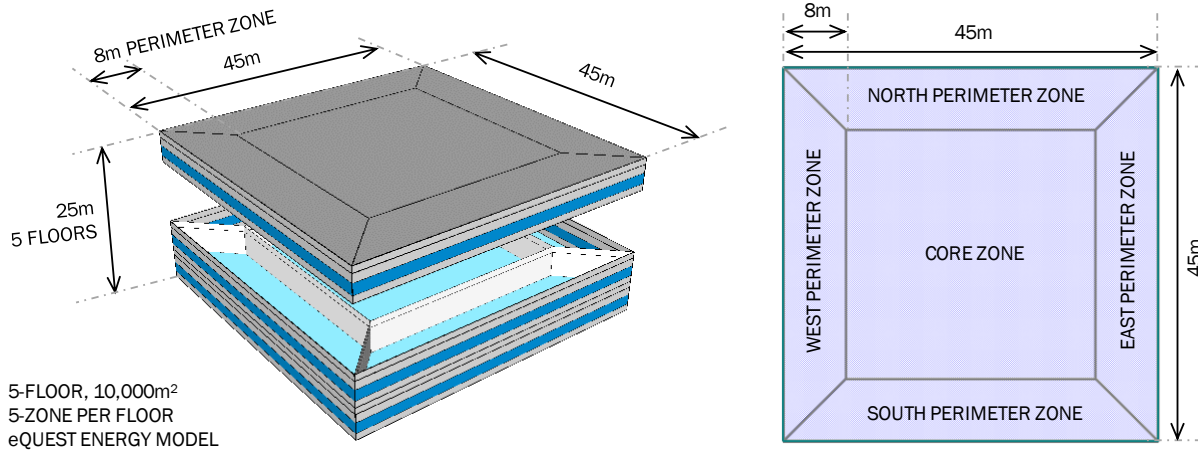


Figure 4-4: Graphic representation of eQuest block energy model.

Table 4-3: Key input parameters for block-energy models.

Input parameters	Residential Spaces	Academic Spaces	Ancillary Spaces	Laboratory Spaces
<i>Envelope Characteristics</i>				
Wall construction	U:0.70 W/m ² K	U:0.40 W/m ² K	U:0.70 W/m ² K	U:0.40 W/m ² K
Roof construction	U:0.60 W/m ² K	U:0.35 W/m ² K	U:0.60 W/m ² K	U:0.35 W/m ² K
Fenestration type	U:5.50 W/m ² K	U:2.50 W/m ² K	U:5.50 W/m ² K	U:2.50 W/m ² K
Glazing ratios	40% of wall area	40% of wall area	40% of wall area	40% of wall area
<i>Internal Loads</i>				
Occupant density	0.5 pp/m ²	0.2 pp/m ²	0.5 pp/m ²	2.0 pp/m ²
Equipment power	10 W/m ²	35 W/m ²	50 W/m ²	150 W/m ²
Lighting power	10 W/m ²	12 W/m ²	12 W/m ²	12 W/m ²
<i>Mechanical systems</i>				
Heating set-point	23.0 °C	22.0 °C	22.0 °C	22.0 °C
Cooling set-point	24.0 °C	24.0 °C	24.0 °C	24.0 °C
Zone terminal units	-	Hot water reheat	Hot water reheat	Hot water reheat
Ventilation flowrate	-	140 ls ⁻¹ /person	-	12 ACH
Fan system power	-	2.5 W/ls ⁻¹	2.5 W/ls ⁻¹	4.0 W/ls ⁻¹
Pump power	-	220 W/ls ⁻¹	-	220 W/ls ⁻¹
Heating source	Campus steam	Campus steam	Campus steam	Campus steam
Cooling source	Electric DX, COP 3.0	Campus chilled	Campus chilled	Campus chilled

The resulting “calibrated” block energy models were employed to simulate the energy impact of potential efficiency upgrades. To extrapolate the projected energy savings from these models back to the overall campus model, the energy savings projected by these models for any retrofit scenario were translated into percentage reduction factors, RF_{SU} , for cooling, heating, and electricity end-uses for each space category. The post-retrofit energy use for each building could then be calculated by multiplying the reduction factors for each space category within that building, with the pre-retrofit energy use. This potential energy savings estimate was then expressed via the following simple equation:

$$E_{CR} = \sum_{B=1}^{100} E_{BR}, \text{ and } E_{BR} = \sum_{S=1}^4 A_{BS} \times \sum_{U=1}^3 (EUI_{SU} \times RF_{SU}) \quad \dots (2)$$

where,

E_{CR} : post-retrofit campus total annual energy use

E_{BR} : post-retrofit annual energy use for a specific building

B : 1 of 100 studied campus buildings

S : 1 of 4 campus space categories

U : 1 of 3 campus energy end-uses

A_{BS} : floor area of specific space category in a specific building

EUI_{SU} : pre-retrofit energy use intensity for a specific end-use, for a specific space category

RF_{SU} : reduction factor associated with the studied retrofit measure – for a specific space category, for a specific energy use, based on percentage savings simulated by block energy model for that space category; set at 1 for any building that already incorporates the studied measure

4.1.2. Model 2: UBEM approach

The second campus model is a bottom-up engineering or urban building energy model developed at the Sustainable Design Lab at MIT. It is based on the assumption that building energy use depends on more than floor areas of programmatic use type and that variations in envelope configuration, lighting and mechanical systems, and occupant behavior can result in considerably different energy use profiles for individual buildings even if their predominant programmatic use is the same.

This means that a dynamic energy model has to be individually fitted for each building on campus using the simulation input parameters listed in **Table 4-4**. The resulting model cannot be expressed as a set of simple equations, but as a function of multiple input parameters, θ_{Bn} , specific to each individual building, B:

$$E_C = \sum_{B=1}^{100} E_B, \text{ and } E_B = f(C, \theta_{B1}, \theta_{B2}, \dots, \theta_{Bn}) \quad \dots (3)$$

where,

- E_C : total campus annual energy use
- E_B : modeled energy use of a specific building, calibrated to measured data
- B : one of 100 campus buildings
- f : systems of equations employed by the building energy simulation engine
- C : typical meteorological year climate data file for campus location
- θ_{Bn} : one of multiple model input parameters for each individual building (see Table 4)

In addition to the detailed program type distribution utilized for the spreadsheet model, the UBEM requires the combination of several datasets including climate data, building geometry, construction standards, usage schedules, and loads and systems parameters to simulate individual building energy use. A campus-wide Geographic Information System (GIS) database was utilized to automatically generate extruded massing models of the campus. Additional envelope data, which consisted of floor heights, fenestration configuration, window opening ratios, and construction assemblies, was based on architectural drawings or on visual inspection where drawings were not available. The building stock was then abstracted into four predominant programmatic archetypes that represent a group of buildings with similar non-geometric properties. **Figure 4-5** presents a graphic rendering of the campus energy model showing distribution of academic, laboratory, ancillary and residential archetypes. The UBEM is developed for EnergyPlus v.8.4 whole building energy simulation program using the UMI components for Grasshopper, a plugin to the CAD environment Rhinoceros3D (McNeel, 2015). **Figure 4-6** presents a tree-map for campus floor area distribution, where the colors represent four predominant building types, broken down by individual building areas within each category. The maps suggest that laboratory buildings occupy 38%, academic buildings account for 33% and residential and ancillary buildings constitute 28% and 5% of the total campus floor area, respectively.

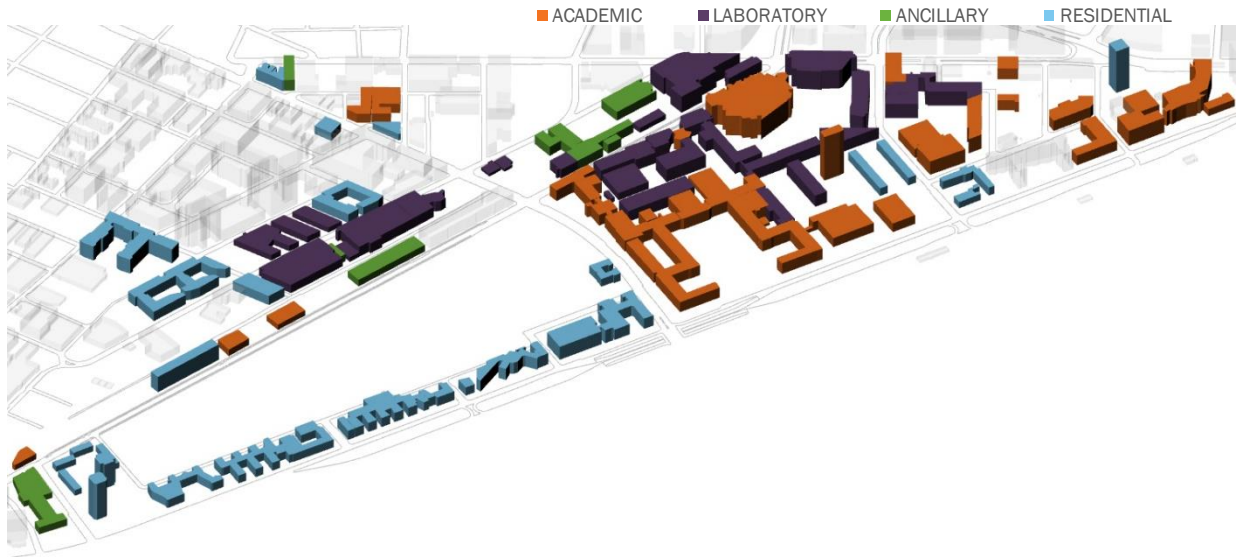


Figure 4-5: Graphic rendering of UBEM showing distribution of programmatic archetype.

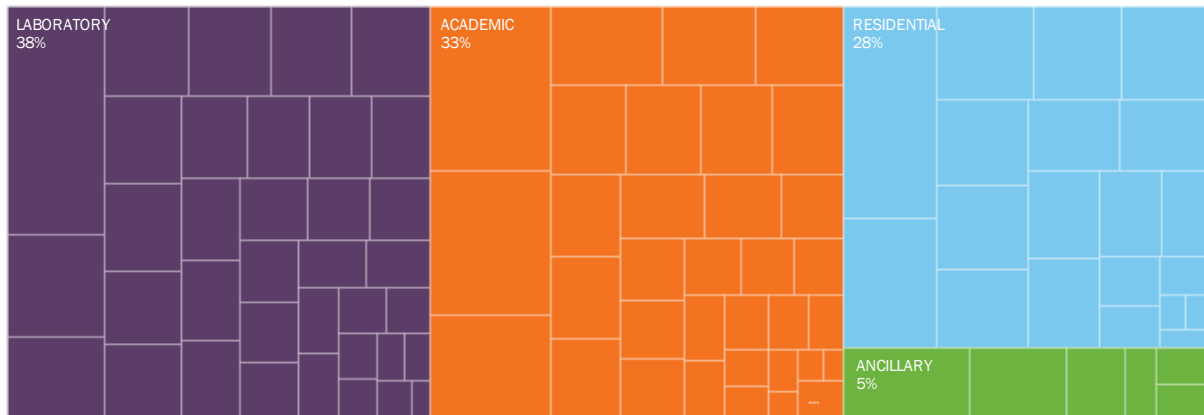


Figure 4-6: Campus floor area distribution by building type.

Input templates were created for each of these archetypes and assigned, one per building, across the campus. Non-geometric performance properties, such as occupant densities, lighting and miscellaneous equipment power, and usage schedules were estimated based on building program uses, and adjusted within defined ranges as part of the process to calibrate individual building models to measured energy use.

Mechanical systems were defined to translate building loads to campus steam and chilled water consumption by applying an overall coefficient of performance of 1.0 to space heating and space cooling energy. These model input parameters, and their defined ranges for different programmatic archetypes, are summarized in **Table 4-4**.

Table 4-4: Summary of key UBE_M input parameter ranges.

Input parameters (θ_n)	Residential Buildings	Academic Buildings	Ancillary Buildings	Laboratory Buildings
<i>Envelope Characteristics</i>				
Building Geometry	GIS dataset	GIS dataset	GIS dataset	GIS dataset
Glazing ratios	15% - 50%	15% - 50%	15% - 50%	15% - 50%
Wall construction	U:0.71–0.38	U:0.71–0.38	U:0.71–0.38	U:0.71–0.38
Roof construction	U:0.62–0.15	U:0.62–0.15	U:0.62–0.15	U:0.62–0.15
Window Conductance	U:5.78–1.96	U:5.78–1.96	U:5.78–1.96	U:5.78–1.96
Glazing SHGC	0.82–0.69	0.82–0.69	0.82–0.69	0.82–0.69
<i>Internal Load Ranges</i>				
Occupants (pp/m ²)	0.5 pp/m ²	0.1 – 0.3 pp/m ²	0.5 pp/m ²	1.5 – 2.5 pp/m ²
Equipment (W/m ²)	8 – 10 W/m ²	25 – 55 W/m ²	50 W/m ²	60 - 200 W/m ²
Lighting (W/m ²)	8 – 10 W/m ²	12 W/m ²	12 W/m ²	12 W/m ²
<i>Mechanical systems</i>				
Heat set-point (°C)	22.0 – 24.0 °C	21.5 – 22.5 °C	22.0 °C	21.5 – 22.5 °C
Cool set-point (°C)	22.0 – 25.0 °C	22.0 – 22.5 °C	n/a	21.5 – 22.5 °C
Ventilation flowrate	-	120 - 180 ls ⁻¹ /p	-	6 - 12 ACH
Heating source	Campus steam	Campus steam	Campus steam	Campus steam
Cooling source	Electric DX, COP 3.0	Chilled water	n/a	Chilled water

The simulation of different retrofit strategies with this model simply requires the modification of inputs from existing parameters to potential scenarios. The potential campus-wide energy savings could then be simulated by the following model:

$$E_{CR} = \sum_{B=1}^{100} E_{BR}, \text{ and } E_{BR} = f(C, \theta_{BR1}, \theta_{BR2}, \dots, \theta_{BRn}) \quad \dots (3)$$

where,

- E_{CR} : post-retrofit campus total annual energy use
- E_{BR} : post-retrofit annual energy use for a specific building
- B : one of 100 studied campus buildings
- f : systems of equations employed by the building energy simulation engine
- C : typical meteorological year climate data file for campus location
- θ_{BRn} : one of multiple model input parameters associated with the studied retrofit measure for a specific building; set same as θ_{Bn} if not affected by the measure.

4.1.3. Modes of Comparison

While the procedures for setting up the spreadsheet and UBEM models vary considerably, the purpose of both models is to simulate future scenarios to predict potential changes in campus and building-by-building energy use. To better understand the differences between the two models, and to assess their applicability in different situations, the results from both models are compared for various scenarios. First, the baseline results that represent existing conditions are compared to assess the calibration accuracy of each model at the overall campus scale, as well as at an individual building level. The next analysis assumes that all upgrades listed in **Table 4-5** are implemented in the entire building stock across all programmatic archetypes on campus and presents a high-level forecast of potential future energy use to help inform campus level planning issues.

Table 4-5: Summary of pre-programmed parameters considered for retrofit scenarios.

Efficiency Measure	Upgrade parameters
Envelope Upgrades	<ul style="list-style-type: none"> - Add insulation to existing wall assemblies to achieve assembly performance of U:0.20 W/m²K - Add insulation to existing roof assemblies to achieve assembly performance of U:0.15 W/m²K - Upgrade fenestration to achieve assembly performance U:1.96 W/m²K, SHGC: 0.40
Lighting Upgrades	<ul style="list-style-type: none"> - Install vacancy sensors to control ambient lighting in all non-regularly occupied spaces - Incorporate photo-sensor based automated dimming controls in all perimeter spaces - Upgrade all lighting fixtures to achieve an installed lighting power density of 8 W/m²
Mechanical Upgrades	<ul style="list-style-type: none"> - Install zone CO₂ sensors in all high occupancy spaces for demand controlled ventilation - Incorporate active air quality sensing in all laboratories to setback unoccupied airflow rates - Incorporate sensible heat recovery in laboratory exhaust, enthalpy heat recovery elsewhere

Finally, three buildings – one each from laboratory, academic and residential categories – were picked to compare results at individual building scale. The retrofit scenarios are simulated for each building, and the results from both models are compared against projections from separately developed reference calibrated BEMs. These reference models, graphically represented in **Figure 4-7**, incorporate building massing characteristics, floor-by-floor spatial programmatic distribution, as well as detailed operational, electrical, and mechanical system parameters for each building.

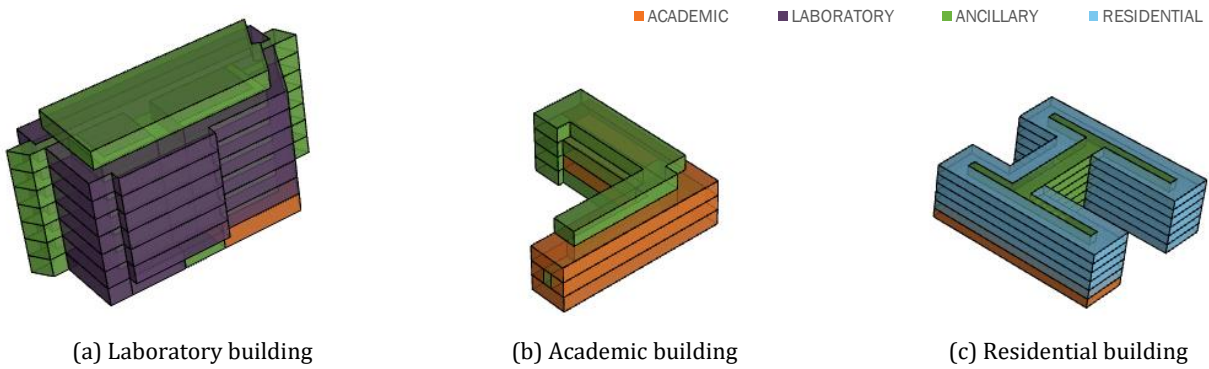


Figure 4-7: Graphic representation of reference whole building energy models showing program distribution.

As discussed earlier, the models used in the spreadsheet approach account for distribution of various program types within each building but assume campus average performance parameters for each program type, while the UBEMs which incorporate building specific performance parameters but assume a single set of operational characteristics for all spaces within the building. The aim of this last study is to assess the effectiveness of the two studied campus modeling approaches, which simplify individual building models in distinct ways, against a reference BEM, which incorporates all details, for various upgrade scenarios.

4.2. Results

In its baseline state, the spreadsheet model statistically represents overall campus energy use without relying on building level energy analysis. **Table 4-6** lists the baseline energy use intensities calculated by the spreadsheet model for the four predominant space categories that were earlier presented in **Table 4-2**. The UBEM, on the other hand, explicitly simulates each building individually to predict energy use based on detailed input parameters. To enable comparison between the results from two models, **Table 4-6** also organizes simulation results for the UBEM baseline by campus-average energy use intensities for the four predominant building types.

4.2.1. Campus level baseline

The results in **Table 4-6** show that while the overall campus areas are within 10% of each other between the two models, the area distribution by program type differs considerably. This is because the first model is a statistical representation of existing conditions where multiple programmatic uses are distributed within each building, whereas the UBEM calculates building area based on GIS footprint data and defined number of floors, and assigns each building with a single programmatic archetype based on the predominant use in that building.

Table 4-6: Baseline energy use intensities for predominant space categories: spreadsheet and UBEM approach.

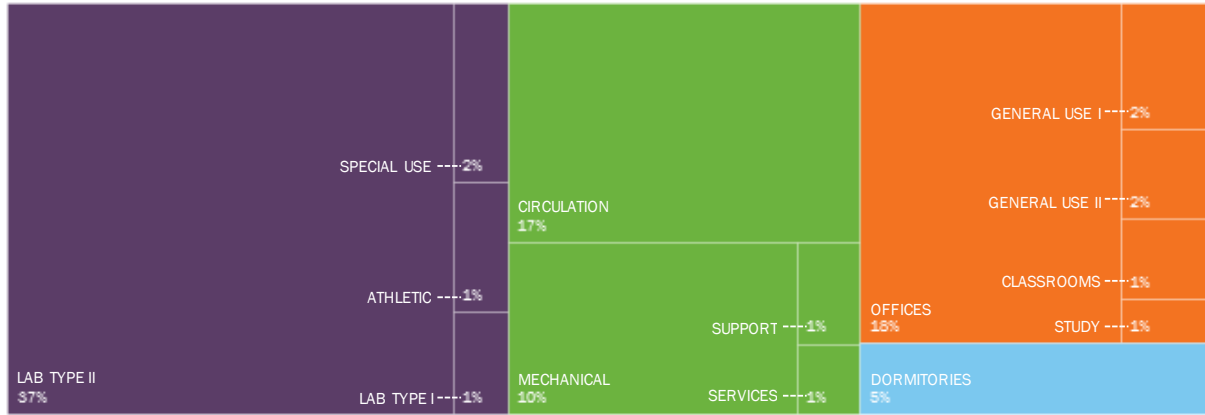
	Spreadsheet model EUI (kWh/m ² -yr)				
	Area (m ²)	Electricity	Steam	Chilled Water	Total
Residential	169,852	12	144	87	243
Academic	324,836	145	222	213	580
Ancillary	425,795	155	272	112	539
Laboratory	192,639	430	847	421	1,698
Campus	1,113,123	178	338	191	706

	UBEM EUI (kWh/m ² -yr)				
	Area (m ²)	Electricity	Steam	Chilled Water	Total
Residential	262,144	16	177	114	307
Academic	338,762	151	246	184	581
Ancillary	50,940	0	36	253	289
Laboratory	366,769	348	480	338	1,166
Campus	1,018,616	180	302	225	706

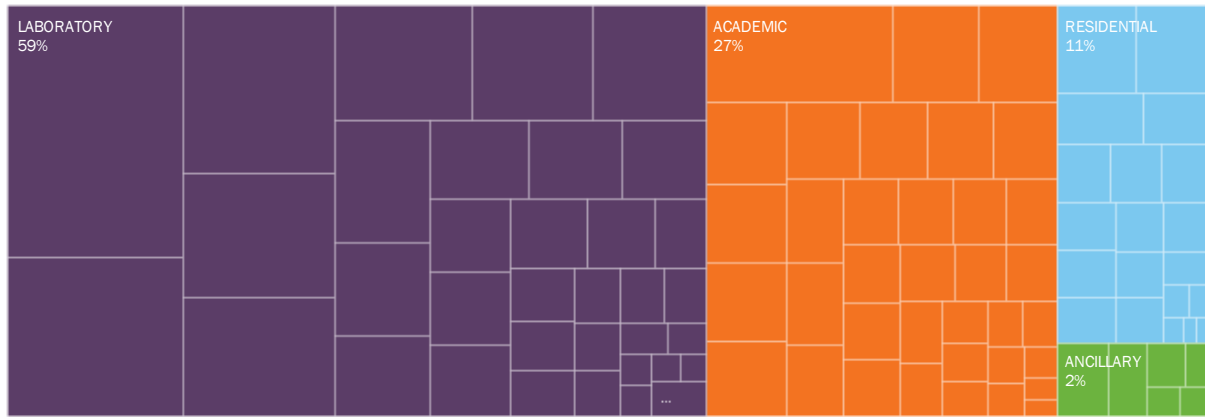
The overall campus energy use intensity results, however, match closely between the two models illustrating that both models are successfully calibrated to measured energy use at the campus scale. **Figure 4-8** compares the energy use distribution between the two models through tree-maps where the colors represent four predominant program types. A comparison of these maps for baseline conditions show that lab spaces in the spreadsheet model (a) result in just under 40% of the campus energy, whereas lab buildings in the UBEM (b) account for almost 60% of total campus energy use. This difference can be attributed primarily to ancillary uses, such as lab support spaces, that account for just under 30% of the campus energy in the spreadsheet model, but are included within other building types in the UBEM. The buildings that are classified as ancillary in the UBEM only constitute 2% of total energy.

4.2.2. Individual building baselines

Figure 4-9 compares measured against simulated annual energy use for individual buildings according to both campus models. The coefficients of determination for the spreadsheet and UBEM are 0.85 and 0.96, respectively, while the number of building whose measured and simulated energy uses diverge by more than 20% are 57 for the spreadsheet and 25 for the UBEM model. For the spreadsheet models, differences are smallest for lab buildings whose energy use is driven primarily by functional requirements. In contrast, the UBEM approach performs best for envelope dominated buildings.

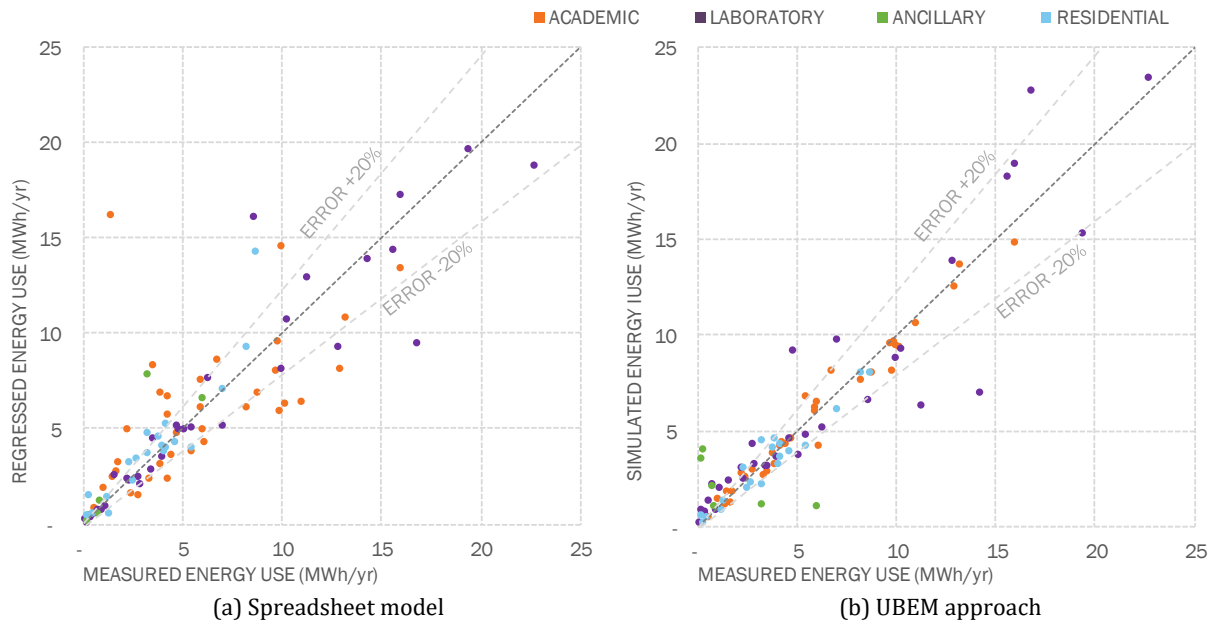


(a) Spreadsheet model (Each block represents a program type)



(b) UBEW approach (Each block represents an individual building)

Figure 4-8: Comparison of campus energy use distribution by program type between two models.



(a) Spreadsheet model

(b) UBEW approach

Figure 4-9: Correlation of measured vs modeled energy use for individual buildings.

4.2.3. Campus level upgrades

To calculate the energy impact of identified lighting, envelope, and mechanical system retrofits listed in **Table 4-5**, the spreadsheet model employs block energy models for each predominant space category discussed earlier. The simulation output from these block energy models for each of these upgrade scenarios is translated into reduction factors for cooling, heating, and electricity end-uses. The resulting reduction factors for each program type are presented in **Table 4-7**.

Table 4-7: Retrofit energy reduction factors by energy end-use.

Upgrades	Envelope Upgrades			Lighting System Upgrades			Mechanical System Upgrades		
	Cooling	Heating	Electricity	Cooling	Heating	Electricity	Cooling	Heating	Electricity
Residential	0.85	0.80	1.00	0.85	1.00	0.70	0.75	0.75	0.80
Academic	0.95	0.85	1.00	0.95	1.00	0.90	0.70	0.70	0.90
Ancillary	0.90	1.00	0.85	0.95	0.75	1.00	0.65	0.55	0.60
Lab Spaces	0.95	0.95	1.00	0.95	1.00	0.90	0.70	0.80	0.70

To extrapolate the projected energy savings from these block energy models, the spreadsheet model calculates the post-retrofit energy use by multiplying the reduction factors for each program type with the respective energy end-use prior to that retrofit. The UBEM approach, in contrast, utilizes engineering models to simulate performance with changes in various lighting, envelope and mechanical system parameters. **Figure 4-10** compares the cumulative energy savings with upgrade measures implemented in the entire building stock across campus, as projected by each model.

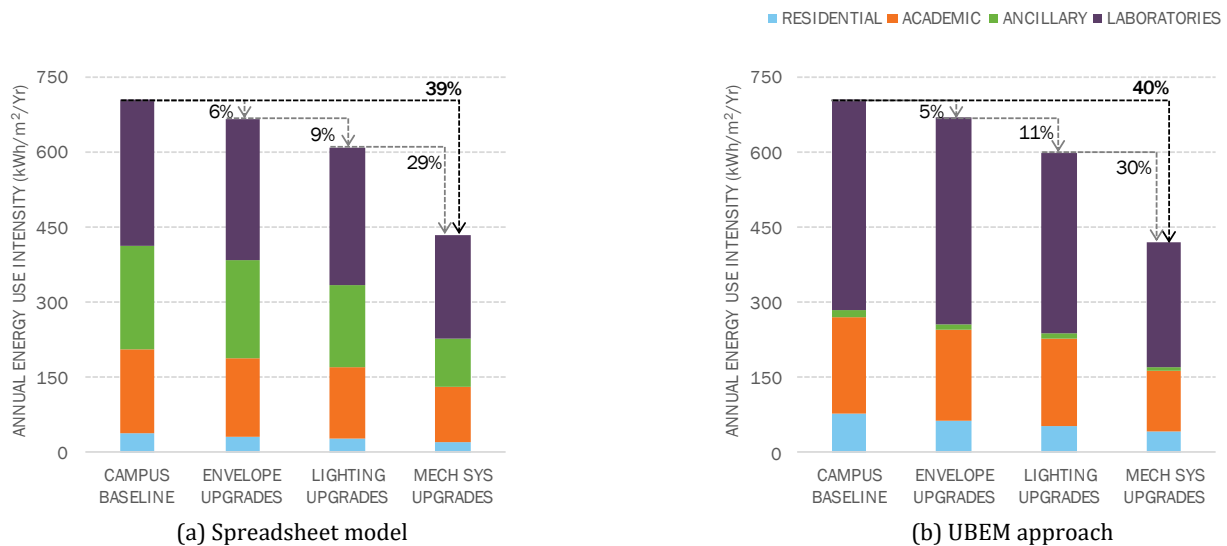


Figure 4-10: Modeled retrofit energy savings from campus level upgrades.

As discussed earlier, although the total baseline energy use intensity is an identical 706 kWh/m²/yr between the two models, there is significant difference in energy use distribution by program types most prominently seen in the considerably higher proportion of laboratory program in the UBEM approach. The relative savings with individual upgrades differ only slightly between the two models, with the spreadsheet model projecting a 6% savings from envelope upgrades and 9% savings from lighting upgrade vis a vis 5% and 11% savings according to the UBEM. The mechanical system upgrades result in relatively high, very similar savings across all program types in both models of 29% and 30%. Overall projected energy savings for both models are – practically identical – 39% and 40%. The similarity in results suggests that individual building nuances tend to average out when multiple buildings are evaluated simultaneously.

4.2.4. Building level retrofits

To further investigate the differences between the two models, these retrofit scenario results were evaluated for the representative buildings from **Figure 4-7**. The three buildings were selected because their measured energy use intensity is closest to the campus average for their respective building type, ensuring that the baseline results from both models closely match. **Table 4-8** lists the built-up area for each studied building and compares their baseline annual energy use intensities by utility type against the results from the previously discussed reference model.

Table 4-8: Area details and baseline annual energy use intensities for studied buildings.

Building	Laboratory	Academic	Residential
Total Area (m ²)	30,233	8,851	14,044
<i>Reference model EUI (kWh/m²-yr)</i>			
Electricity	330	102	173
Steam	642	290	229
Chilled Water	264	102	-
Total	1236	494	402
<i>Spreadsheet model EUI (kWh/m²-yr)</i>			
Electricity	330	102	173
Steam	643	288	224
Chilled Water	266	105	-
Total	1239	495	397
<i>UBEM EUI (kWh/m²-yr)</i>			
Electricity	330	102	170
Steam	643	290	229
Chilled Water	264	102	-
Total	1237	494	399

Figure 4-11 compares the projections for energy savings from these models for the residential building, broken down by energy end-uses, for various upgrade scenarios, from the two studied approaches. Campus average envelope parameters in the spreadsheet model translate to projected savings potential of 11% with envelope upgrades, considerably lower than the 19% projected by the reference model. The UBEM with building specific characteristics, on the other hand, projects a much closer 17% savings with envelope upgrades. Although the lighting upgrades offer a similar 14%-15% savings in both models, the spreadsheet model projects a higher 23% savings with mechanical system upgrades, compared to 20% for the UBEM which is closer to the 18% savings from the reference model. For the final case which incorporates all upgrades, however, the overall energy savings projection over the baseline is a similar 42% - 44% for all three models.

A comparison of the academic building evaluation presents similar trends in **Figure 4-12**. While all three models predict overall energy savings between 34% and 37%, the relative savings of the spreadsheet is off by up to a factor of two for the upgrade categories, lighting (3% for reference and UBEM versus 6% for spreadsheet). For the combined upgrades the reference and spreadsheet models project higher chilled water use and lower electricity use than the UBEM.

For the load dominated laboratory building, presented in **Figure 4-13**, all three models predict a total of 30% to 31% savings for all three upgrades. There is further agreement that mechanical system upgrades yield the highest savings between 23% and 25%. Compared to reference and spreadsheet, the UBEM model shows no electricity savings for the mechanical system upgrade. This is because the former models calculate savings in fan and pump system electricity separately from the space cooling chilled water and heating steam, whereas the UBEMs incorporate fan and pump systems within the overall cooling and heating systems and translate total mechanical system savings into chilled water and steam use reduction without affecting the electricity use.

The results show that there can be appreciable differences between the two models with regards to results for individual upgrade scenarios. However, both models project similar overall energy savings with the cumulative incorporation of all upgrades.

The annual energy use intensities for the final cases projected by the two models are very close, within 3% of each other. There are, however, considerable differences in the electricity and chilled water use for the academic and laboratory buildings with the UBEM showing 10%-22% higher electricity use and 25%-35% lower chilled water use compared to the spreadsheet model.

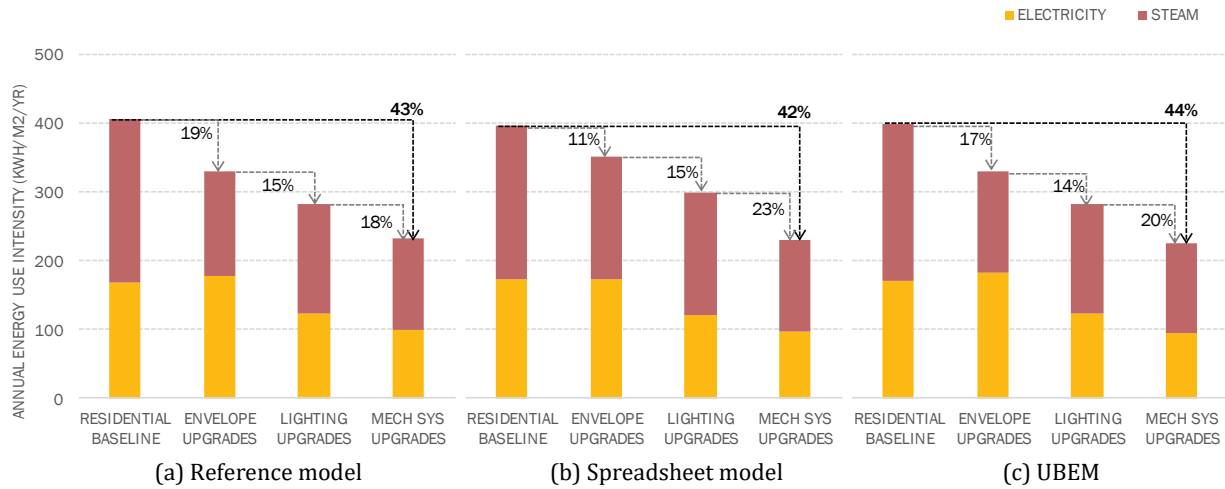


Figure 4-11: Comparison of energy savings for a representative campus residential building.

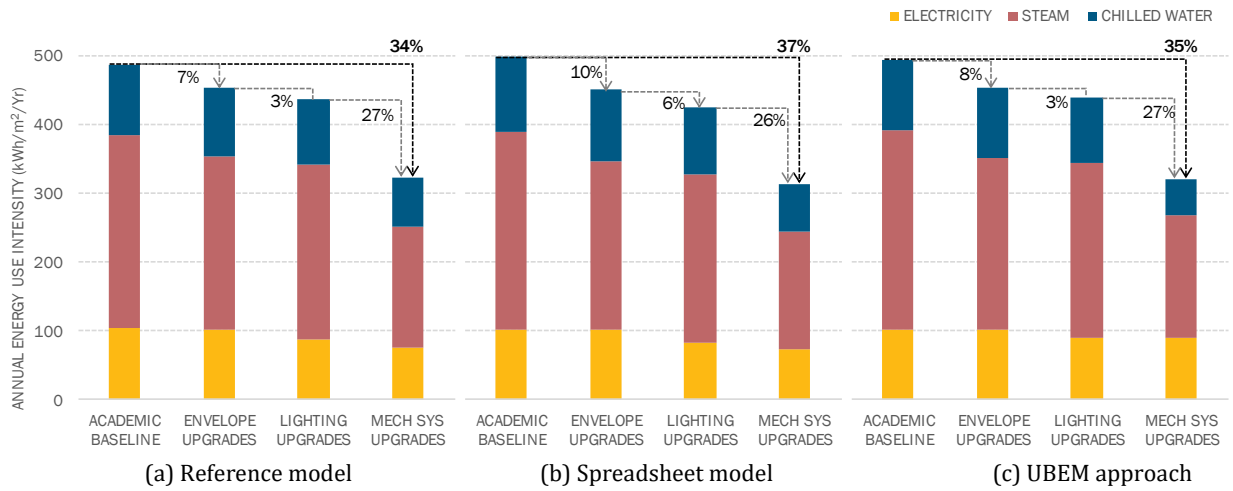


Figure 4-12: Comparison of energy savings for a representative campus academic building.

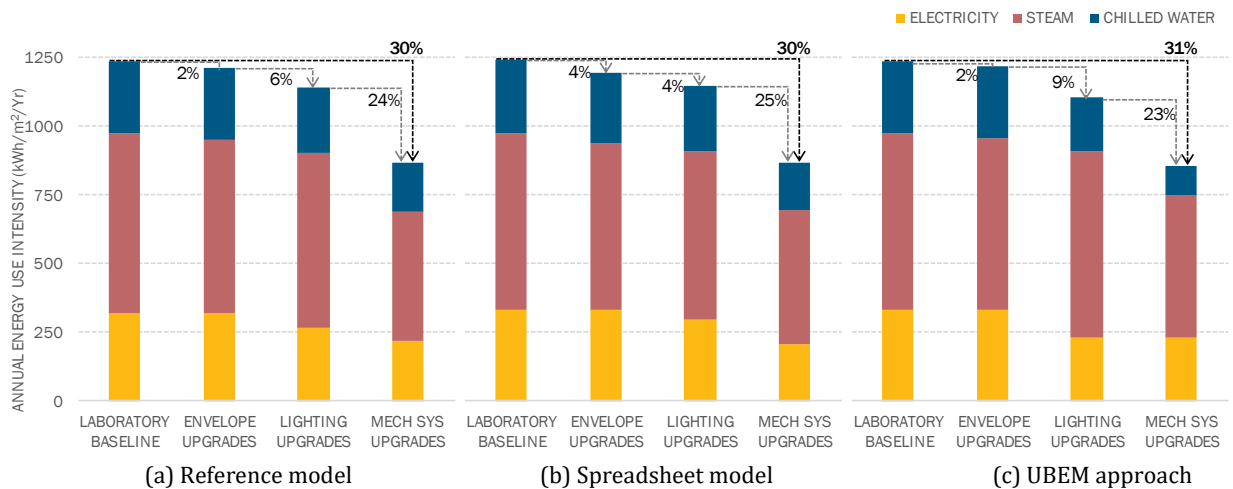


Figure 4-13: Comparison of energy savings for a representative campus laboratory building.

4.3. Discussion and limitations

While the two campus modeling approaches rely on rather different assumptions, one that programmatic use is the key predictor of building energy use and the other that building form matters, it is surprising to see the similarity in their predictions when applied to a hundred diverse campus buildings, reinforcing the trust in these results. Both models project energy savings from off-the-shelf energy efficiency measures of close to 40% revealing the enormous potential for campus owners to significantly reduce energy use across their jurisdictions. The comparison of energy saving predictions of both models against reference BEMs for the three campus buildings, however, revealed that the models can significantly diverge in their ability to predict the impact of individual saving measures applied to individual buildings.

When it comes to the effort level required to build and run either model, the spreadsheet model clearly outperforms the UBEM model in its current state. **Figure 4-14** presents a rough assessment of the time spent by the author to construct the different phases of both models. While the collection of campus level parameters took a similar 40 hours for both models, the UBEM model, which relies on modeling detailed building level information from geometry to window sizes etc., required three times more hours. The decisive difference came during the calibration steps which racked up almost 400 hours for the UBEM which needed to be calibrated building by building, compared to the calibration of a few block energy models in the spreadsheet approach. Simulating system upgrades took slightly less time for the UBEM. The 260 total hours for the spreadsheet and 600 for the UBEM to evaluate broad campus-level forecasts reveals why the latter approach is currently restricted to research settings.

On the other hand, results suggest that the UBEM model is capable of predicting individual building level energy savings from individual energy efficiency upgrades. There is hence a potential advantage for campus owners to invest in an UBEM, especially if a campus model is to be used for an extended period of time for building fault detection during operation, and to validate the effectiveness of specific retrofits. In short, while a spreadsheet model is a significantly faster way to evaluate and set portfolio or campus-wide energy savings targets, UBEMs can be eventually employed to assess the relative impact of specific measures in specific buildings.

Given that the UBEM approach supports the modification of any input parameter for any building at any time with minimal effort, it can hence evolve into a “living campus model” that is automatically informed by new information as it becomes available.

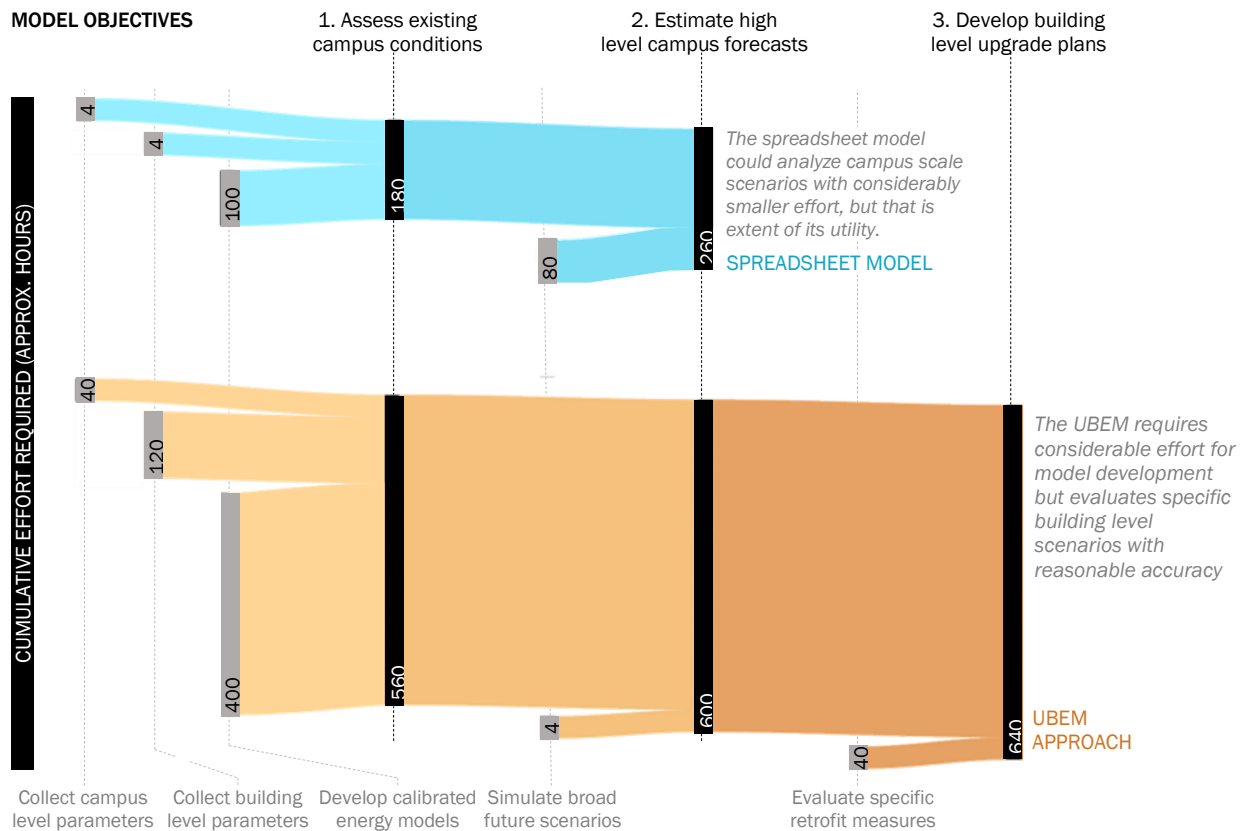


Figure 4-14: Qualitative assessment of incremental level of effort required based on model objectives.

Within the limits of use as a planning and forecasting tool to inform high-level decisions about campus level upgrades, the spreadsheet model efficiently provides results within reasonable limits of error and realistic time frames. The model simulates future scenarios using easy to build form-agnostic block energy models, but can only evaluate pre-programmed scenarios, and cannot reliably capture the energy impact of a specific upgrade measure on individual buildings. In contrast, the UBEM approach currently requires substantial effort and expertise for detailed geometric model building, and considerable amount of information and time for setup and calibration of individual building models. Once developed, however, the models incorporate variations in envelope configuration, internal load parameters and usage profiles across the building stock, and therefore, accurately capture the effects of a large range of energy conservation measures at a variety of scales, from campus and archetype level strategies to individual building, or even specific building retrofits. A key barrier towards this vision is the considerable time associated with the building-by-building calibration process. There is a need for an automated and flexible rapid-response methodology, in order to reduce the manual as well as computational cost of developing calibrated energy models. Such a methodology is introduced in Chapter 5.

5. Automated Calibration¹

This chapter aims to develop a hybrid approach that combines established urban building energy model generation techniques with auto-calibration methods based on a data-driven approximation technique, called surrogate modeling, to reduce the computational cost of energy calculations. As shown in **Figure 5-1**, the first step is to collect measured energy use data and to decide which building properties are considered to be known as opposed to unknown or uncertain for a given building. A whole building energy model, or engineering model, of the building is then generated and used to train a surrogate model by running the engineering model for a set of combinations of the unknown parameter properties and determining a goodness of fit error (Reddy et al. 2006) between the observed monthly energy use and the simulation results for each sample. The resulting trained surrogate model is then combined with an optimization algorithm to determine the combinations of unknown parameter values that offer the least error.

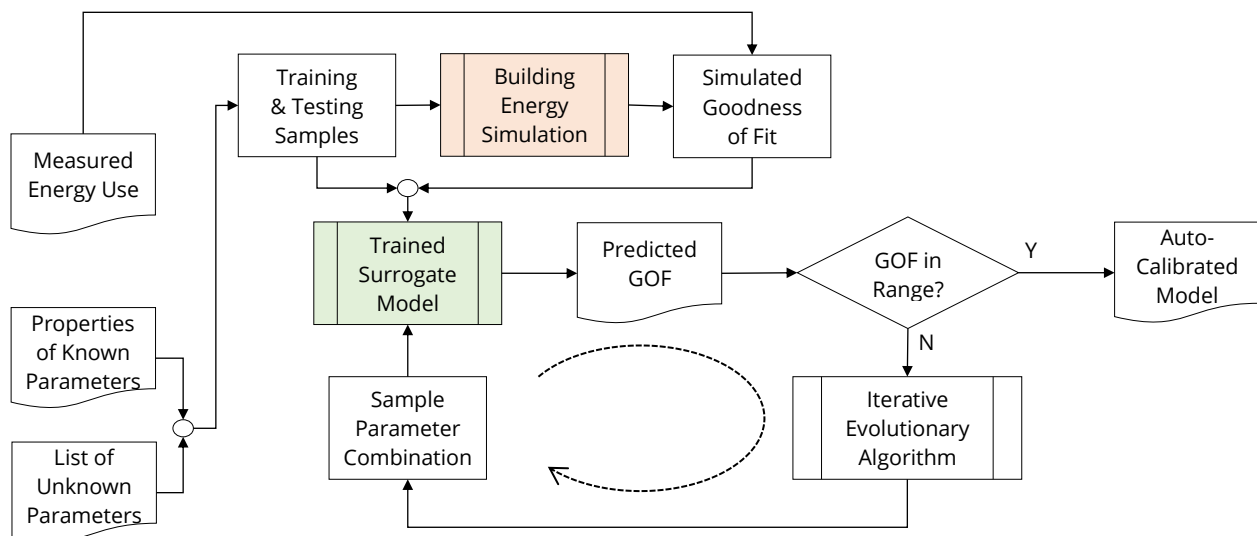


Figure 5-1: Flowchart illustrating the proposed auto-calibration methodology. A surrogate model, trained by a set of detailed energy model simulation results, is combined with an optimization algorithm to determine the combination of unknown parameter values that offer the lowest error.

Sections in this chapter test this workflow by attempting to automatically calibrate whole building energy models of the three buildings at the campus of the Massachusetts Institute of Technology studied in detail in Chapter 4. The overall motivation for this study is to develop an automated and flexible rapid-response methodology that, based on measured energy use data and a few known performance characteristics, can estimate the properties of several unknown parameters for buildings with diverse programmatic uses, and thus generate calibrated baseline energy models.

¹ A version of this chapter has been published: S. Nagpal, C. Mueller, A. Aijazi, C. Reinhart, A methodology for auto-calibrating urban building energy models using surrogate modeling techniques, Journal of Building Performance Simulation, 2018.

5.1. Proposed workflow

As explained above, the goal of this study is to propose a simulation workflow that automatically estimates the properties of several unknown building performance characteristics. As shown in **Figure 5-1**, the first step is to collect monthly energy use data for a whole year and to identify which building properties are known as opposed to unknown or uncertain for a given building. A whole building energy model, or an engineering model using a simulation engine such as EnergyPlus v.8.4, is then generated for each building and used to train a surrogate model by running for a set of combinations of the unknown parameter properties and determining a goodness of fit (GOF) error between the observed monthly energy use and the simulation results for each sample.

5.1.1. Goodness of Fit

This GOF, defined by ASHRAE Research Procedure 1051 (Reddy et al., 2006) as a single statistical index that represents an overall ranking of simulation results, is a weighted combination of normalized mean bias error (NMBE) which quantifies the percentage error between observed and simulated values summed over the year, and the coefficient of variation of root mean square error (CV) which characterizes the variability of difference on a month by month basis for the different energy-use types. In accordance with ASHRAE Guideline 14 recommendations, a 3:1 weight is assigned for NMBE compared to CV, and for electricity compared to both steam and chilled water. The calculation of overall GOF can be expressed as:

$$GOF = \sqrt{\frac{w_{CV}^2 \cdot GOF_{CV}^2 + w_{NMBE}^2 \cdot GOF_{NMBE}^2}{w_{CV}^2 + w_{NMBE}^2}} \quad \dots (1)$$

$$GOF_{CV} = \sqrt{\frac{w_{Elec}^2 \cdot CV_{Elec}^2 + w_{Steam}^2 \cdot CV_{Steam}^2 + w_{CHW}^2 \cdot CV_{CHW}^2}{w_{Elec}^2 + w_{Steam}^2 + w_{CHW}^2}} \quad \dots (2)$$

$$GOF_{NMBE} = \sqrt{\frac{w_{Elec}^2 \cdot NMBE_{Elec}^2 + w_{Steam}^2 \cdot NMBE_{Steam}^2 + w_{CHW}^2 \cdot NMBE_{CHW}^2}{w_{Elec}^2 + w_{Steam}^2 + w_{CHW}^2}} \quad \dots (3)$$

and,

$$CV = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{11 \times \bar{y}^2}} \times 100 \quad \dots (4)$$

$$NMBE = \frac{\sum (y_i - \hat{y}_i)}{12 \times \bar{y}} \times 100 \quad \dots (5)$$

where,

- w : weighting factor 3 for NMBE and Elec; 1 for everything else
- i : one of 12 months of the year
- y_i : observed energy use for a specific month
- \hat{y}_i : simulation predicted energy use for a specific month
- \bar{y} : mean value of observed monthly energy use

The training data sets of simulation generated GOF output, and the corresponding combination of input variables are then used to construct statistical models. There are several approximation algorithms that are designed to fit detailed simulation results to a statistical function, a few of which such as Radial Bias Functions, Kriging, Random Forests and Artificial Neural Networks, have been studied for their effectiveness in reducing the computational expense associated with detailed building energy simulations (e.g., Aijazi & Glicksman, 2016; Tsanas & Xifara, 2012).

The key assumption for these functions is that performance values can be derived from model inputs via a rapidly evaluated black box function by being agnostic about the underlying physical behavior. Two of these techniques were employed in this study via a previously developed component (Mueller, 2014) illustrated in **Figure 5-2** that was designed to provide a systematic, automated approach for generating surrogate models for designers who are not experts in statistics or surrogate modeling.

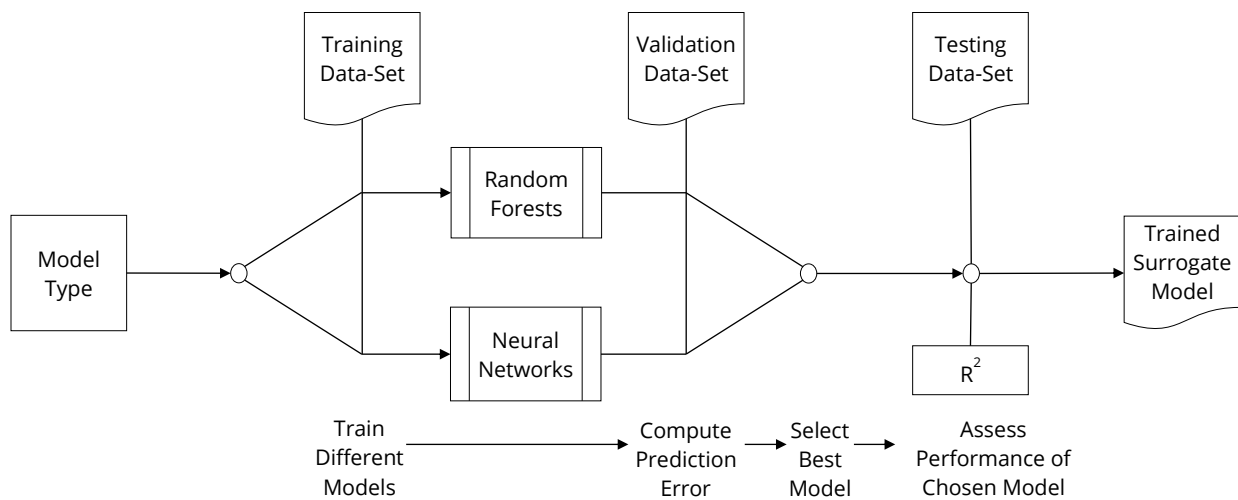


Figure 5-2: Schematics of the surrogate modeling component. Redrawn (Mueller, 2014).

5.1.2. Surrogate models

The first model, Random Forests (RF), sequentially divides data into tree-like structures and uses an average rule to make a prediction for the output of all trees (Brieman, 2001). A simple illustration of a regression tree model is given in **Figure 5-3(a)**, showing the basic approach of a decision tree that uses repeated binary splitting, based on design variable values. To use the tree for prediction, one simply moves down the branches, following the path based on given design variables. The terminus of a branch gives the predicted output, or design performance, value. As more branches are added, the predictive output gets increasingly refined, allowing it to match the shape of any design space.

The second, Neural Networks (NN) (ALGLIB, 2012), comprise a computational modeling approach that simulates groups of interconnected biological neurons found in the nervous system. While this modeling technique was originally developed to study brain activity, it has been found to be an effective predictive modeling tool for regression problems in general. A diagram of a simple neural network is given in **Figure 5-3(b)**, showing multiple input variables connected to nodes in an intermediate layer, called a hidden layer, which are connected to nodes that represent output values. Mathematically, a neural network fits a function of a linear combination of inputs to produce outputs at each layer.

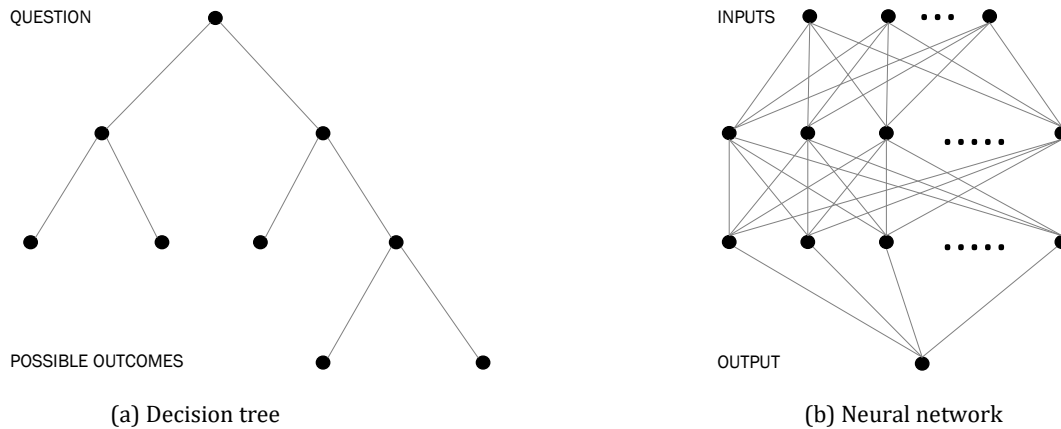


Figure 5-3: Diagrams illustrating studied surrogate modeling techniques.

The first two steps of training, that fit the model to the data are repeated ten times to create multiple candidate models. These candidates differ in the surrogate model type, or in the tuning of other model-specific parameters, called nuisance parameters, that require experimentation to find the optimal setting for a particular problem. The model that produces the minimum error on the validation set is then chosen for the final phase of testing.

The testing data-set is finally used to objectively assess the performance of the model by measuring the associated coefficient of determination, (R^2), between the surrogate model's predicted GOF and the results from detailed building energy simulation for each sample in the data-set. This can be expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (GOF_i - \overline{GOF_i})^2}{\sum_{i=1}^n (GOF_i - \overline{GOF})^2} \quad \dots (6)$$

where,

n : total number of samples in testing data-set

i : 1 of n samples

GOF_i : testing data-set goodness of fit for a specific sample

$\overline{GOF_i}$: surrogate model predicted goodness of fit for a specific sample

\overline{GOF} : mean value of testing data-set goodness of fit for all samples

5.1.3. Optimization algorithm

Once the surrogate models are trained and tested, and show R^2 values higher than 0.7 (Reddy et al., 2006), a genetic algorithm (Flory, 2018) is used to search for the optimal combination of unknown parameter values that results in the lowest overall GOF. This optimization algorithm searches from a population of all possible combinations, by first randomly sampling within the design space. It then uses stochastic operators to direct the process of finding the lowest GOF. The approximate evaluation of GOF using surrogate models, in contrast to detailed building simulations, vastly reduces the computational expense otherwise needed to estimate the properties of unknown building performance characteristics. The parameter properties estimated by the optimization routine are then used to develop detailed engineering models using EnergyPlus. Finally, monthly energy-use results from these resulting EnergyPlus models are compared to the initial observed energy use to assess the effectiveness of this calibration workflow.

The hypothesis is that if the simulation results match closely with observed data, the estimated properties of unknown parameters can be used to determine, with reasonable accuracy, their relative impact on overall building energy use. The next section tests this hypothesis for the three specific buildings on the MIT campus studied in detail in Chapter 4.

5.2. Application case study

Three representative buildings - one residential, one academic, and one laboratory presented earlier in **Figure 4-7** were selected for this study because they represent considerably different programmatic uses, so the energy use intensities as well as the relative contributions of envelope, internal load and mechanical system parameters to energy consumption are different for each building. All three buildings are served by MIT's central co-generation plant and monitored via building utility meters for steam and electricity consumption. The academic and laboratory buildings are served by campus chilled water for space cooling. The residential building, in contrast, incorporates individual electric packaged terminal air conditioners for dormitories, and the energy associated with space cooling is included in the metered electricity consumption.

Calibrated whole building energy models were developed utilizing the building geometry information available from campus GIS data, and known performance characteristics. EnergyPlus whole building energy simulation program was employed using the UMI components for Grasshopper, a plugin to the CAD environment Rhinoceros3D (McNeel, 2015). To test the workflow from **Figure 5-1**, a total of 32 parameters that affect building energy use were initially manually determined for the three buildings and their values are listed in **Table 5-1**.

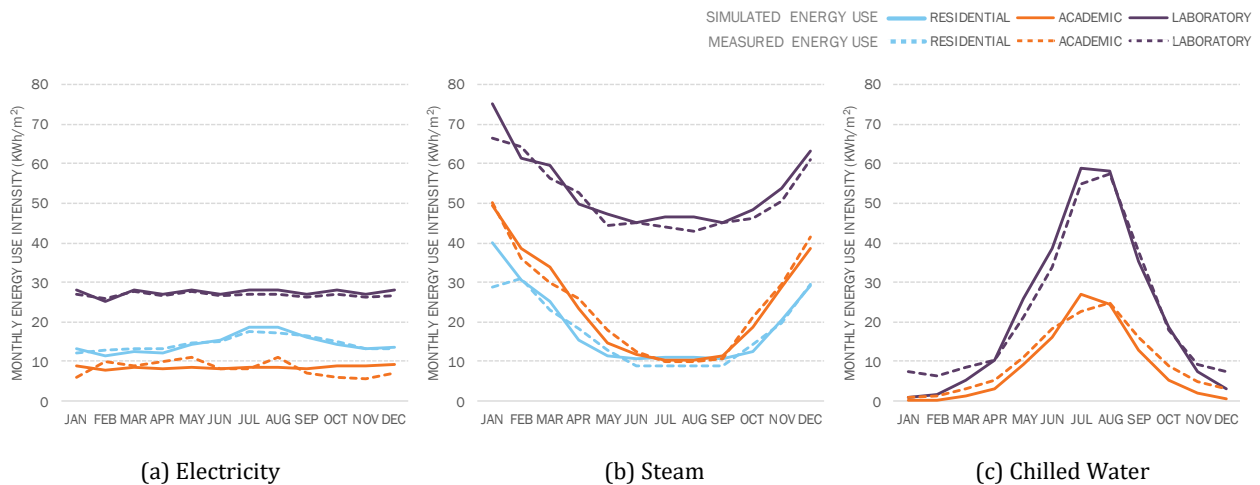


Figure 5-4: Observed monthly energy use data for studied buildings.

In **Figure 5-4**, monthly energy use results from the manually calibrated EnergyPlus models, broken down by utility, are compared to the measured energy data for the buildings. The simulated monthly energy use data for the three buildings lie within 10% of the measured data for the three buildings.

Table 5-1: Known performance characteristics for studied buildings.

Input parameters	Residential Building	Academic Building	Laboratory Building
1. Floor to floor height	3 m	4 m	6 m
2. Perimeter zone depth	7 m	6 m	5 m
3. Fenestration type	Punched windows	Curtain wall	Curtain wall
4. Fenestration shading	Recessed windows	Exterior overhangs	None
5. North window to wall ratio	40%	40%	60%
6. South window to wall ratio	40%	40%	60%
7. East window to wall ratio	40%	60%	20%
8. West window to wall ratio	40%	60%	20%
9. Window frame conductance	U:15 W/m ² K	U:15 W/m ² K	U:10 W/m ² K
10. Wall construction	U:0.5 W/m ² K	U:0.5 W/m ² K	U:0.3 W/m ² K
11. Roof construction	U:0.4 W/m ² K	U:0.4 W/m ² K	U:0.2 W/m ² K
12. Glazing type	Single pane	Double pane	Double pane
13. Window leakage	0.5 ACH	1.0 ACH	0.5 ACH
14. Natural ventilation	All hours	Never	Never
15. Daylight response	On/off controls	Continuous	None
16. Thermostat set-point	24 °C	24 °C	26 °C
17. Occupancy schedule	Always on	60 hr/wk	Always on
18. Equipment usage	30 hr/wk	30 hr/wk	60 hr/wk
19. Lighting usage	Always on	60 hr/wk	Always on
20. Service hot water usage	0.003 ls ⁻¹	0.001 ls ⁻¹	0.003 ls ⁻¹
21. Perimeter occupant density	0.05 pp/m ²	0.25 pp/m ²	0.5 pp/m ²
22. Core occupant density	0.05 pp/m ²	0.25 pp/m ²	0.5 pp/m ²
23. Perimeter outside air flow	0.5 ACH	180 ls-1/pp	0.5 ACH
24. Core outside air flowrate	0.5 ACH	180 ls-1/pp	12 ACH
25. Perimeter equipment power	15 W/m ²	15 W/m ²	35 W/m ²
26. Perimeter lighting power	20 W/m ²	15 W/m ²	20 W/m ²
27. Core equipment power	15 W/m ²	15 W/m ²	35 W/m ²
28. Core lighting power	20 W/m ²	15 W/m ²	20 W/m ²
29. Perimeter outside air schedule	Always on	Always on	Always on
30. Core outside air schedule	Always on	Always on	Always on
31. Exhaust air energy recovery	None	None	None
32. Economizer cycle	None	None	None

Going forward, the authors used the simulated energy data from **Figure 5-4** as the energy baseline to test the surrogate modeling approach. In the following sections, this simulated data is referred to as “observed data.” These observed energy use intensities by utility type, as well as the built-up area for each building, presented in detail earlier in **Table 4-8**, are listed in **Table 5-2**.

Table 5-2: Area details and observed energy use intensities for studied buildings.

Building	Area (m ²)	Energy Use Intensity (kWh/m ² -yr)			Total
		Electricity	Steam	Chilled Water	
Residential	14,044	173	229	0	402
Academic	8,851	102	290	102	494
Laboratory	30,233	330	642	264	1236

The reason for using observed or synthetic rather than measured monthly energy data was to ensure that a unique combination of simulation input parameters existed for each building for which simulation results exactly match the observed energy use. This allowed the author to evaluate the results from surrogate models for absolute accuracy.

5.2.1. Evaluation scenarios

Three scenarios with different numbers and types of unknown building parameters were evaluated. In all three cases it is assumed that the information related to building massing and geometry parameters, i.e. the first four parameters in **Table 5-1**, is either available from GIS or LiDAR data or has been collected through building audits. This is the minimum level of information required to develop a building energy model. The first case assumes that all the remaining 28 performance characteristics are unknown and need to be determined via a calibration process. The second case reduces the number of unknown parameters to 20 by assuming that information about building envelope, including window to wall ratios and envelope constructions is also available from building audits, construction drawings or otherwise. The third case further assumes that operational and usage profiles are available, either via observation or through building monitoring systems, and reduces the number of unknowns to 12 electrical and mechanical system characteristics that are typically the most difficult to determine for existing buildings.

Table 5-3 presents the details of assumed unknown parameters for the three evaluation cases, along with the possible range of values considered in this study for each unknown parameter.

Table 5-3: Evaluation scenarios with different number, and type, of unknown parameters.

	Unknown parameters			Possible unknown parameter values		
	Case 1	Case 2	Case 3	Low energy (0)	Typical energy (1)	High energy (2)
Input parameters	1	2	3	(0)	(1)	(2)
1. North window to wall ratio	x			20%	40%	60%
2. South window to wall ratio	x			20%	40%	60%
3. East window to wall ratio	x			20%	40%	60%
4. West window to wall ratio	x			20%	40%	60%
5. Window frame conductance	x			U:5.0 W/m ² K	U:10 W/m ² K	U:15 W/m ² K
6. Wall construction	x			U:0.3 W/m ² K	U:0.4 W/m ² K	U:0.5 W/m ² K
7. Roof construction	x			U:0.2 W/m ² K	U:0.3 W/m ² K	U:0.4 W/m ² K
8. Glazing type	x			Triple pane	Double pane	Single pane
9. Window leakage	x	x		0.05 ACH	0.5 ACH	1 ACH
10. Natural ventilation	x	x		All hours	Occupied hrs	Never
11. Daylight response	x	x		Continuous	On/off	Never
12. Thermostat set-point	x	x		22 °C	24 °C	26 °C
13. Occupancy schedule	x	x		30 hr/wk	60 hr/wk	Always on
14. Equipment usage	x	x		30 hr/wk	60 hr/wk	Always on
15. Lighting usage	x	x		30 hr/wk	60 hr/wk	Always on
16. Service hot water usage	x	x		0.001 ls ⁻¹	0.002 ls ⁻¹	0.003 ls ⁻¹
17. Perimeter occupant density	x	x	x	0.05 pp/m ²	0.25 pp/m ²	0.5 pp/m ²
18. Core occupant density	x	x	x	0.05 pp/m ²	0.25 pp/m ²	0.5 pp/m ²
19. Perimeter outside air flowrate	x	x	x	0.5 ACH	180 ls-1/pp	12 ACH
20. Core outside air flowrate	x	x	x	0.5 ACH	180 ls-1/pp	12 ACH
21. Perimeter equipment power	x	x	x	15 W/m ²	25 W/m ²	35 W/m ²
22. Perimeter lighting power	x	x	x	10 W/m ²	15 W/m ²	20 W/m ²
23. Core equipment power	x	x	x	15 W/m ²	25 W/m ²	35 W/m ²
24. Core lighting power	x	x	x	10 W/m ²	15 W/m ²	20 W/m ²
25. Perimeter outside air schedule	x	x	x	30 hr/wk	60 hr/wk	Always on
26. Core outside air schedule	x	x	x	30 hr/wk	60 hr/wk	Always on
27. Exhaust air energy recovery	x	x	x	Enthalpy	Sensible	None
28. Economizer cycle	x	x	x	Enthalpy	Dry bulb	None

5.2.2. Surrogate models

To assess the optimal number of initial samples that should be used to construct surrogate models, three training data sets with 100, 200 and 400 samples each, and a fourth testing data-set with 50 samples, were generated for each building for each of the three evaluation scenarios. To ensure an even distribution of samples across the design space, a Latin hypercube scheme was employed via a previously developed sampling tool (Brown, 2016) to generate random values for each unknown parameter, for each sample. To prevent assigning unrealistic importance and bias towards some parameters, each parameter was normalized so it can only have a discrete value of 0, 1, or 2 to reflect low, typical, or high energy use as listed in **Table 5-3**. In addition to the combination of normalized values for unknown parameters that serve as training input, each iteration in the data set includes as training output the overall GOF between the observed monthly energy use and the detailed building energy simulation results for that combination.

A total of 270 surrogate model candidates were developed by the previously discussed component. **Figure 5-5** graphically visualizes the root mean square errors results for validation tests from all examined cases, where the horizontal axes show the 27 model cases (3 building types x 3 evaluation scenarios x 3 training data-set sizes) for which one trained model was to be selected, each dot represents error from a different set of nuisance parameters, and the dot color represents the model type. As expected, the examined cases show lower errors for cases with lesser number of unknown parameters, and a large number of training samples. NN models typically performed better for cases with the least unknowns, while RF showed lower errors for cases with 20 and 28 unknown parameters, irrespective of the building type or the number of training samples.

Between the two surrogate model generation methodologies examined, it was found that while RF models displayed a high variability in errors with changing nuisance parameters, the lowest-error candidate performed consistently high and RF models were picked over NN models for almost all cases with high number of unknown parameters. In contrast, all NN candidates performed very well for cases with the lowest number of unknown parameters, but their performance fell sharply as the number of unknowns increased. In other words, while NN models offered a more accurate approach for a few cases, RF models provided adequate performance across all cases, especially those with the highest overall performing surrogate models.

Therefore, if the option to test multiple algorithms, such as in this study, is not available, RF becomes the recommended choice based on this study.

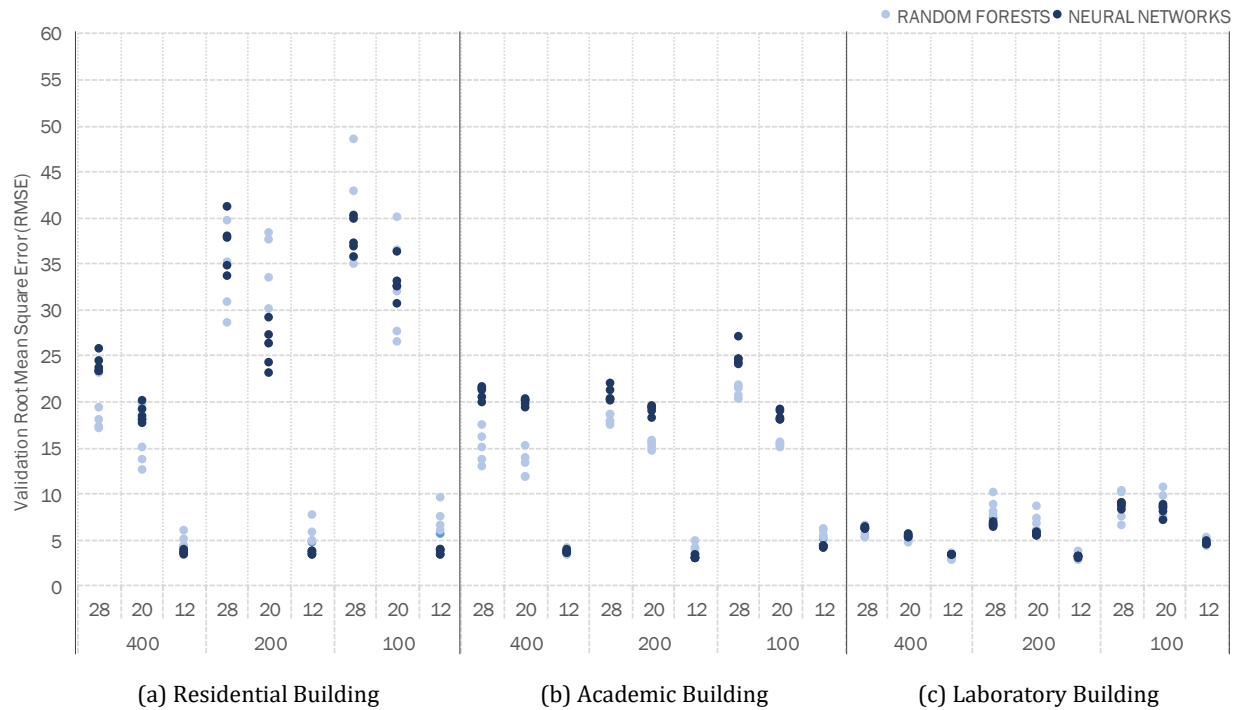


Figure 5-5: Summary of validation results from surrogate modeling component, showing error for all cases with different number of unknown parameters (28, 20 and 12) and number of training samples (400, 200 and 100).

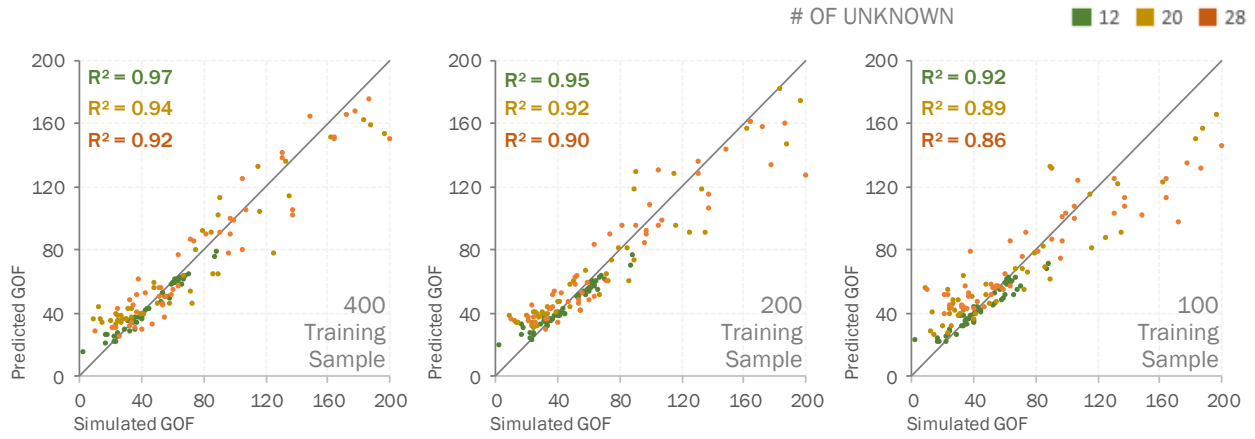
One surrogate model was selected for each of the 27 cases based on the lowest error and was designated as the “*trained model*” for that case. In order to quantify the ability of the surrogate models to mimic the engineering model, **Figure 5-6** shows a scatterplot between the simulated GOF, based on the engineering model, and the predicted GOF by each trained surrogate model for each sample in the testing data-set.

The models for the academic building present the highest coefficients of determination for all evaluation scenarios with R^2 values as high as 0.97 for the best-case scenario and higher than 0.85 even for the worst-case scenario. This is closely followed by laboratory buildings with R^2 values between 0.93 and 0.84. Surrogate model results show the lowest correlation with simulation results for the residential building with the best-case scenario R^2 value of 0.90 with a sharp drop to 0.12 for the worst-case scenario.

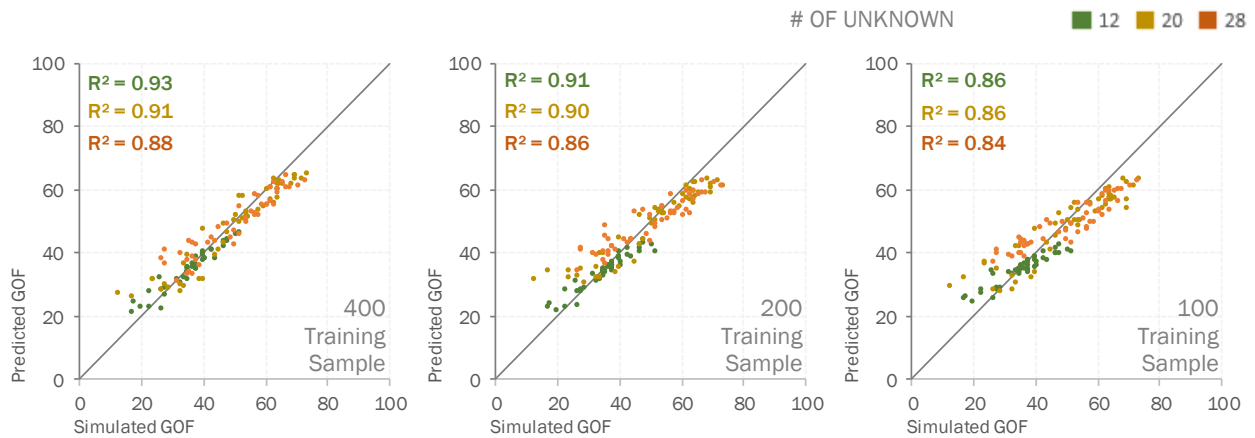
The results show that while 200 training samples are sufficient to develop robust models for all academic and laboratory building scenarios, high fidelity surrogate models with R^2 values higher than 0.7 are developed for residential buildings only when there are at least 400 training samples and at most 20 unknowns.



(a) Residential Building



(b) Academic Building



(c) Laboratory Building

Figure 5-6: Correlation between simulated and predicted GOFs for testing data-sets from all models. A perfectly predicting model would result in all data points falling along the diagonal line.

5.2.3. Detailed engineering models

The selected surrogate models are then combined with an optimization algorithm to determine the combinations of unknown parameter values that offer the least error for each case. **Figure 5-7** shows the graphical output from the optimization process for all studied scenarios where the function typically searched between 5,000 and 10,000 iterations of possible parameter combinations in 5 to 10 minutes before finding the combination with lowest GOF for that scenario.

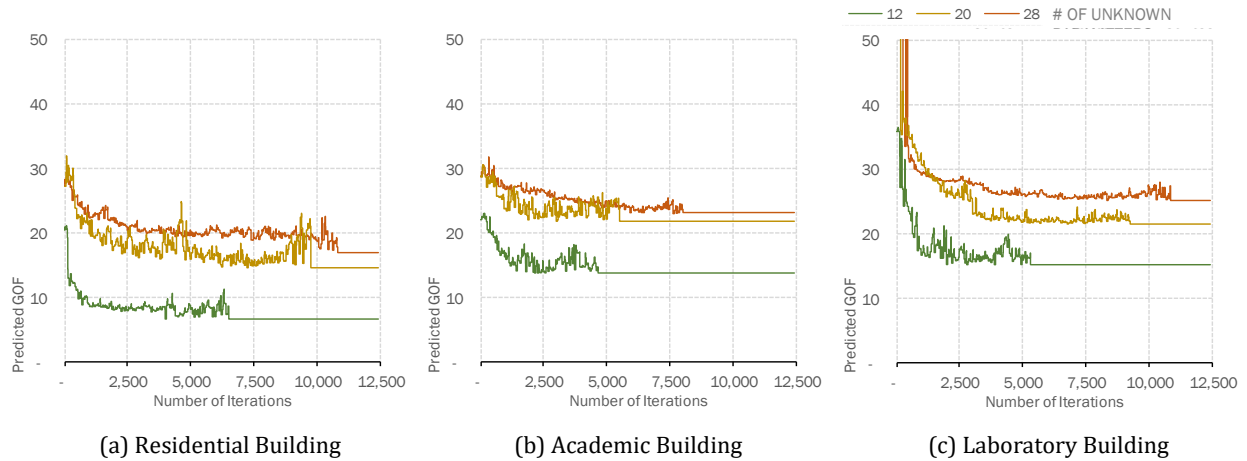


Figure 5-7: Graphic representation of genetic algorithm optimization process output.

Detailed EnergyPlus models were developed next using parameter properties estimated by the optimization routine as inputs, and are graphically represented in **Figure 5-8**. **Figure 5-9** presents the simulation results from these models. The thick dotted lines show the observed energy use, presented earlier in **Figure 4-7**, and the colored lines within solid bands presents the range of results from the energy models. For each building, the surrogate models developed with the least number of unknown parameters yielded models that result in monthly results closest to observed energy use.

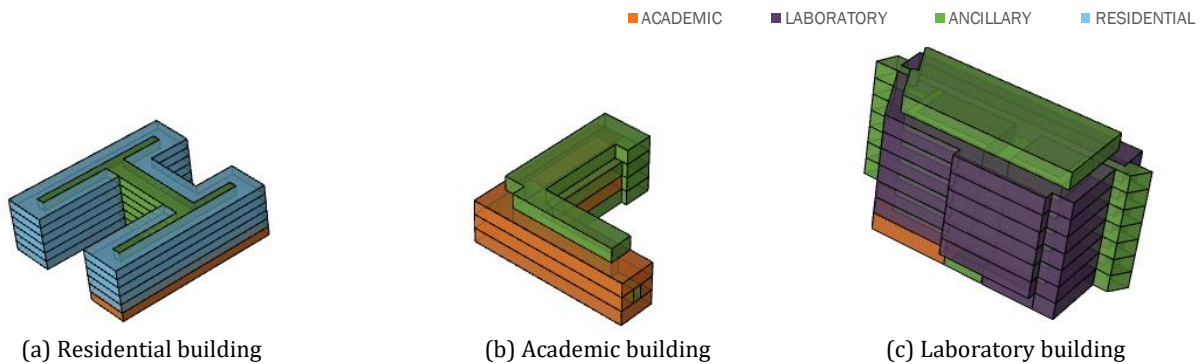
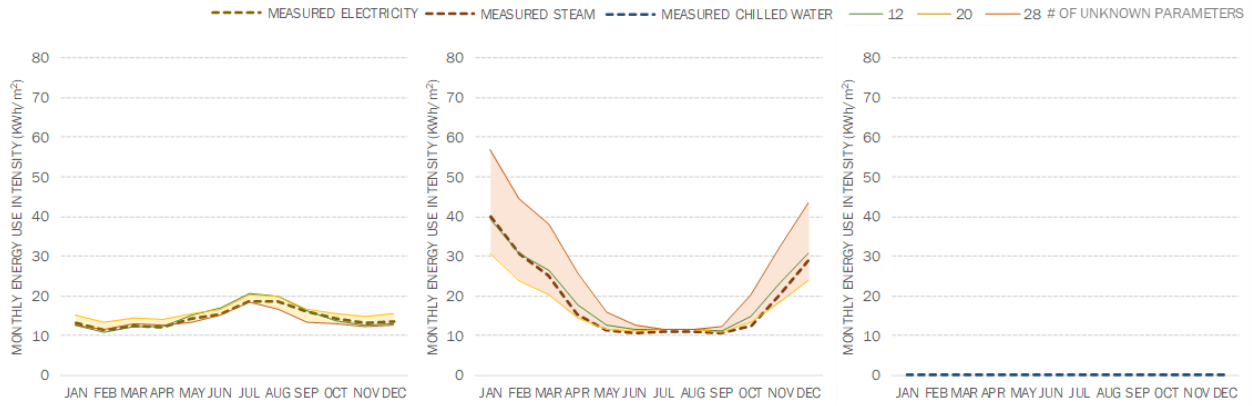
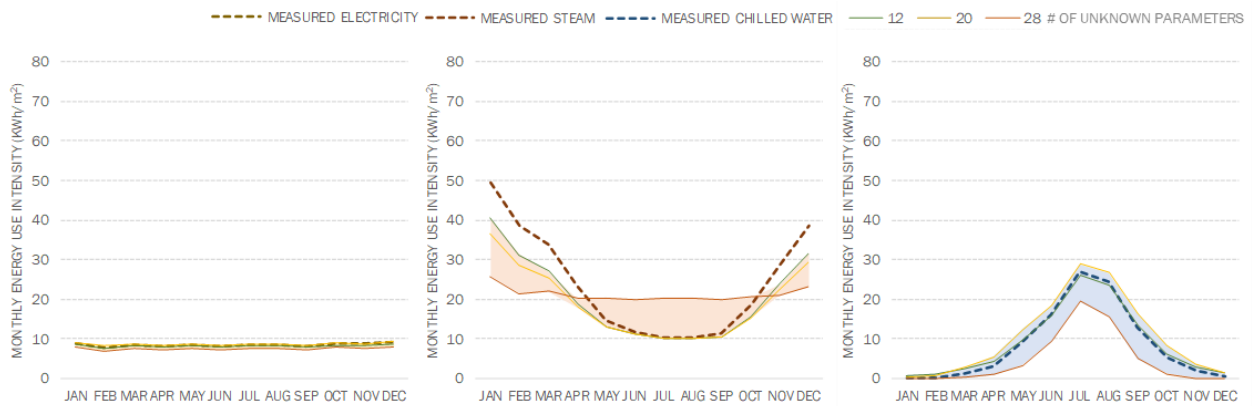


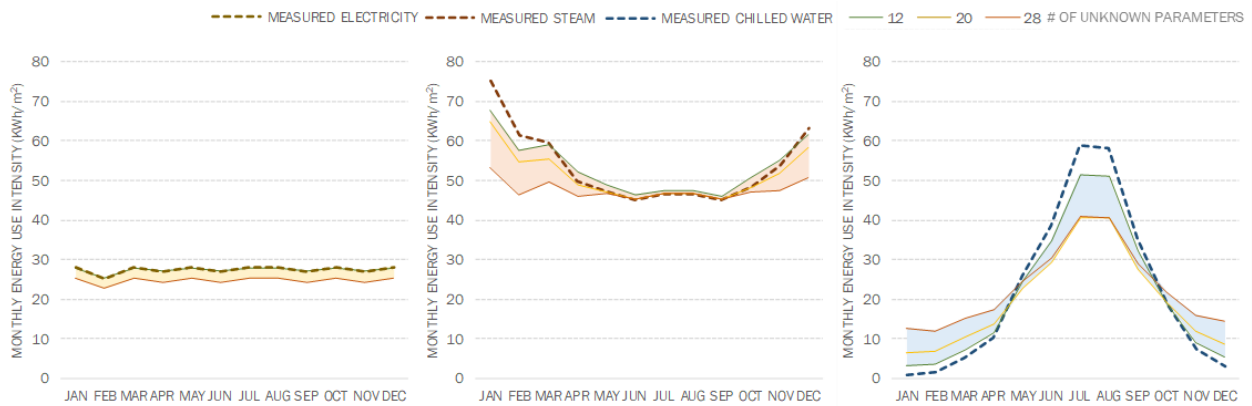
Figure 5-8: Graphic representation of reference whole building engineering models



(a) Residential Building



(b) Academic Building



(c) Laboratory Building

Figure 5-9: Comparison of observed and simulated monthly energy use by utility.

The comparison of monthly energy use, summarized in **Table 5-4**, shows that the resulting models are closely calibrated to electricity use, with both NMBE and CV lower than 5% for most cases except with high unknown variables that show errors just over 10%. The modeled steam use shows significant errors for the residential and academic buildings, with CV over 20% for the case with 20 unknown variables, and over 50% with 28 unknowns. The lab building shows the lowest errors, under 10% for the first two cases, and under 20% for the third case. Modeled chilled water use shows the largest errors, over a 60% CV for the academic, and 50% for the lab building, for the case with most unknowns.

The assumed weight of 3 for electricity relative to other end-uses in the workflow translates to relatively small overall errors, with both NMBE and CV under 10% for all cases with 12 unknowns, under 15% for cases with 20 unknowns, and except the academic building with a 26% CV, under 20% for the cases with most unknowns.

Table 5-4: Errors between observed and simulated monthly energy use for different evaluation scenarios.

Building type, # of Unknowns	Electricity		Steam		Chilled water		GOF	
	NMBE	CV	NMBE	CV	NMBE	CV	NMBE	CV
Residential								
12	-2%	7%	-6%	8%	-	-	3%	7%
20	-11%	12%	12%	22%	-	-	11%	13%
28	4%	8%	-42%	54%	-	-	13%	18%
Academic								
12	3%	3%	16%	21%	-6%	10%	5%	8%
20	-2%	3%	20%	28%	-23%	27%	9%	12%
28	11%	12%	12%	51%	46%	62%	18%	26%
Laboratory								
12	0%	0%	0%	6%	4%	17%	1%	5%
20	0%	1%	4%	8%	10%	42%	3%	13%
28	10%	11%	11%	18%	-4%	50%	10%	19%

ASHRAE Guideline 14 stipulates uncertainty limits of 5% for NMBE and 15% for CV for models to be considered calibrated. The results illustrate that all cases with 12 unknowns, and the laboratory case with 20 unknowns, fall within these uncertainty limits. The residential and academic cases with 20 unknowns meet the CV criteria but fail to meet the NMBE criteria. All cases with 28 unknowns fail to meet either criteria.

5.2.4. Unknown parameter estimates

Even when the simulation results closely match the observed energy use, the proposed methodology is effective only if the estimates for unknown parameters developed using these models with the optimization function are reasonably close to actual building characteristics from **Table 5-1**.

Figure 5-10 plots the discrepancy between the actual building characteristics and their corresponding estimates by the methodology. The vertical axes lists the 28 individual parameters, and also groups them into a broader category that includes 4 inter-dependent parameters as listed in **Table 5-5**, and the bars qualitatively show the deviation of model estimate from actual characteristics, with a bar to the left of the vertical black line representing a model estimate that is worse performing than the actual properties, a bar to the right representing better performing, and the absence of a bar representing an accurate estimate.

While the bars present the discrepancy in individual parameter estimates, the lines present the average discrepancy across a broader category for each case. The plots show that for each building type, the models with lesser number of unknowns result in more estimates closer to actual characteristics, with the residential building showing the maximum discrepancy.

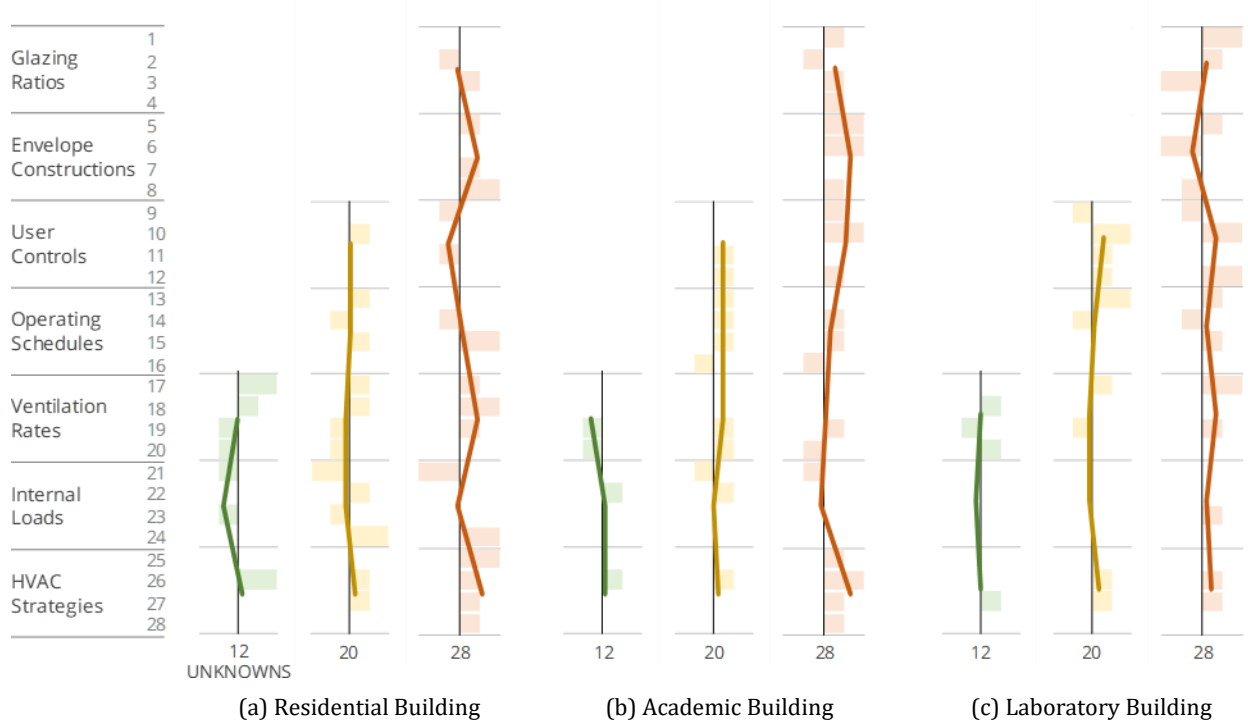


Figure 5-10: Discrepancy between model-estimated properties and actual building characteristics. The bars represent the discrepancy in each of the individual 28 parameters, while the solid lines present the average discrepancy across the 7 broader categories listed in **Table 5-5**.

Table 5-5: List of individual building parameters and broad categories of inter-dependent parameters.

Parameter categories	Individual parameters			
A. Glazing ratios	1. North window to wall ratio	2. South window to wall ratio	3. East window to wall ratio	4. West window to wall ratio
B. Envelope constructions	5. Window frame conductance	6. Wall construction	7. Roof construction	8. Glazing type
C. User controls	9. Window operation	10. Natural ventilation	11. Daylight response	12. Thermostat set-point
D. Operating schedules	13. Occupancy schedule	14. Equipment usage	15. Lighting usage	16. Service hot water usage
E. Ventilation rates	17. Perimeter occupant density	18. Core occupant density	19. Perimeter outside air flowrate	20. Core outside air flowrate
F. Internal loads	21. Perimeter equipment power	22. Perimeter lighting power	23. Core equipment power	24. Core lighting power
G. HVAC strategies	25. Perimeter demand-controlled ventilation	26. Core demand-controlled ventilation	27. Exhaust air energy recovery	28. Economizer cycle

For the case with least unknowns, 8 out of 12 parameters are accurately estimated for the academic and laboratory buildings, but only 5 for the residential building. With 20 parameters unknown, the models accurately estimate 10 for the laboratory and academic, and only 6 for the residential building. For the last case with 28 unknowns, only 10 or less are accurately estimated for each highlighting model limitations in estimating properties of individual parameters when several inter-dependent parameters are simultaneously unknown.

When the inter-dependent parameters are grouped together, however, the average discrepancies for these broader categories are considerably smaller than individual estimates. For the two cases where the envelope parameters are known, shown by the yellow and green lines, the models estimate the overall performance of all remaining categories fairly accurately.

When envelope characteristics are not known, however, the estimates show discrepancies across all categories as can be seen by the red line.

5.3. Discussion and limitations

A close inspection of results reveals that, across all cases, electricity consumption is most closely replicated, even on a month by month basis. The models, therefore, reasonably estimate internal load densities and operating parameters irrespective of the number of other unknowns. Similarly, the service hot water usage that forms the heating base load in summer months is also reasonably estimated for almost all cases. Although the surrogate models did not estimate the exact values for all individual characteristics accurately, they reasonably estimated the average performance of broad categories of climate independent characteristics, and their contribution to overall energy use. Accordingly, although the resulting energy models should not be utilized to assess the effect of changing only one of several internal load parameters, these models can reasonably assess the overall savings potential if the interdependent parameters were simultaneously made more efficient.

In contrast to electricity use, all cases present discrepancies in the heating and cooling energy results, in winter and summer months respectively. These discrepancies are especially pronounced for cases with the largest number of unknown parameters. The models therefore fall short of accurately estimating the climate dependent characteristics, especially when both envelope as well as ventilation parameters are simultaneously unknown. It is therefore important that information regarding the building envelope is known for the models to reasonably estimate other climate dependent characteristics. Although these models should not be utilized to evaluate the effect of changing individual parameters such as incorporating demand-controlled ventilation independently, the models can reasonably assess the overall savings potential if these interdependent ventilation strategies were incorporated simultaneously.

Finally, this methodology is most effective for building types where only a few parameters largely drive the energy use. This is illustrated by the results for the laboratory building in the case study. When the impact of several characteristics such as envelope properties or occupant behavior on building energy use is relatively smaller, the methodology offered better parameter estimates, and lower errors between the observed and simulated energy use from resulting models. In contrast, when the energy use is affected to a similar degree by a large number of performance parameters, the accuracy falls sharply. This can be seen from the large errors in individual parameter estimates for the residential case study where the envelope properties, internal loads, occupant behavior, ventilation rates and mechanical system characteristics all affect the energy use relatively similarly.

A method to address the uncertainty inherent in auto-calibrated energy models generated through this workflow is presented in Chapter 7.

6. Energy Supply Systems¹

This chapter presents a simple planning tool, developed around an existing urban planning & architectural tool, UMI (Reinhart et al. 2013) to evaluate various energy supply configurations to compare the operational energy use, annual energy costs and greenhouse gas emissions associated with purchased grid utilities for different scenarios. **Figure 6-1** presents the schematic arrangement of various thermal plant equipment that are incorporated in this tool and illustrates the translation of campus building loads on the left, to purchased utilities on the right.

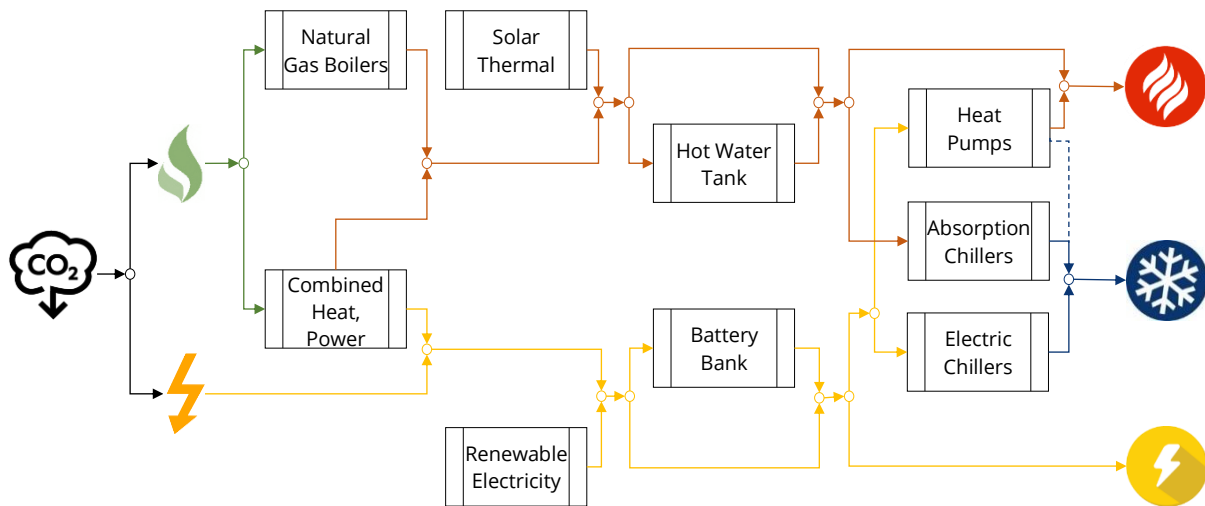


Figure 6-1: Thermal plant schematic to calculate the energy use, energy costs and greenhouse gas emissions associated with purchased utilities based on building energy requirements and user defined characteristics. The model can be easily adapted to rearrange the sequence or add new components with different parameters.

The input to the tool includes hourly load profiles for electricity and hot water as simulated by the distribution network module. As each equipment is individually enabled or disabled by the user, and its performance characteristics are modified, the thermal plant planning tool calculates, in real time, the hourly consumption of purchased grid electricity and natural gas. Based on user defined cost and emission factors for various components and purchased utilities, first costs, annual energy costs and greenhouse gas emissions are then calculated to allow an informed assessment of each scenario.

The workflow is applied to a hypothetical site that is located in a cold-climate region where the electricity carbon content is high. To illustrate one of the many study-schemes this workflow can achieve, a simple comparison of three distinct energy supply scenarios is presented and compared for their impact on campus energy costs and greenhouse gas emissions. The calculations at each step, and the user defined input parameters are discussed in detail in the following sub-section.

¹ A version of this chapter has been published: S. Duchesne, S. Nagpal, M. Kummert, C. Reinhart, Balancing demand & supply: Linking neighborhood level building load calculations with detailed district energy network analysis models, Energy, 2018.

6.1. Proposed workflow

A district level thermal energy plant consists of several components that serve the distribution network for a project's hot water, chilled water and electricity requirements by converting grid purchased utilities into usable thermal and electrical energy. The plant inputs, usually a combination of grid electricity and natural gas, can vary considerably based on the selection, capacities and efficiencies of various plant equipment. The thermal plant should be configured carefully after considering the load balance between project electricity and thermal energy requirements, and the relative emissions and costs associated with grid electricity and natural gas.

For instance, natural gas-powered cogeneration can offer substantial operational energy cost savings in regions where the relative cost of grid electricity is considerably higher than purchased natural gas; however, if grid electricity is generated from low emission sources such as wind, solar or even nuclear, the natural gas consumption in the cogeneration plant will result in higher greenhouse gas emissions. In this scenario, an all-electric thermal energy plant, with heat pumps to serve the project hot water requirements, will eliminate onsite fossil fuel consumption and reduce greenhouse gas emissions, but result in higher operational energy costs.

To make informed decisions, it is therefore important to evaluate various possible thermal plant configurations, especially at initial design stages, to compare the operational energy use, annual energy costs and greenhouse gas emissions associated with purchased grid utilities for different scenarios. This section presents the underlying equations used at each step in the custom energy-supply scenario-planning tool, developed especially for this purpose using custom Grasshopper and Rhino components.

6.1.1. Energy supply equipment

Chilled water equipment: The chilled water load profile from the distribution network, (CHW_n), for each hour, (n), serves as one of the inputs into the chilled water generation module. Additional user inputs include the cooling capacity of absorption chillers (CAP_{ABS}) and the coefficient of performance for absorption ($CCOP_{ABS}$) and electric ($CCOP_{ECH}$) chillers. The model assumes that, when present, the absorption chillers are base-loaded, and the annual hot water (HW_{ABS}) required to generate project chilled water can be expressed as:

$$HW_{ABS} = \sum_{n=1}^{8760} [MIN (CHW_n, CAP_{ABS}) \div CCOP_{ABS}] \quad \dots (1)$$

Any loads in surplus of the absorption chiller capacity are met by electric chillers for each hour. The results from this component are hourly profiles for electricity consumption, ($ELEC_{ECH}$), to generate project chilled water, and the annual total can be expressed as:

$$ELEC_{ECH} = \sum_{n=1}^{8760} [(CHW_n - CAP_{ABS}) \div CCOP_{ECH}] \text{ if } CHW_n > CAP_{ABS} \quad \dots (2)$$

Hot water equipment: Similar to chilled water, hourly hot water load profile (HW_n) is input to the model from the distribution network module. The model assumes that these loads are first met by electric heat pumps, and only loads in surplus of their user defined capacity are sent to the remaining equipment. The electricity consumption ($ELEC_{EHP}$) required to generate hot water from heat pumps is based on their capacity (CAP_{EHP}) and heating coefficient of performance ($HCOP_{EHP}$):

$$ELEC_{EHP} = \sum_{n=1}^{8760} [MIN (HW_n, CAP_{EHP}) \div HCOP_{EHP}] \quad \dots (3)$$

After subtracting the hot water load met by electric heat pumps (HW_{EHP}) the hot water equipment within the thermal plant serves the previously calculated hourly hot water requirement of absorption chillers in addition to the project loads. This total remaining demand is assumed to be served first by a combination of solar thermal collectors (HW_{SHW}) and hot water storage tanks (HW_{HWT}) and then by a cogeneration plant (HW_{CHP}) based on user defined parameters and model calculated discharge capacity for each equipment, for each hour. These components are discussed in detail in following sub sections. Any loads in surplus of the combined capacities of above equipment, for each hour, are assumed to be serve by natural gas boilers based on the user defined efficiency (EFF_{NGB}). The annual boiler natural gas consumption to generate project hot water ($NGAS_{NGB}$) can be expressed as:

$$NGAS_{NGB} = \sum_{n=1}^{8760} [\{HW_n - HW_{EHP} + HW_{ABS} - HW_{SHW} - HW_{HWT} - HW_{CHP}\} \div EFF_{NGB}] \quad \dots (4)$$

Solar thermal collectors and storage tanks: This module calculates hot water generation potential per unit collector area based on user defined values of collector efficiency (EFF_{SHW}) an area utilization factor to account for collector frames and other infrastructural requirements ($UTIL_{SHW}$) and miscellaneous losses ($LOSS_{SHW}$). In addition to these performance parameters, users input an offset target as a percentage of total annual hot water demand.

In combination with the hourly solar radiation data available from the weather file (RAD_n), the model calculates the overall area needed for solar collectors ($AREA_{SHW}$) and the annual total solar hot water generation to meet building loads (HW_{SHW}) which can be expressed as:

$$HW_{SHW} = \sum_{n=1}^{8760} MIN[\{RAD_n \times AREA_{SHW} \times EFF_{SHW} \times UTIL_{SHW} \times LOSS_{SHW}\}, \{HW_n - HW_{EHP}\}] \dots (5)$$

Any generation in surplus of the project loads for each hour is assumed to charge a hot water tank. Based on a user defined tank capacity (CAP_{HWT}) the previous hour's charge (CHG_{n-1}) and current hour's surplus (SUR_n) or deficit (DEF_n) the model calculates the tank charge for each hour (CHG_n), which can be expressed as:

$$CHG_n = \sum_{n=1}^{8760} MIN [(CHG_{n-1} + SUR_n - DEF_n), (CAP_{HWT})] \dots (6)$$

For hours when the project demand is greater than the generated solar hot water, the tanks discharge to meet the deficit up to a user defined discharge rate ($DCHG_{HWT}$). The annual demand met by hot water tanks (HW_{HWT}) can be expressed as:

$$HW_{HWT} = \sum_{n=1}^{8760} MIN [(CHG_n), (DCHG_{HWT})] \dots (7)$$

Renewable electricity and battery bank: The electric load profile from the distribution network ($ELEC_n$) for each hour, (n), serves as one of the inputs into the renewable electricity generation module. This module incorporates two different technologies and calculates electricity generation potential per unit cell area for photovoltaics, and per unit rotor area for wind turbines.

The photovoltaic calculation is based on user defined values for panel efficiency (EFF_{PV}) an area utilization factor to account for panel frames and other infrastructural requirements ($UTIL_{PV}$) and miscellaneous losses ($LOSS_{PV}$). In addition to these performance parameters, users input an offset target as a percentage of total electricity demand.

In combination with the hourly solar radiation data available from the weather file (RAD_n) The model calculates the overall area needed for the photovoltaic array ($AREA_{PV}$) and the total electricity generation ($ELEC_{PV}$) expressed as:

$$ELEC_{PV} = \sum_{n=1}^{8760} (RAD_n \times AREA_{PV} \times EFF_{PV} \times UTIL_{PV} \times LOSS_{PV}) \quad \dots (8)$$

The wind turbine calculation is based on user defined values for turbine coefficient of performance (COP_{WND}), the rotor area per turbine (ROT_{WND}), and miscellaneous losses ($LOSS_{WND}$). In addition to these performance parameters, users input an offset target as a percentage of total electricity demand. In combination with the hourly wind velocity data available from the weather file ($WIND_n$), The model calculates the number of turbines needed (NUM_{WND}) and the annual electricity generation ($ELEC_{WND}$) which can be expressed as:

$$ELEC_{WND} = \sum_{n=1}^{8760} (0.6375 \times WIND_n^3 \times ROT_{WND} \times NUM_{WND} \times COP_{WND} \times LOSS_{WND}) \quad \dots (9)$$

The total renewable electricity ($ELEC_{REN}$) that can be attributed to offset project demand for each hour can be expressed as:

$$ELEC_{REN} = \sum_{n=1}^{8760} MIN [(ELEC_{PV} + ELEC_{WND}), (ELEC_n)] \quad \dots (10)$$

Any generation that is surplus of the project loads for each hour is assumed to charge a battery bank. Based on a user defined battery capacity (CAP_{BAT}) the previous hour's charge (CHG_{n-1}) and current hour's surplus (SUR_n) or deficit (DEF_n) the model calculates the battery charge for each hour (CHG_n), which can be expressed as:

$$CHG_n = \sum_{n=1}^{8760} MIN [(CHG_{n-1} + SUR_n - DEF_n), (CAP_{BAT})] \quad \dots (11)$$

For hours when the project demand is greater than the renewable generation, the batteries discharge to meet the deficit up to a user defined discharge rate ($DCHG_{BAT}$). The annual demand met by the battery bank ($ELEC_{BAT}$) can be expressed as:

$$ELEC_{BAT} = \sum_{n=1}^{8760} MIN [(CHG_n), (DCHG_{BAT})] \quad \dots (12)$$

Combined heat and power: By default, the combined heat and power component tracks and serves the remaining project hot water demand up to its maximum heating capacity. The heating capacity is calculated by the model based on user defined electrical capacity (CAP_{CHP}), electricity generation efficiency (EFF_{CHP}), and heat recovery effectiveness ($HREC_{CHP}$). The annual heating energy recovered from the combined heat and power plant and supplied to the project (HW_{CHP}):

$$HW_{CHP} = \sum_{n=1}^{8760} \text{MIN} [(CAP_{CHP} \div EFF_{CHP} \times HREC_{CHP}), (HW_n - HW_{EHP} + HW_{ABS} - HW_{SHW})] \dots (13)$$

In the thermal tracking mode, the natural gas consumed ($NGAS_{CHP}$) and the electricity generated ($ELEC_{CHP}$) by the combined heat and power plant can be expressed as:

$$NGAS_{CHP} = \sum_{n=1}^{8760} (HW_{CHP} \div HREC_{CHP}) \dots (14)$$

$$ELEC_{CHP} = \sum_{n=1}^{8760} (NGAS_{CHP} \times EFF_{CHP}) \dots (15)$$

The module can also be assigned to track electricity instead of the thermal load. In this case the combined heat and power component tracks and serves the project electrical load up to its capacity, that remains after subtracting the renewable system ($ELEC_{REN}$) and battery bank ($ELEC_{BAT}$) supply from overall demand ($ELEC_n$). The hourly electricity generated by the combined heat and power plant and supplied to the project ($ELEC_{CHP}$) can be expressed as:

$$ELEC_{CHP} = \sum_{n=1}^{8760} \text{MIN} [CAP_{CHP}, (ELEC_n - ELEC_{REN} - ELEC_{BAT})] \dots (16)$$

In the electrical tracking mode, the natural gas consumed ($NGAS_{CHP}$) and the hot water recovered (HW_{CHP}) by the combined heat and power plant can be expressed as:

$$NGAS_{CHP} = \sum_{n=1}^{8760} (ELEC_{CHP} \div EFF_{CHP}) \dots (17)$$

$$HW_{CHP} = \sum_{n=1}^{8760} (NGAS_{CHP} \times HREC_{CHP}) \dots (18)$$

Similar to surplus hourly generation from the renewable technologies, any surplus electricity generated by the combined heat and power plant in the track-thermal mode, and surplus hot water recovered in the track-electricity mode, can be used to charge the previously discussed battery bank, and hot water storage tanks respectively.

6.1.2. Purchased utilities

The model combines the results of all the above modules, and calculates the total project site energy in terms of hourly purchased grid electricity ($ELEC_{PROJ}$) and natural gas ($NGAS_{PROJ}$), which can be expressed as:

$$ELEC_{PROJ} = ELEC_n - ELEC_{REN} - ELEC_{BAT} - ELEC_{CHP} \quad \dots (19)$$

$$NGAS_{PROJ} = NGAS_{NGB} + NGAS_{CHP} \quad \dots (20)$$

Once the annual electricity and natural gas consumption is determined, the associated operational energy costs and greenhouse gas emissions can be calculated based on user input cost and emission factors for each purchased utility.

6.1.3. Input and output template definition

All model calculations are based on various user inputs that define plant configuration, equipment capacities, and performance parameters. **Table 6-1** presents the inputs associated with each component in the thermal plant model, their associated units, and the default parameter values that are used for calculations in case there are no specific user assignments. The default performance values are based largely on the estimates from guidance published by US Green Building Council (USGBC, 2010). Since this model is developed for early design stage analysis, detailed information about number of equipment, individual equipment capacities, and control sequences are not expected to be available. Accordingly, detailed calculations for items such as equipment hourly part load performance, or ancillary equipment such as pumps and cooling towers, will only add unnecessary precision without any gains in the accuracy of results. The model, therefore, relies on annual average component efficiencies or coefficients of performance for overall components that incorporate the impact of all associated factors within that component. Design sizes for all equipment are calculated by the model based on the user-defined capacity and energy-offset factors. Electric chillers and natural gas boilers are modeled to serve any demand that cannot be met by other plant equipment.

Table 6-1: Model input parameters.

Model component / Input parameter	Symbol	Default Value
Hourly chilled water load profile (kWh)	CHW_n	
Hourly hot water load profile (kWh)	HW_n	From distribution network
Hourly electricity load profile (kWh)	$ELEC_n$	
Hourly location solar radiation data (kWh/m ²)	RAD_n	From selected weather file
Hourly location wind speed data (m/s)	$WIND_n$	
1. Absorption chillers		
Capacity as percent of peak cooling load (%)	OFF_{ABS}	50
Cooling coefficient of performance	$CCOP_{ABS}$	0.90
2. Electric chillers		
Cooling coefficient of performance	$CCOP_{ECH}$	4.40
3. Electric heat pumps		
Capacity as percent of peak heating load (%)	OFF_{EHP}	0
Heating coefficient of performance	$HCOPEHP$	3.20
4. Natural gas boilers		
Heating efficiency (%)	EFF_{NGB}	70
5. Solar thermal collectors		
Target offset as percent of annual energy (%)	OFF_{SHW}	10
Collector efficiency (%)	EFF_{SHW}	45
Area utilization factor (%)	$UTIL_{SHW}$	75
Miscellaneous losses (%)	$LOSS_{SHW}$	15
6. Hot water storage tanks		
Capacity as number of days of autonomy (#)	AUT_{HWT}	1.0
Miscellaneous losses (%)	$LOSS_{HWT}$	15
7. Photovoltaic array		
Target offset as percent of annual energy (%)	OFF_{PV}	5
Cell efficiency (%)	EFF_{PV}	15
Area utilization factor (%)	$UTIL_{PV}$	75
Miscellaneous losses (%)	$LOSS_{PV}$	15
8. Wind turbines		
Target offset as percent of annual energy (%)	OFF_{WND}	5
Turbine coefficient of performance	COP_{WND}	0.3
Cut-in speed (m/s)	CIN_{WND}	5
Cut-out speed (m/s)	COU_{WND}	25
Rotor area per turbine (m ²)	ROT_{WND}	15
9. Battery bank		
Capacity as number of days of autonomy (#)	AUT_{BAT}	1
Miscellaneous losses (%)	$LOSS_{BAT}$	15
10. Combined heat and power		
Tracking mode	$TMOD_{CHP}$	Thermal
Capacity as percent of peak electric load (%)	OFF_{CHP}	50
Electrical efficiency (%)	EFF_{CHP}	22
Waste heat recovery effectiveness (%)	$HREC_{CHP}$	29

Table 6-2: Model Output parameters.

Model component / Output parameter	Symbol
1. Absorption chillers	
Design cooling capacity (kW)	CAP_{ABS}
Hot water consumption (kWh)	HW_{ABS}
2. Electric chillers	
Design cooling capacity (kW)	CAP_{ECH}
Electricity consumption (kWh)	$ELEC_{ECH}$
3. Electric heat pumps	
Design heating capacity (kW)	CAP_{EHP}
Electricity consumption (kWh)	$ELEC_{EHP}$
4. Natural gas boilers	
Design heating capacity (kW)	CAP_{NGB}
Natural gas consumption (kWh)	$NGAS_{NGB}$
5. Solar thermal collectors	
Design heating capacity (kW)	CAP_{SHW}
Area footprint required (m ²)	$AREA_{SHW}$
Annual energy offset (kWh)	HW_{SHW}
6. Hot water storage tanks	
Design tank capacity (kWh)	CAP_{HWT}
Annual energy offset (kWh)	HW_{HWT}
7. Photovoltaic array	
Peak electric power (kW)	CAP_{PV}
Area footprint required (m ²)	$AREA_{PV}$
Annual energy offset (kWh)	$ELEC_{PV}$
8. Wind turbines	
Peak electric power (kW)	CAP_{WND}
Number of turbines required (#)	NUM_{WND}
Annual energy offset (kWh)	$ELEC_{WND}$
9. Battery bank	
Design battery storage capacity (kWh)	CAP_{BAT}
Annual energy offset (kWh)	$ELEC_{BAT}$
10. Combined heat and power	
Peak electric power (kW)	CAP_{CHP}
Annual electricity offset (kWh)	$ELEC_{CHP}$
Annual hot water offset (kWh)	HW_{CHP}
Natural gas consumption (kWh)	$NGAS_{CHP}$
11. Annual purchased electricity requirement (kWh)	$ELEC_{PROJ}$
12. Annual purchased natural gas requirement (kWh)	$NGAS_{PROJ}$

The design capacity outputs for each component can be utilized to develop estimates for first costs and other infrastructural requirements for further analyses such as life cycle costing or space planning. The results from energy calculations at each step, combined with user-defined source energy, cost and emission factors for grid purchased electricity and natural gas are applied within the model to calculate the project total source energy, energy costs and greenhouse gas emissions for any scenario. **Table 6-3** lists the operational energy factors and their default assumptions used by the model when no user assignments are specified. The final set of results from the model output for any configuration are presented in **Table 6-4**. A comparison of these results for multiple scenarios will allow for an informed assessment of the feasibility of each scenario.

Table 6-3: Operational energy cost and emissions factors.

Operational energy factors	Default Value
Source energy (kWh/kWh)	
Electricity	3.34
Natural Gas	1.05
Costs (\$/kWh)	
Electricity	0.15
Natural Gas	0.05
Greenhouse gas emissions (CO _{2e} mTon/MWh)	
Electricity	0.45
Natural Gas	0.16

Table 6-4: Model final results.

Parameter	Units
Annual source energy	MWh
Annual energy costs	\$
Annual greenhouse gas emissions	MTons

To illustrate one of the many study schemes this workflow can achieve, a simple comparison of two distinct urban density development scenarios is presented and compared in the next section. The presented workflow and the discussion of results highlights the impacts of design decisions that should occur at an early stage in the design process.

6.2. Application case study

The workflow is applied to a small neighborhood of 0.5 km²: approximately 370,000 m² of floor area for ~15,000 occupants. It is assumed that this hypothetical site is located in a cold-climate region where the electricity carbon content is high. Therefore, the Madison, WI weather file is used in the model. To help setup this example, the building 3D model and street grid is based on an existing location. A neighborhood Geographic Information System (GIS) database is utilized to automatically generate extruded massing models of the campus. Additional envelope data, which consists of floor heights, fenestration configuration, window opening ratios, and construction assemblies, is based on architectural drawings or on visual inspection where drawings are not available. The building stock is then abstracted into six predominant land uses and ten programmatic feature archetypes that represent a group of buildings with similar non-geometric properties. **Figure 6-2** presents a graphic rendering of the UBEM model showing the distribution of different land uses.

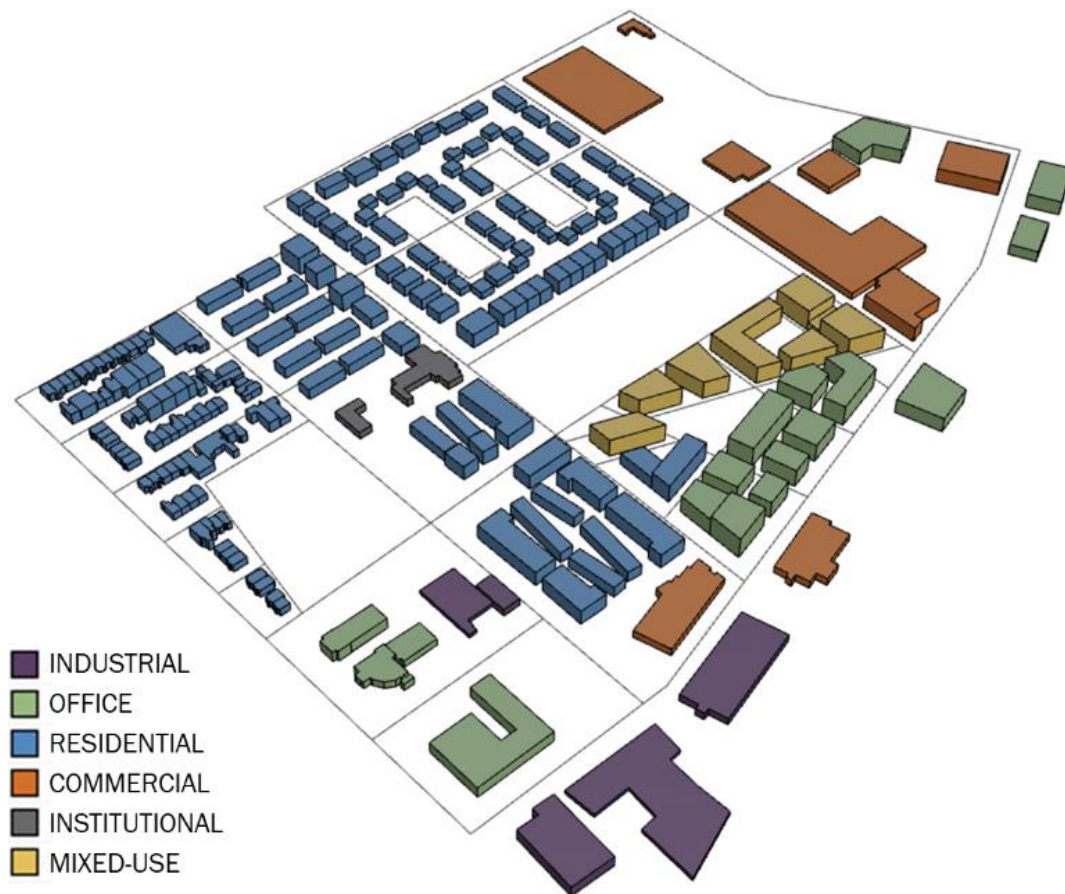


Figure 6-2: Graphic rendering of the neighborhood. Buildings are colored according to their programmatic usage. Circled blocks in pink identify buildings emphasized in scenario A and B.

Input templates are created for each of these archetypes and assigned, one per building, across the neighborhood. Non-geometric performance properties, such as occupant densities, lighting and miscellaneous equipment power, and usage schedules are estimated based on building program uses. These model input parameters for different programmatic archetypes are summarized in **Table 6-5**.

Table 6-5: Summary of key UBEEM input parameters.

Land Use	Industrial	Residential	Institutional	Commercial	Mixed-Use		
Archetype	Warehouse	Residential	Kindergarten	Office	Restaurant	Retail	Mixed-Use
Average WWR	0.20	0.30	0.40	0.40	0.50	0.50	0.40
Wall U (W/m ² K)	0.62	0.62	0.62	0.52	0.52	0.52	0.52
Roof U (W/m ² K)	0.38	0.38	0.38	0.28	0.28	0.28	0.28
Window U (W/m ² K)	3.12	3.12	3.12	2.72	2.72	2.72	2.72
Glazing SHGC	0.76	0.76	0.76	0.69	0.69	0.69	0.69
Infiltration (ACH)	0.15	0.15	0.15	0.10	0.10	0.10	0.10
Occupants (pp/m ²)	0.015	0.028	0.050	0.050	0.086	0.086	0.050
Equipment (W/m ²)	15.0	5.0	2.5	7.5	5.0	2.5	7.5
Lighting (W/m ²)	9.7	6.5	15.1	9.7	15.1	15.1	9.7
DHW (m ³ /h/m ²)	0.0001	0.0005	0.0002	0.0002	0.0005	0.0001	0.0002
Heat set-point (°C)	21	22	22	21	21	21	21
Cool set-point (°C)	24	24	24	24	24	24	24
Ventilation (m ³ /s/pp)	-	-	0.0025	0.0025	-	-	-
Ventilation (m ³ /s/m ²)	0.0003	-	0.0003	0.0003	0.0006	0.0003	0.0006

6.2.1. Evaluation scenarios

To demonstrate the approach, this section compares carbon emissions and operational costs for three energy supply scenarios for the neighborhood proposal. Their performance parameters are taken from **Table 6-1** and the techno-economic parameters for this optimization are taken from **Table 6-3** for all scenarios. As illustrated in **Figure 6-3**, the reference scenario assumes heating needs are met by individual natural gas boilers while electricity demand is met by the grid. For the all-electric scenario, grid electricity drives heat pumps to supply hot water to connected buildings, meeting the space heating and domestic hot water demand. Electric demand is met by the local grid. In the all-gas scenario, a Combined Heat & Power plant, with gas fired backup boilers, is modeled and supplies hot water and electricity to connected buildings.

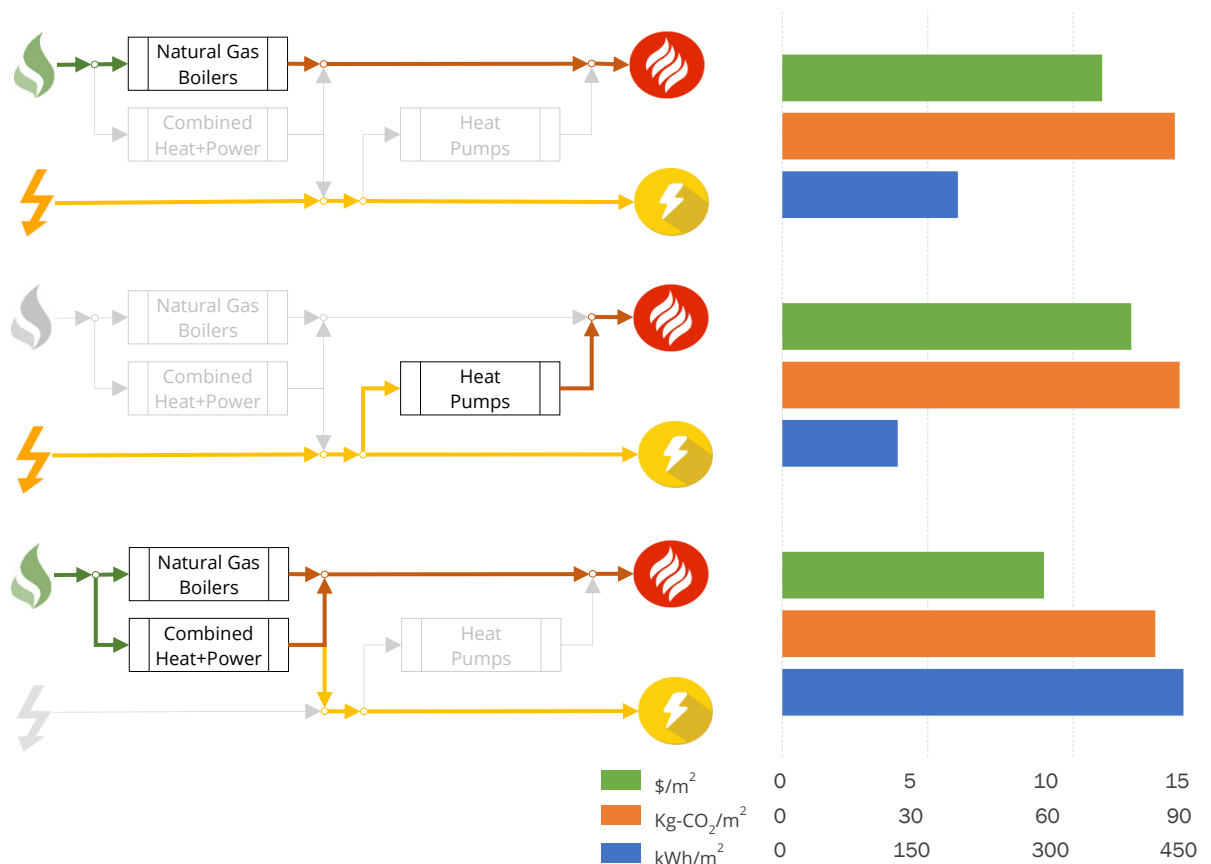


Figure 6-3: Heat generation schemes for the reference subcase (top), the all-electric subcase (middle) and the all-gas subcase (bottom). The chart shows site energy use intensity, GHG emissions and purchased utility costs.

6.2.2. Results

The method application to this case study with different energy supply scenarios yields differing results, as shown in **Figure 6-3**, and their performance, as summarized in **Table 6-6**. For the example analysis, All-Gas has the lowest operational energy costs with assumed gas and electricity prices of 0.04 US\$/kWh and 0.19 US\$/kWh, respectively. In contrast, annual carbon emissions are lowest for all electric because in 2018 close to 50% of electricity were being generated by renewable energy sources and nuclear power plants leading to associated GHG emissions of 0.257 kgCO_{2e}/kWh for electricity and 0.180 kgCO_{2e}/kWh for natural gas (US-EPA, 2018). In the case of new developments, where buildings and their energy supply systems have to be designed and constructed, the analysis presents an approach where simulated building load curves can be combined with energy supply models ranging from building level systems to micro grids. This type integrated cost and carbon analysis can be complemented with financing schemas, allowing decision makers to understand the long term financial and environmental viability of a project.

Table 6-6: Full site performance.

Model component	Reference	All-Electric	All-Gas
1. Annual performance			
kWh/m ²	181	119	414
CO _{2e} /m ²	81	82	77
\$/m ²	11	12	9
2. Heating demand met by the DH network			
Peak load [MW]	-	74.4	74.4
Annual Energy [GWh]	-	31.4	31.4
3. Electricity demand met by utility grid			
Peak load [MW]	40.1	42.3	4.2
Annual Energy [GWh]	39.9	49.7	1.9

6.3. Discussion and limitations

Planning for district energy systems is a challenging task especially in areas where district energy is not a common technology. While bringing together different actors ranging from the developer to the urban planner, engineer and future users, is a recognized means to initiate a discussion whether centralized energy supply systems could be suitable for a given project, a practical challenge has been for planning and engineering teams to conduct an integrated analysis during those early planning stages. The methodology presented in this chapter overcomes some of those challenges, demonstrating a new way of designing for future district energy systems.

The methodology follows a simple workflow. First, the UBEM is defined and simulated. Then, exploring different thermal plant schemes informs the environmental and economic performance of the whole neighborhood. Together with a more streamlined workflow, it is possible, at any time, to go back to previous steps and change modeling assumptions and their impact on the final design. Different actors can thus share and explore various aspects of the problem at hand, making this tool a more collaborative platform.

The method presented here is a simple way of identifying the impact of a design decision on the performance of a neighborhood with a district energy system. A number of simplifications are necessary to facilitate data input and reduce computational time. Ultimately, however, an easy exploration of different plant scenario properties should trigger the optimization thought process that should reflect changes back to the thermal plant model.

7. Continuous Planning Framework¹

This chapter proposes an approach that combines the campus energy model generation techniques, presented in Chapter 4, and the auto-calibration methodology to rapidly estimate properties of unknown building performance characteristics developed in Chapter 5; and proposes methods to develop baseline individual building energy models that address the inherent and allow for evaluation of future energy scenarios.

7.1. Workflow

7.1.1. Auto-calibrated UBEM

As discussed in Chapter 5, when detailed information regarding a performance characteristic is not available for a specific building, the previously developed auto-calibration methodology employs surrogate models, a class of machine learning algorithms, to create mathematical approximations of the physical behavior of building systems based on the known performance characteristics and measured energy use data. These approximation models are then used in combination with optimization routines to estimate the properties of unknown building performance parameters that result in simulated monthly energy consumption closely matching to observed data for that building. **Figure 7-1** shows the graphical output from the optimization process for the example building where the function searched around 10,000 iterations of possible parameter combinations before identifying the solution with the least error between modeled and observed energy use.

In addition to measured energy use, the key input data required for the development of such models includes a database of all known building performance characteristics. For each building, information related to building massing and geometry, and window to wall ratios and envelope constructions, i.e. the first 12 parameters in **Table 7-1**, is populated in the database either through available GIS data or collected through building audits and design drawings. The remaining 20 variables include operational and usage profiles, and electrical and mechanical system characteristics that are typically the most difficult to document for existing buildings. These are assumed to be unknown for the purposes of calibration. **Table 7-1** illustrates the structure of this database with the details of all known energy model parameters for the example building, as well as the list of all parameters that are unknown. When any of these parameters cannot be determined via observation or building monitoring systems, they are marked as unknown in the database, are estimated by the auto-calibration process, and incorporated in the baseline models as discussed ahead.

¹ A version of this chapter has been published: S. Nagpal, J. Hanson, C. Reinhart, A framework for using calibrated campus-wide building energy models for continuous planning & greenhouse gas emissions reduction tracking, Applied Energy, 2019.

Table 7-1: Performance characteristics for a representative building.

Input parameters	Characteristics	Possible unknown parameter values		
		Low energy	Typical energy	High energy
1. Floor to floor height	4 m			
2. Perimeter zone depth	6 m			
3. Fenestration type	Curtain wall			
4. Fenestration shading	Exterior			
5. North window to wall ratio	40%			
6. South window to wall ratio	40%			
7. East window to wall ratio	60%			
8. West window to wall ratio	60%			
9. Window frame conductance	U:15 W/m ² K			
10. Wall construction	U:0.5 W/m ² K			
11. Roof construction	U:0.4 W/m ² K			
12. Glazing type	Double pane			
13. Window leakage	<i>unknown</i>	0.05 ACH	0.5 ACH	1 ACH
14. Natural ventilation	<i>unknown</i>	All hours	Occupied hours	Never
15. Daylight response	<i>unknown</i>	Continuous	On/off controls	Never
16. Thermostat set-point	<i>unknown</i>	22 °C	24 °C	26 °C
17. Occupancy schedule	<i>unknown</i>	30 hr/wk	60 hr/wk	Always on
18. Equipment usage	<i>unknown</i>	30 hr/wk	60 hr/wk	Always on
19. Lighting usage	<i>unknown</i>	30 hr/wk	60 hr/wk	Always on
20. Service hot water usage	<i>unknown</i>	0.001 ls ⁻¹	0.002 ls ⁻¹	0.003 ls ⁻¹
21. Perimeter occupant density	<i>unknown</i>	0.05 pp/m ²	0.25 pp/m ²	0.5 pp/m ²
22. Core occupant density	<i>unknown</i>	0.05 pp/m ²	0.25 pp/m ²	0.5 pp/m ²
23. Perimeter outside air flowrate	<i>unknown</i>	0.5 ACH	180 ls-1/pp	12 ACH
24. Core outside air flowrate	<i>unknown</i>	0.5 ACH	180 ls-1/pp	12 ACH
25. Perimeter equipment power	<i>unknown</i>	15 W/m ²	25 W/m ²	35 W/m ²
26. Perimeter lighting power	<i>unknown</i>	10 W/m ²	15 W/m ²	20 W/m ²
27. Core equipment power	<i>unknown</i>	15 W/m ²	25 W/m ²	35 W/m ²
28. Core lighting power	<i>unknown</i>	10 W/m ²	15 W/m ²	20 W/m ²
29. Perimeter outside air schedule	<i>unknown</i>	30 hr/wk	60 hr/wk	Always on
30. Core outside air schedule	<i>unknown</i>	30 hr/wk	60 hr/wk	Always on
31. Exhaust air energy recovery	<i>unknown</i>	Enthalpy	Sensible	None
32. Economizer cycle	<i>unknown</i>	Enthalpy	Dry bulb	None

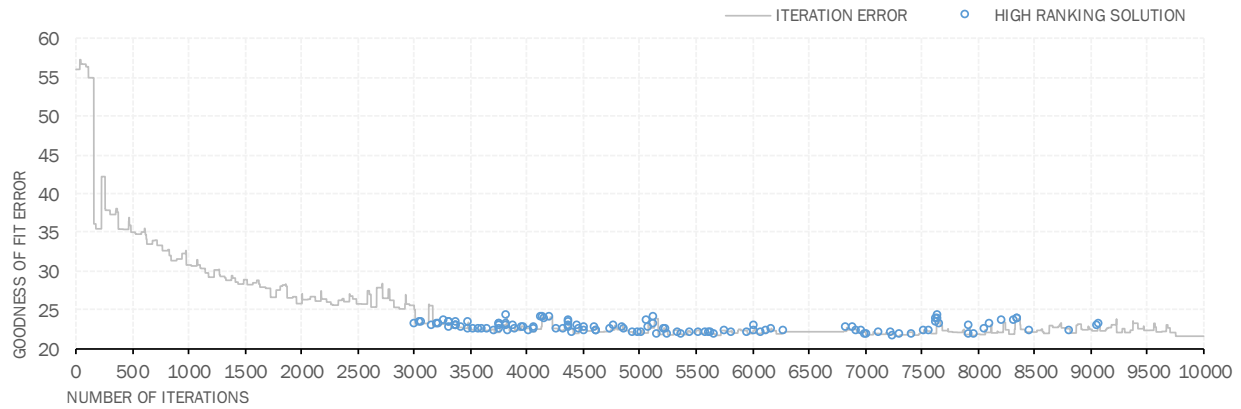


Figure 7-1: Graphic representation of the optimization process output, highlighting 100 high-ranking solutions.

7.1.2. Ensemble Baseline Model

The parameter properties estimated by the optimization routine are then used to develop detailed engineering models using EnergyPlus. Given the over-parameterized nature of this problem, the highest-ranking solution does not always determine the exact value for all unknown characteristics accurately. Therefore, instead of using the single highest-ranking solution as the baseline, this study employs a collection of 100 unique high-ranking solutions as an “*Ensemble-Baseline*”, highlighted in **Figure 7-1**, that are all considered equally likely to represent actual conditions. Since these 100 high-ranking models are chosen from the history of the genetic algorithm run, it is possible that many are similar since the unknown parameter values are only changed by small amounts as the algorithm reaches convergence. Future work, discussed in Section 9.1.2, could extend this ensemble approach to include diversity-boosting techniques in the optimization algorithm. **Figure 7-2** compares the distribution of simulated monthly energy use from the resulting ensemble model, shown by the blue band, to the observed energy data, shown by the dotted black line, for the example building.

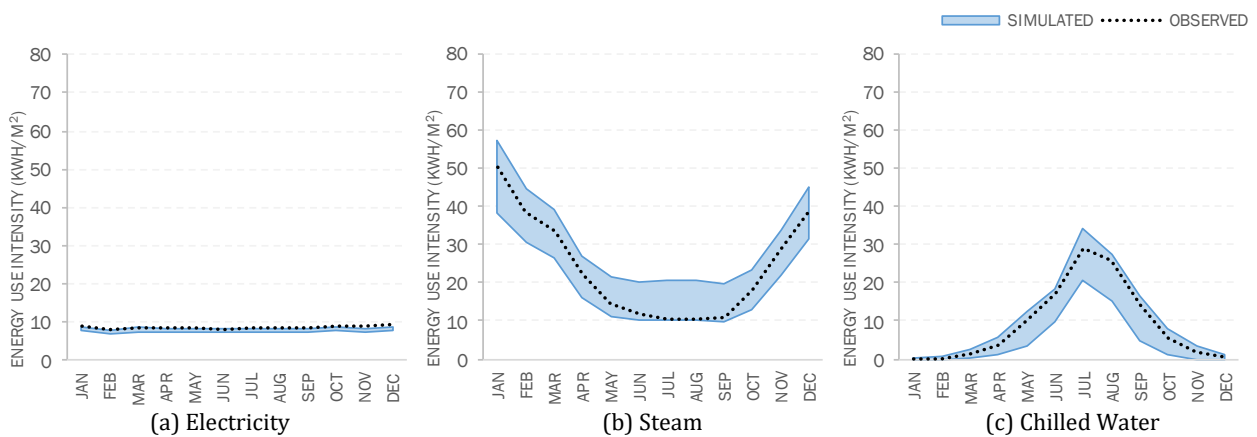


Figure 7-2: Comparison of simulated ensemble monthly energy distribution with observed data.

7.1.3. Scenario evaluation

This section explains the method employed to assess different upgrade strategies for specific individual buildings once their ensemble baselines have been developed. The ensemble-baseline models are utilized to simulate the potential for energy savings by changing the relevant input parameters to reflect a future retrofit or an upgrade in each of the 100 high-ranking models. Instead of a single savings projection, the ensemble-baseline projects a distribution of possible energy savings when a performance parameter is changed. **Figure 7-3** illustrates the type of output from this step as a distribution of projected savings for the example building when three independent upgrade scenarios listed earlier in **Table 4-5** are implemented. Results are saved for the upper and lower quartiles, and the upper and lower extremes, of projected savings distribution for each energy end-use.

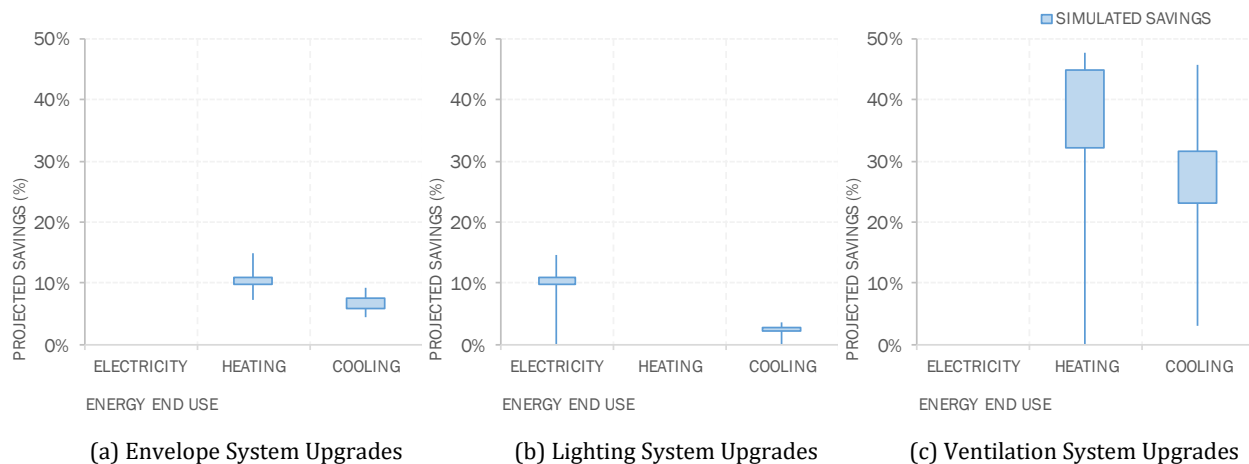


Figure 7-3: Distribution of projected annual energy savings by end-use from the ensemble-baseline model for the studied upgrade measures. The boxes represent the upper and lower quartiles of projected savings, while the whiskers extend to the upper and lower extremes.

The resulting savings distribution is then extrapolated back to observed data to calculate the projected consumption distribution, for each energy end-use, after implementation of the studied upgrade. **Figure 7-4** presents the resulting energy consumption distribution by end-use after applying the projected savings from **Figure 7-3** with the baseline observed energy use for the example building. Individual end-use distributions are then added to calculate projected total annual energy use distributions with different upgrades. **Figure 7-5** presents the results for two example evaluations: first where the envelope, lighting and ventilation system upgrades are studied independently as three different scenarios, and second where the same upgrades are studied for implementation cumulatively phased over several years,

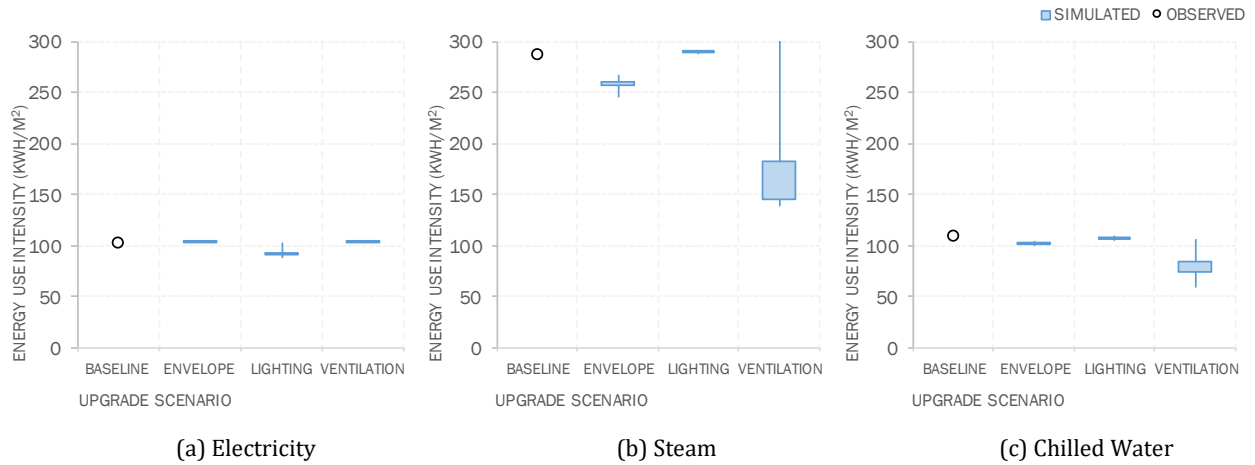


Figure 7-4: Projected energy consumption distribution by end-use after implementation of upgrade measures.

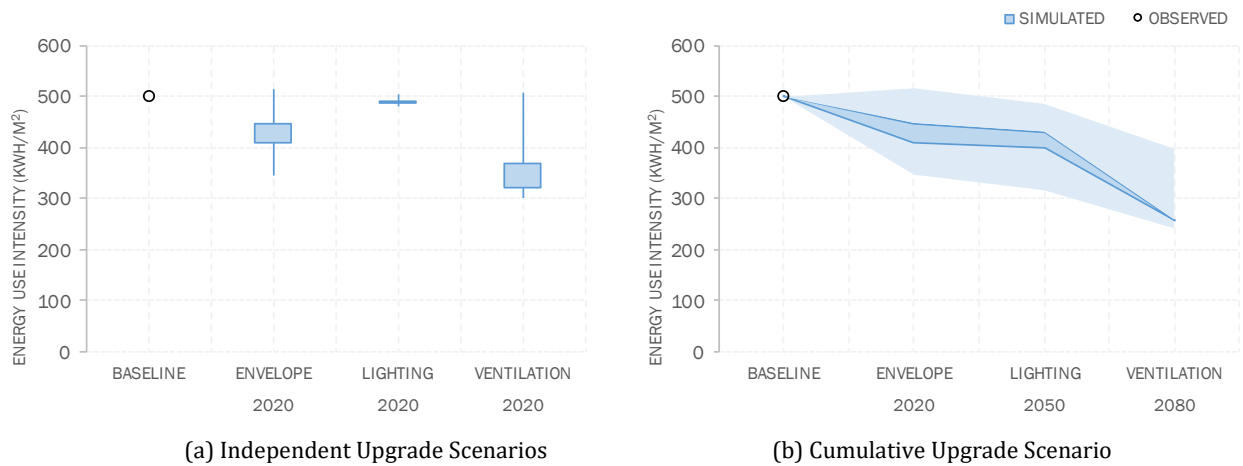


Figure 7-5: Projected annual energy consumption distribution after implementation of the studied upgrade measures (a) individually and (b) cumulatively phased over several years.

Similar to the box and whisker plots employed for independent scenarios, the potential energy use for the cumulative scenarios is presented as a distribution, with the dark band representing the probable upper and lower quartiles, and the light band extending to the possible upper and lower extremes. All future scenario evaluations are simulated using weather files generated using CCWorldWeatherGen that transforms present-day EPW weather files into climate-change weather files that represent future condition estimates from the Intergovernmental Panel on Climate Change (IPCC) assessment models.

By providing the extent of potential savings within reasonable limits of uncertainty, such results can help campus administrators to quickly evaluate multiple scenarios simultaneously and prioritize the suitability of specific upgrades in specific buildings.

7.2. Application case study

Employing the workflow discussed above, detailed ensemble-baseline models were developed using the auto-calibration process for 100 buildings on the MIT campus. A campus-wide GIS database was first utilized to generate extruded massing models of the campus. Additional envelope data, which consisted of floor heights, fenestration configuration, window opening ratios, and construction assemblies, was based on architectural drawings or on visual inspection where drawings were not available. All other performance characteristics were assumed as unknown. Chapter 3 provided a rough assessment of the time spent to develop the different phases of a manually calibrated UBEM for the MIT campus. That assessment, graphically presented in orange in **Figure 7-6** shows that after 160 hours of campus and building level information collection, the development of building-by-building calibrated energy models took another 400 hours. As shown by the blue chart, the auto-calibration workflow not only drastically reduces the model development time to under 40 hours of computation time, it also results in a significant reduction in manual data collection time.

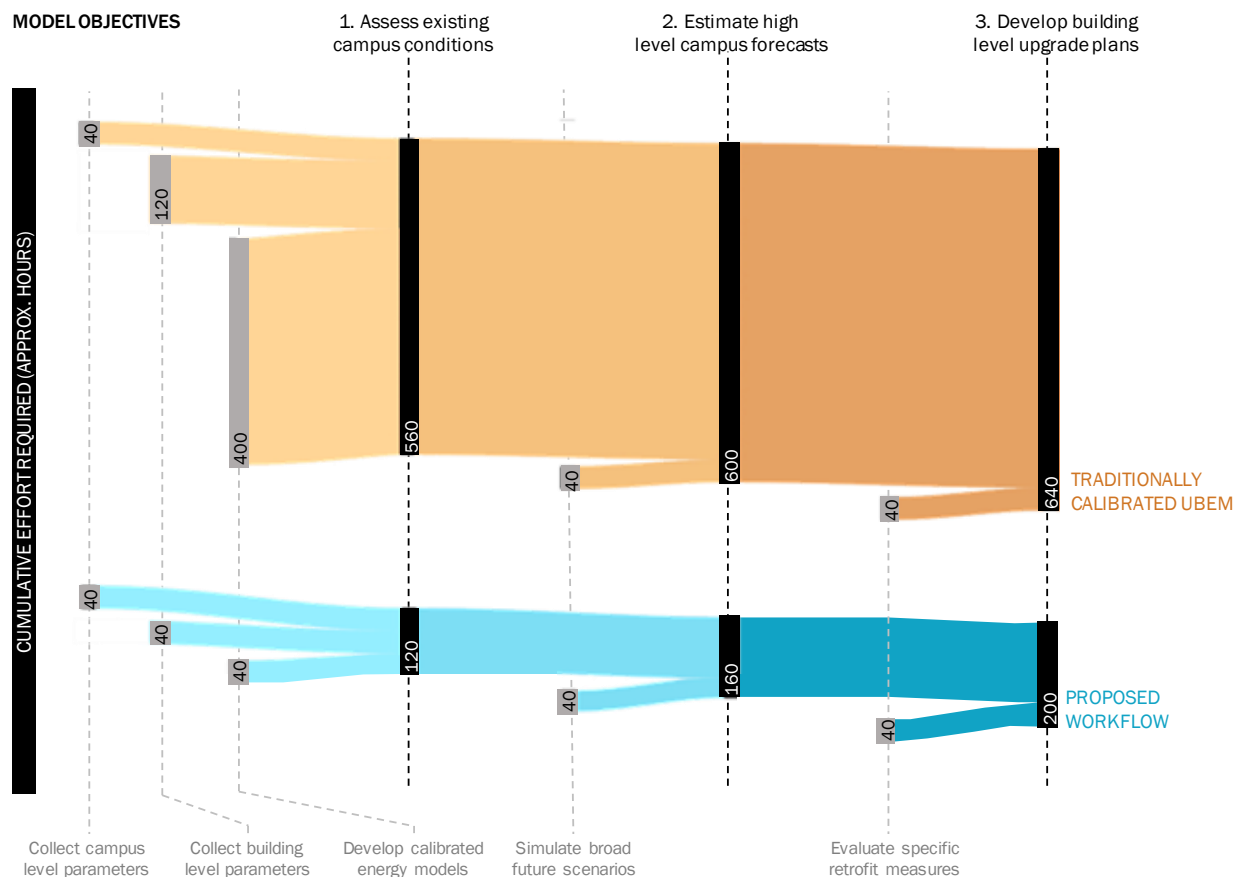
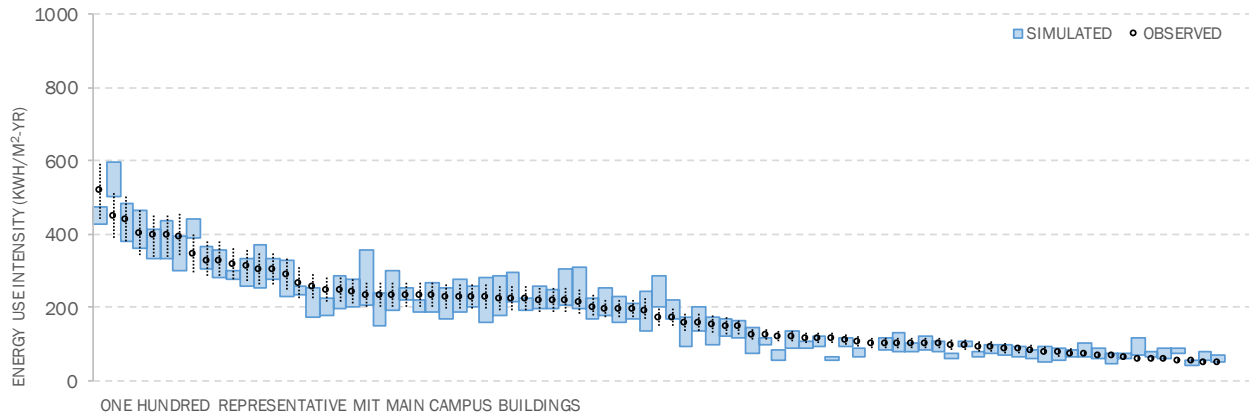
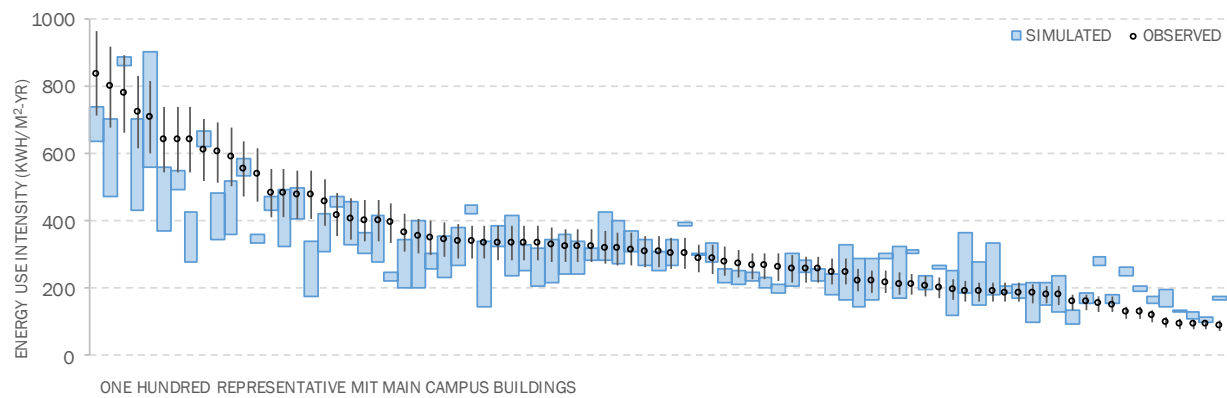


Figure 7-6: Qualitative assessment of incremental level of effort required based on model objectives. The proposed workflow drastically reduces the data collection as well as calibrated model development effort.

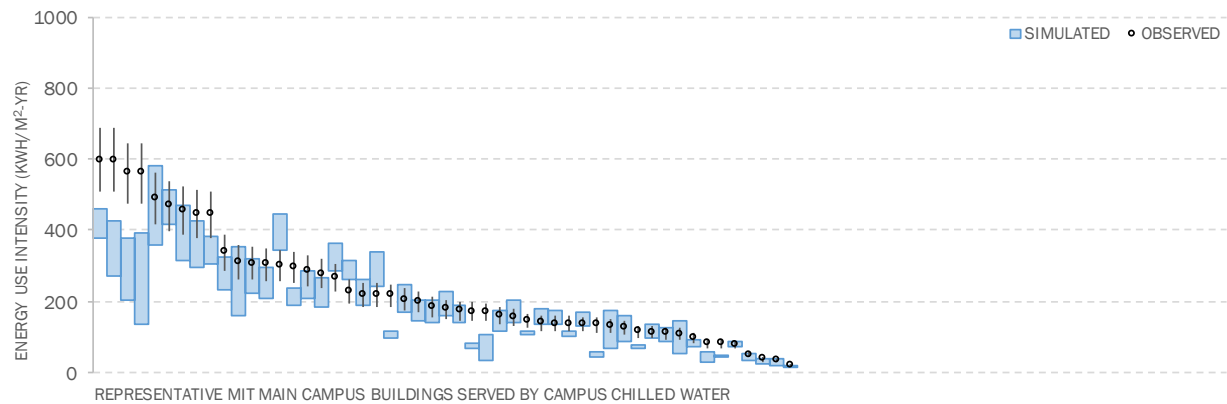
Figure 7-7 compares the range of results from the auto-calibrated ensemble-baselines for these 100 campus buildings arranged in order of reducing end-use energy use intensity, shown by blue bars, with the respective observed energy use and 15% error shown by black dots and whiskers.



(a) Electricity



(b) Steam



(c) Chilled Water

Figure 7-7: Comparison of results from auto-calibrated ensemble-baselines for one hundred MIT main campus buildings arranged in order of reducing end-use energy use intensity with the respective observed energy use.

The results show that the baseline models are closely calibrated to observed electricity use with the simulation results falling nearly within +/-15% for all buildings. The simulated steam use ranges also closely follow observed data for most buildings except for a few laboratory buildings with steam use intensity higher than about 600 kWh/m²-yr where the models under-predict the expected steam use. This discrepancy is even more pronounced in chilled water use comparison for a few laboratory buildings where the chilled water use intensity is higher than about 600 kWh/m²-yr. For all other buildings, the simulated results range around 15% of the observed energy use.

7.2.1. Building upgrade assessment

To illustrate the effectiveness of the proposed approach, detailed analysis results for three representative buildings, studied earlier in Chapters 4 and 5, are presented in this section. These buildings represent considerably different programmatic uses, so the relative contributions of envelope, internal load and ventilation system parameters to energy consumption are different for each building. The existing observed energy use intensities by utility type, as well as the built-up area for each building, detail earlier in **Table 4-8**, are listed in **Table 7-2**.

Table 7-2: Area details and observed energy use intensities for three representative buildings.

Building	Area (m ²)	Energy Use Intensity (kWh/m ² -yr)			Total
		Electricity	Steam	Chilled Water	
Residential	14,044	173	229	0	402
Academic	8,851	102	290	102	494
Laboratory	30,233	330	642	264	1236

Several upgrade scenarios are simulated for each building using the workflow discussed in the previous section, and the results are compared against energy savings projections from separately developed reference calibrated BEMs for these respective buildings. These reference models, graphically represented in **Figure 7-8**, are detailed EnergyPlus whole-building energy models that incorporate building massing characteristics, floor-by-floor spatial programmatic distribution, as well as detailed operational, electrical, and mechanical system parameters for each building. The baseline energy-use intensity for each building, as well as the reduction projected for different upgrade scenarios by these reference models are also presented in **Figure 7-8**. These results are referred to as ‘reference’ when compared with results from the studied workflow that are referred to as ‘simulated’ in this section.

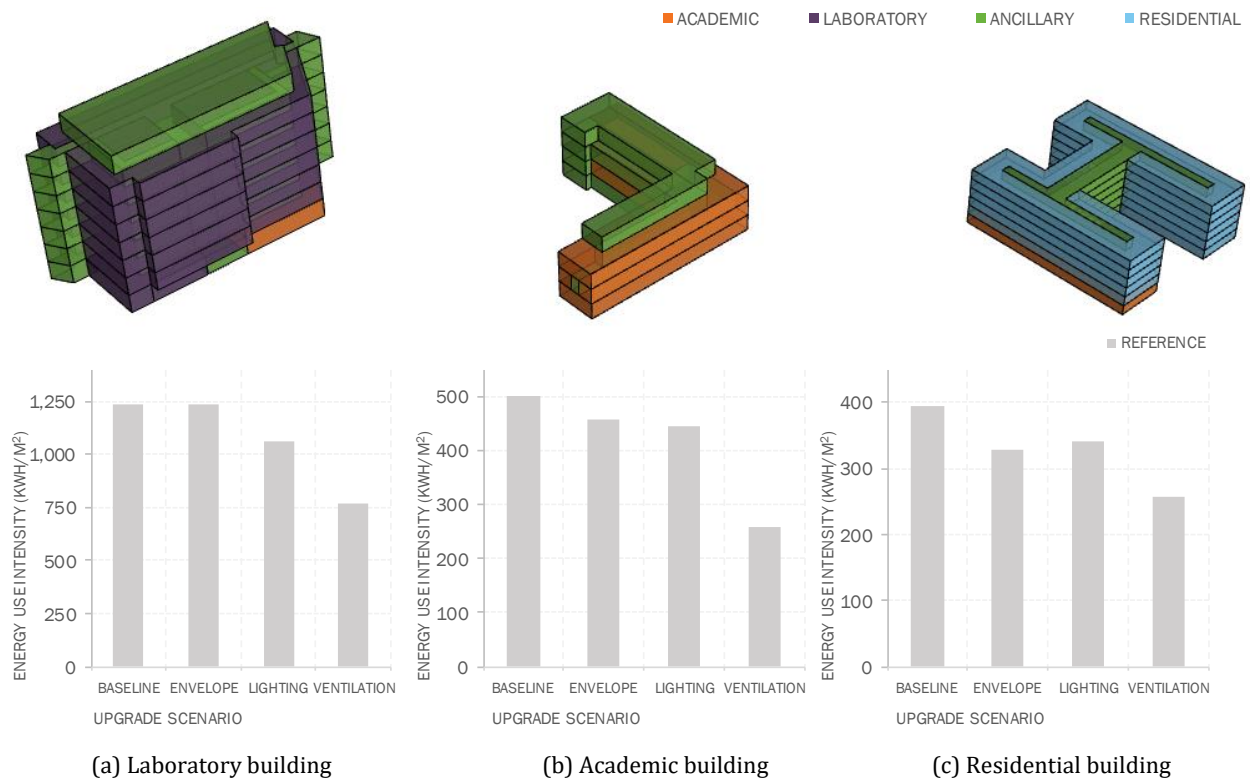


Figure 7-8: Energy-use projection for different upgrade scenarios from reference whole-building energy models.

7.2.2. Ensemble-baseline models

Figure 7-9 presents the range of monthly energy use results from the ensemble-baseline models, by end-use, for each of the three studied buildings. The black dotted lines show the energy use from the reference models discussed earlier, and the colored bands presents the range of results from the ensemble-baseline models. Similar to the results at the campus scale, the comparison of energy use intensities, summarized in **Table 7-3** shows that the reference building models are closely calibrated to reference electricity use, with differences within 10% for almost all cases.

Simulated chilled water use shows the largest error range, 20-30% for academic and laboratory buildings. The simulated steam use ranged from 30% lower than the reference for the residential building, but within a 20% error for all other cases. Of all buildings, the laboratory building shows the smallest error range of simulated total energy use, within 10% from the reference. For academic and residential buildings, the simulated results range from about 20% lower to about 5% higher total energy use compared to the reference data.

Overall, for all three buildings and all three end-uses, the ensemble-baseline resulted in annual energy-use ranges that fully encompass the reference case results.

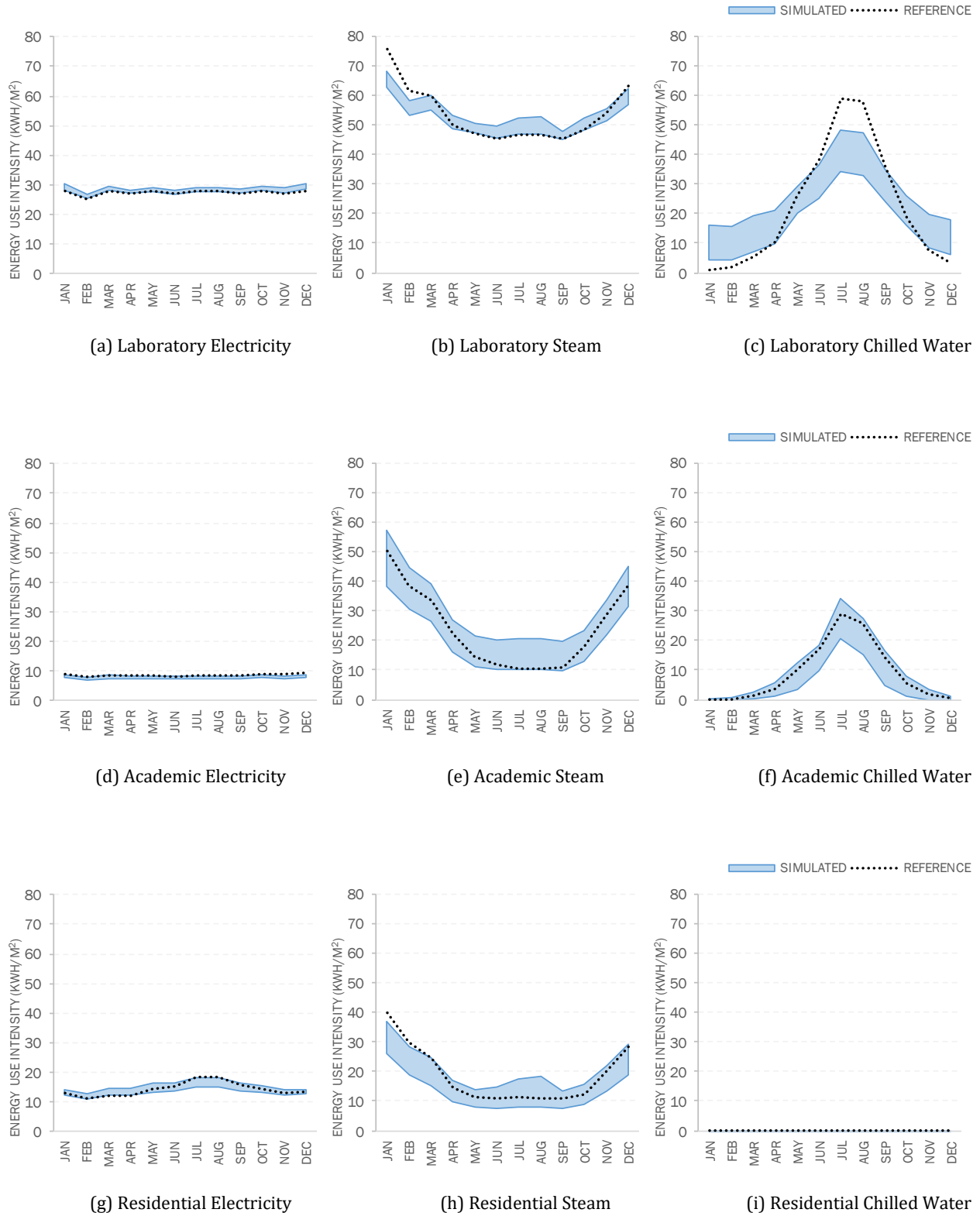


Figure 7-9: Comparison of simulated monthly energy use distribution from ensemble-baseline models with reference data.

Table 7-3: Baseline energy use intensity range for studied buildings and comparison to reference data.

	Reference EUI (kWh/m ² -yr)				Simulated EUI range (kWh/m ² -yr)			
	Electricity	Steam	Chilled Water	Total	Electricity	Steam	Chilled Water	Total
Laboratory	330	643	266	1239	309 to 357	550 to 662	220 to 344	1132 to 1293
Academic	102	289	109	500	88 to 104	236 to 356	56 to 131	418 to 538
Residential	171	224	-	395	158 to 185	158 to 250	-	327 to 412

7.2.3. Energy savings estimates

To assess the effectiveness of this approach, several upgrades are simulated with the developed ensemble-baseline models and the projected savings are compared with results from the reference models. **Figure 7-10** presents this comparison for the laboratory building, broken down by energy end-uses, for the three upgrade scenarios listed earlier in **Table 4-5**. For the internal and ventilation load dominated laboratory building, both models predict similarly insignificant savings with envelope upgrades. With lighting upgrades however, the simulation results from the ensemble-baseline models seriously under-predict the 13%-17.4% savings in electricity and associated 11.4% to 16.3% savings in cooling energy compared to the 43.9% and 31.5% reference savings respectively.

This is because even though the models were calibrated well to the overall electric use, the auto-calibration process did not accurately determine the relative split of lighting and equipment contribution to the overall electricity use. The resulting ensemble-baseline underestimated the existing lighting power, and consequently, the simulated savings are considerably smaller than the reference. The simulated savings of up to 11.7% in cooling and 47.7% in heating with ventilation system upgrades, in contrast, show a closer match with the reference results of 13.9% and 45.2% respectively.

A comparison of the academic building evaluation presents considerably better trends. The simulated cooling energy savings of 5.9% to 7.6% are slightly over-predicted compared to 2.0% reference savings with envelope upgrades, the reference 14.6% savings in heating are within the simulated range of 7.2% to 14.8% savings. For lighting upgrades, the simulated cooling savings of up to 3.6% are slightly under-predict compared to the 5.2% reference savings, but the simulated electricity savings up to 14.7% effectively cover the reference 11.2% savings. For the ventilation system upgrade scenario, the simulated savings in cooling energy are mostly lower than reference, but the heating reference 32.0% savings are right at the lower quartile from the simulation results.

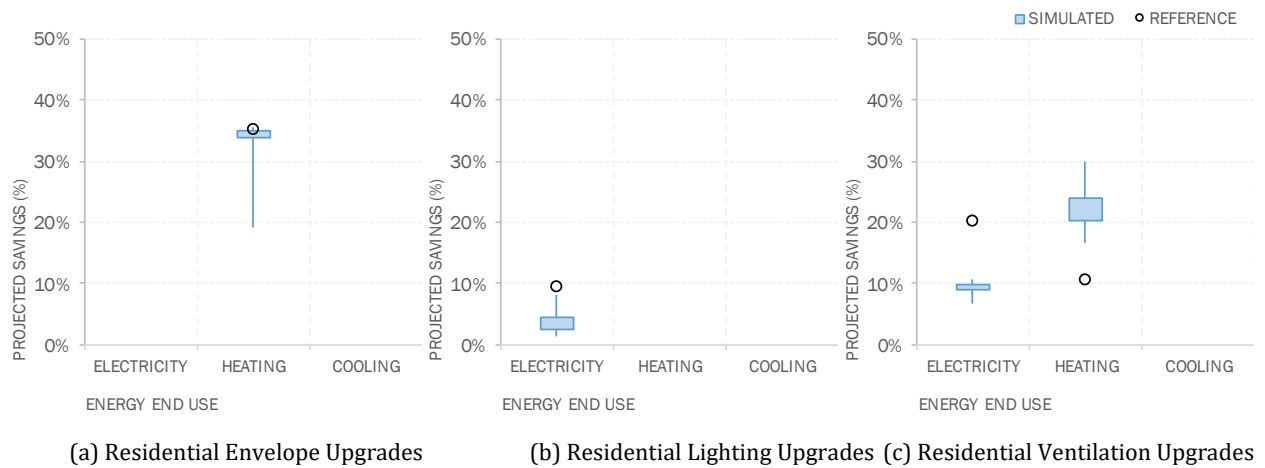
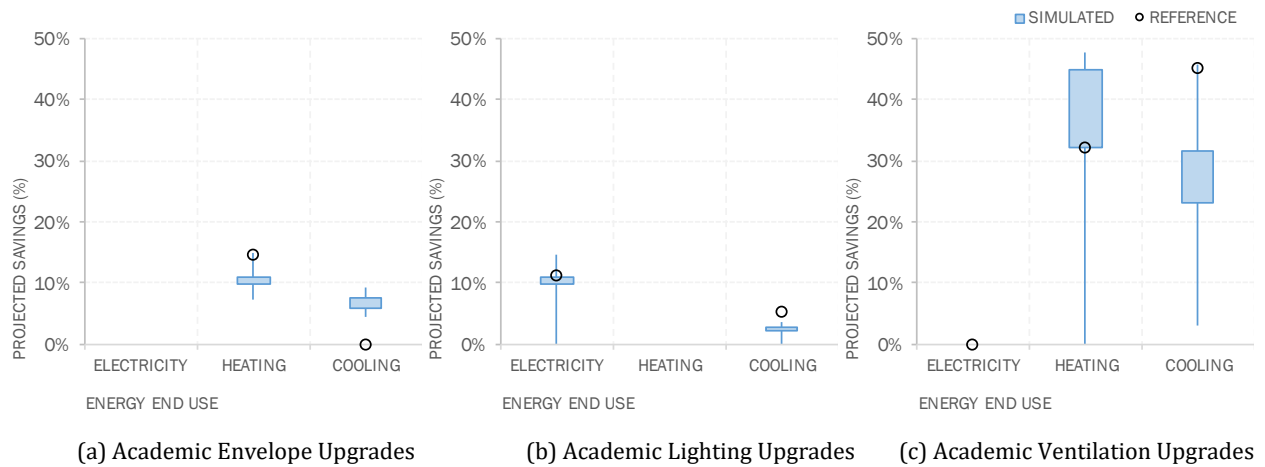
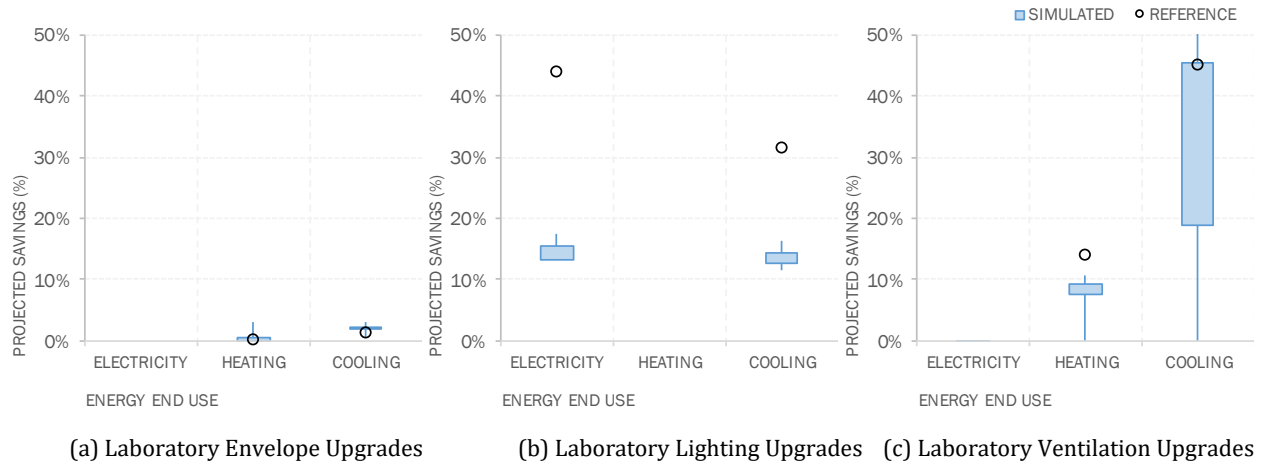


Figure 7-10: Comparison of projected energy savings from the ensemble-baseline models with reference results for the laboratory building (top), academic building (middle) and residential building (bottom).

Similarly, for the residential building results, the simulated savings in heating energy with a quartile range of 33.8% to 34.9% match closely with reference results of 35.3% savings with envelope upgrades. Since upgradable hard-wired lighting forms only a small component of the residential lighting system, both models project similarly small electricity savings of up to 8.0% with lighting upgrades.

Finally, for residential ventilation system upgrades, the simulated savings are considerably misaligned for both the heating energy and the electricity required for cooling. This is because residential energy depends on several inter-dependent ventilation parameters including infiltration, operable windows as well as kitchen and toilet exhausts; the relative split of which could not be accurately determined by the auto-calibration process.

Figure 7-10 shows that, except for laboratory lighting and residential ventilation upgrades, the auto-calibrated ensemble-baselines project similar energy savings to the respective reference cases, for all upgrade scenarios, for all building types.

The savings in individual energy end-uses are then applied to the respective end-use in the reference results, and projected total energy use intensity ranges for each building are calculated with the implementation of various upgrades.

Figure 7-11 presents these ranges for the three buildings, and show that, except for the lighting upgrade scenario in the laboratory building, and to a certain extent the residential building, the simulation projected total energy use intensity ranges reasonably cover the reference case results for all upgrade scenarios, for all building types.

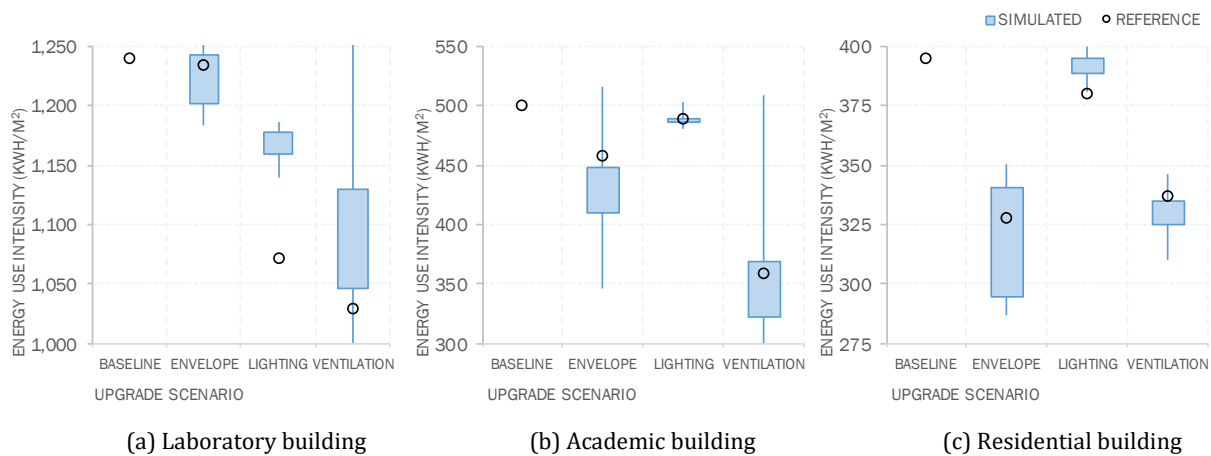


Figure 7-11: Projected energy use reduction with independent upgrade scenarios from ensemble-baseline and reference models.

7.2.4. Future energy scenario evaluation

Along with providing a framework to evaluate independent upgrade scenarios for individual buildings to help develop a prioritization plan, the goal is to enable campus administrators to utilize this workflow as a continuous planning tool to forecast energy-use reduction scenarios with phased upgrades over time. Since campus transformations can stretch over several decades, this section evaluates possible scenarios where the previously studied envelope, lighting, and ventilation system upgrades are implemented incrementally in 2020, 2050 and 2080 respectively. **Figure 7-12** compares the trends in projected energy use intensity ranges for these scenarios from ensemble-baseline models with results from the reference models shown earlier in Figure 7-8. **Table 7-4** summarizes these results in form of a projected total energy savings comparison between ensemble-baseline and the reference model results.

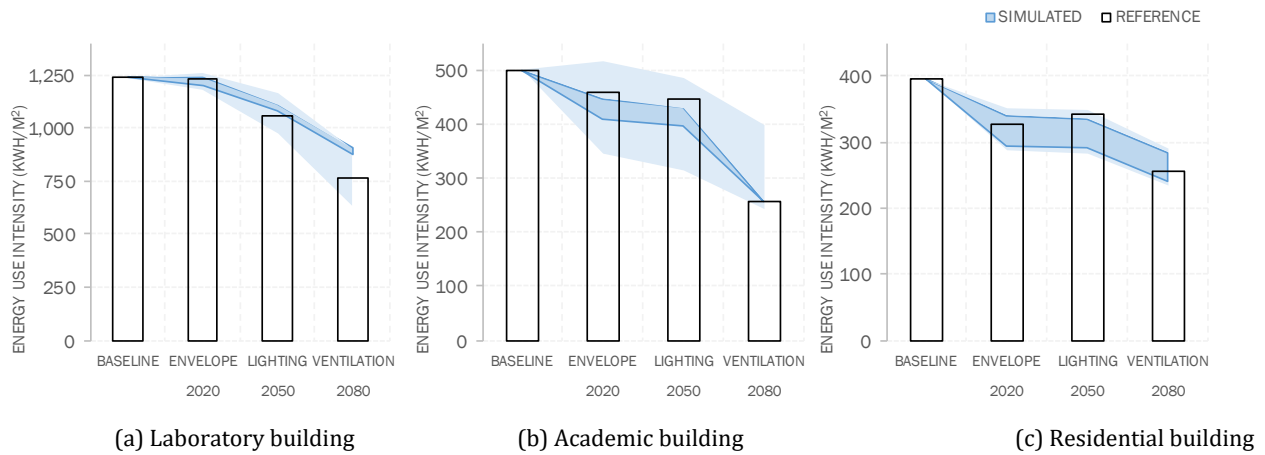


Figure 7-12: Energy savings results with cumulative upgrades from ensemble-baseline and reference models.

Table 7-4: Annual energy savings for studied buildings with all upgrade measures evaluated cumulatively.

Building Type	Upgrade Scenario	Reference Savings (%)	Simulated Savings (%)	
			Lower to Upper Quartiles	Lower to Upper Extremes
Laboratory	Envelope	0.4%	0.2% - 3.1%	-1.7% - 4.5%
	+ Lighting	14.3%	10.3% - 12.4%	6.3% - 21.5%
	+ Ventilation	38.2%	26.9% - 29.1%	26.9% - 49.1%
Academic	Envelope	8.3%	10.5% - 18.1%	-3.2% - 30.8%
	+ Lighting	10.8%	13.8% - 20.5%	3.1% - 36.9%
	+ Ventilation	48.5%	48.4% - 48.6%	20.5% - 51.7%
Residential	Envelope	17.1%	13.9% - 25.5%	11.2% - 27.4%
	+ Lighting	13.4%	15.1% - 26.4%	12.0% - 28.3%
	+ Ventilation	35.1%	27.8% - 38.8%	26.3% - 40.4%

7.2.5. Proof-of-concept prioritization plan

Using the ensemble-baselines developed for MIT campus, shown in **Figure 7-7**, upgrade scenarios listed earlier in **Table 4-5**, were simulated for each individual building. The resulting energy use reduction projections were translated to potential savings in greenhouse gas emissions as well as operating energy costs using the energy supply systems models presented in **Chapter 6**. These results, presented in **Figure 7-13**, quantify the range of achievable savings if specific retrofits were implemented in specific buildings. The initial prioritization plan, developed by rapidly and automatically evaluating a hundred campus buildings, identifies which broad areas of improvement offer the highest potential for greenhouse gas emissions or energy cost savings, and therefore, should be investigated in further detail in which specific buildings.

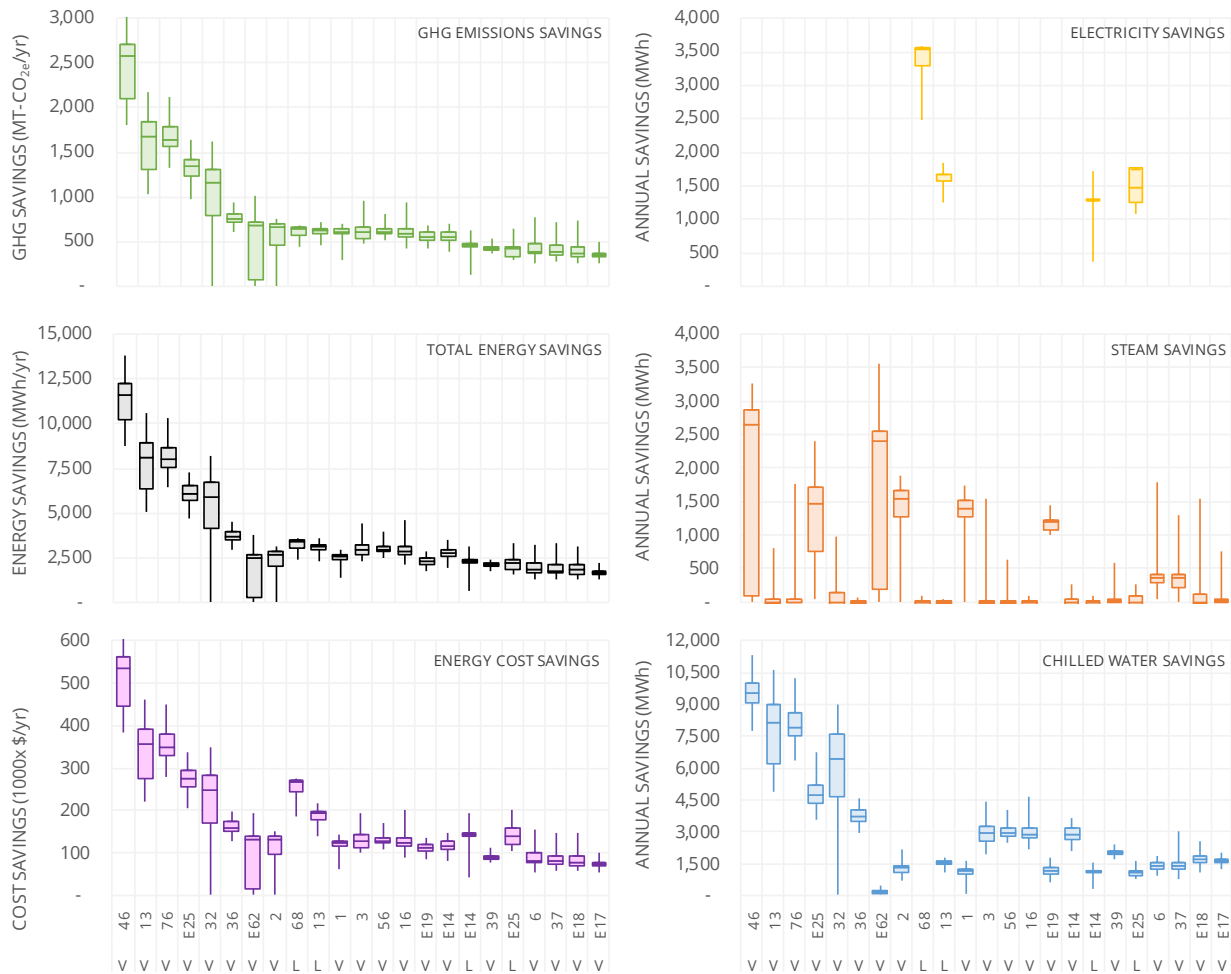


Figure 7-13: Projected savings in greenhouse gas emissions, annual energy use, and energy costs (left), as well the breakdown of savings by individual energy end-use (right), with the implementation of specific upgrades in specific buildings on MIT campus. The horizontal axis presents 25 campus buildings and recommended upgrades (V: ventilation system, L: lighting system) arranged in order of reducing GHG emissions reduction potential.

7.3. Discussion and limitations

Evaluation results show that, across all cases, electricity consumption is most closely replicated, suggesting that the models could reasonably estimate the combined effect of lighting and equipment load densities and operating parameters. However, the discrepancies in projected savings with lighting upgrades for individual buildings illustrate that the models could not estimate the relative breakdown of lighting and equipment energy accurately. Therefore, unless detailed information about lighting or equipment is known and used to inform the calibrated models, it is important to note that improving only one of several electricity consuming parameters could result in significant errors in projected savings.

This is especially true for the studied laboratory building where the identical 24x7 continuous operation of lights as well as equipment makes it impossible for the models to mathematically differentiate between equipment and lighting energy use. If the analysis needs to focus specifically on lighting upgrades in a specific building, the installed lighting power densities, which are relatively easy to determine, should be explicitly documented and input in the respective building model.

In contrast to electricity use, the baseline models show a bigger distribution of results for heating and cooling energy use. As a result, the models show a large range of potential cooling and heating energy savings with ventilation system upgrades and fall short of accurately estimating these savings when several unknown building characteristics could similarly affect ventilation loads. This is especially true for the studied residential building where, similar to previous discussions, unless the baseline models incorporate known information regarding weatherization, window operation, exhaust flowrates, etc., there could be significant errors in projected savings. The models, however, can reasonably assess the overall savings potential if all interdependent ventilation characteristics were upgraded simultaneously.

Finally, one of the key data sources required for baseline model development - the known input parameter database - is currently maintained and updated manually. An important next step for the project is the development of a data-flow infrastructure that facilitates the mapping of campus developments over time; specifically, the entering and interpretation of this data by the university campus administration to modify specific energy model input parameters as individual buildings systems are upgraded, or as new buildings are added. Such an infrastructure will allow for new baseline models that represent specific points-in-time to be automatically developed as buildings are upgraded and will provide a platform to compare and validate the predicted energy savings use with the upgrade strategies against actual energy use on an ongoing basis.

III. CONCLUSIONS

This thesis set out to explore three main hypotheses that were laid out in chapter 3. As this dissertation concludes, this chapter addresses those hypotheses based on the findings of this work. The development of campus-wide building energy models traditionally requires substantial effort and expertise for detailed geometric model building, and considerable amount of information and time for setup and calibration of individual building models. Moreover, once developed, these models are typically used only for a single point-in-time analysis to evaluate static proposals. While such models help to evaluate potential future scenarios for the unique set of existing conditions, they are not designed to evolve as retrofit programs are implemented, new buildings are added, or building use or occupancy changes. This dissertation proposed new workflows that automatically track energy-use and develop calibrated models, allowing the resulting framework to serve as a facility planning platform for the assessment of ongoing comprehensive building level retrofitting programs. Chapter 8 summarizes the specific contributions of this thesis and discusses how the proposed workflows could be employed as an integrated framework. Chapter 9 discusses its potential impact, envisioned applications, and identifies important directions for future research.

8. Summary and Discussion

This work set out by studying different methodologies to evaluate campus energy use reduction potential and compared their results for baseline as well as various retrofit scenarios. It found that each model has its benefits as well as limitations, depending on the objective of the model, the level of detail of known model input parameters, and the time and effort that can be afforded to develop the models. Chapter 4 offered detailed procedures to set up two such models and provided a thorough analysis of simulation results from these models, addressing an important area of concern for large university campuses that are looking to determine the most effective strategies to reduce their energy footprint, but which cannot rely on traditional building energy modeling workflows because of the size of their building portfolio. The comparison found that while a campus-level analysis yielded similar results between the spreadsheet and engineering models, the results of implementing specific measures in specific buildings were considerably different. The bottom-up engineering models outperformed the spreadsheet approach, especially for envelope dominated buildings. The engineering models, however, required substantial expertise for detailed geometric model building, and considerable amount of information and time for setup and calibration of individual building models. This finding is significant if campus planners intend to use these models to prioritize which buildings to upgrade and highlights the need to reduce the effort required to develop calibrated campus energy models.

To address this issue, this work was based on three main hypotheses: (1) it can be *feasible* to considerably reduce this effort by employing data-driven surrogate modeling techniques; (2) the resulting models can provide *reliable* results for building level retrofit assessments; and (3) these models can serve as *significant* tools to aid the implementation of campus GHG reduction action plans.

8.1. Feasibility

Chapter 5 proposed, and validated, a novel automated methodology to estimate properties of several unknown building performance characteristics. First, the results from a few detailed simulations were fit to a surrogate model that uses several combinations of unknown parameter values as training inputs and a single statistical index that represents an overall ranking of each simulation as the training output. Then, instead of iteratively simulating a detailed engineering model, the surrogate model was utilized with an optimization function to find the highest-ranking combination of unknown parameter values, reducing the computational expense from several days of simulation time to a matter of minutes.

The study employed multiple open-source components to generate training and testing data-sets, to develop surrogate models, and to run optimization routines; none of which were designed specifically for use in the field of building energy simulation. The resulting energy models successfully captured the relative importance of climate-independent internal loads in all cases, and in addition, reasonably estimated the significance of ventilation loads for cases when building envelope characteristics were known. The results showed that these mathematical techniques, all adopted from different disciplines, can be applied successfully to reasonably estimate unknown parameter values, even when information regarding several building characteristics is unavailable. The iterative process to estimate existing building characteristics using these surrogate models offered significant reduction in computation time, from 30 seconds per simulation with detailed engineering models to just 0.06 seconds in this study, or about 500 times faster.

This work shows that surrogate modeling techniques could be successfully employed to considerably reduce the required time and effort to generate calibrated bottom-up energy models for large university campuses that enable building-by-building evaluation of potential retrofits and future energy scenarios.

8.2. Reliability

For campus projects, or portfolios with multiple diverse-use buildings with access to energy-use data, the results showed that if information regarding envelope characteristics of buildings is collected, surrogate models can estimate the relative impact of internal load and ventilation system characteristics on building energy with high confidence. This is significant for campus operators since envelope properties can generally be easily collected either from design documents or through building audits, whereas the electrical and mechanical system parameters are the most difficult to document and rely heavily on modeler judgement and trial and error.

Chapter 6 presented a tool that takes as inputs the hourly load profiles for electricity, hot water and chilled water as simulated by the calibrated campus energy models. It allows for various energy supply equipment to be individually enabled or disabled and performance characteristics defined to reflect the existing campus energy supply systems. Based on the hourly load profiles for different energy end-uses, this thermal plant planning tool calculates, in real time, the hourly consumption of purchased grid electricity and natural gas. Based on user-defined cost and emission factors for various components and purchased utilities, first costs, annual energy costs and greenhouse gas emissions are then calculated to allow an informed assessment of each evaluation scenario.

Chapter 7 addressed the issue of uncertainty in evaluation results from the previously generated auto-calibrated campus energy models by proposing a workflow that employs a collection of one-hundred highest-ranking combinations of unknown parameter values as an ensemble-baseline model. When utilized to simulate the potential for energy savings by changing the relevant input parameters that reflect a future retrofit, the ensemble model projects a distribution of possible energy savings instead of a single savings projection. The auto-calibration process can be repeated over time, resulting in a continuous planning framework that provides information on the historic energy use breakdown as well as a mechanism to assess potential changes in energy use with any energy retrofits, at the campus and individual building level.

These results demonstrate that the auto-calibrated energy models could successfully evaluate potential savings with retrofit strategies within reasonable limits of uncertainty.

8.3. Significance

Finally, a proof-of-concept framework was presented that compares the modeled energy-use results with measured data, allows the evaluation of potential upgrades at the campus or specific building level, runs multiple energy models in the background, and presents the predicted energy-use and greenhouse-emissions impact of evaluated upgrades.

For campus owners with time and budget constraints, this framework can help to develop a prioritization plan by identifying which broad areas of improvement should be investigated in further detail in which specific buildings. It can assess hundreds of individual buildings using rapid-response automated workflows and determine the specific characteristics of individual buildings that would be driving the overall energy use. Depending on where this initial assessment identifies the potential for maximum energy savings, immediate next efforts can be prioritized to make the evaluation of only those characteristics more accurate.

The proposed workflows are computationally inexpensive and fully automated, and therefore can be repeated as frequently as needed to maintain current baseline models that continuously evolve to reflect any changes in campus conditions; thus, making these models available for ongoing assessments. Finally, in addition to providing a platform for campus administrators as well as the larger community to explore future scenarios, the proposed framework models can provide an effective way of combining measured building energy data with simulation results to automatically, and continuously, track whether a given retrofitting measure has led to expected outcomes, and to determine the actual performance of implemented measures.

9. Research Outlook

The different workflows proposed in this dissertation can be used alone, in pairwise combinations, or integrated into a unified approach to help develop comprehensive campus planning platforms. Although each workflow realizes a number of advances, further steps are necessary to fully enable their widespread application as envisioned in the previous section. The following section organizes the directions for future work into three categories: modeling, calibration, and implementation.

9.1. Directions for future work

9.1.1. Modeling: aerial thermography to inform energy models

Chapter 5 established that for the proposed workflow to be effective, it is important that information regarding building envelope is known. Otherwise, the models fell short of accurately estimating several unknown characteristics. When building envelope specifications are not readily available, Infrared thermography is frequently utilized to analyze existing envelope properties. Thermal inspection using a hand-held infrared camera is a common way to assess thermal performance, but can be time-intensive when the building skin has a complex form, or a large surface area. Recent ongoing work (Bayomi et al. 2019) is examining the applicability of utilizing Unmanned Aerial Vehicles equipped with IR cameras for automatically mapping, imaging, data collection and calculation of building envelope’s thermal properties. **Figure 9-1** illustrates this framework, where further work has the potential to automate the process of collecting one of the key data inputs that are critical for the proposed auto-calibration workflow.

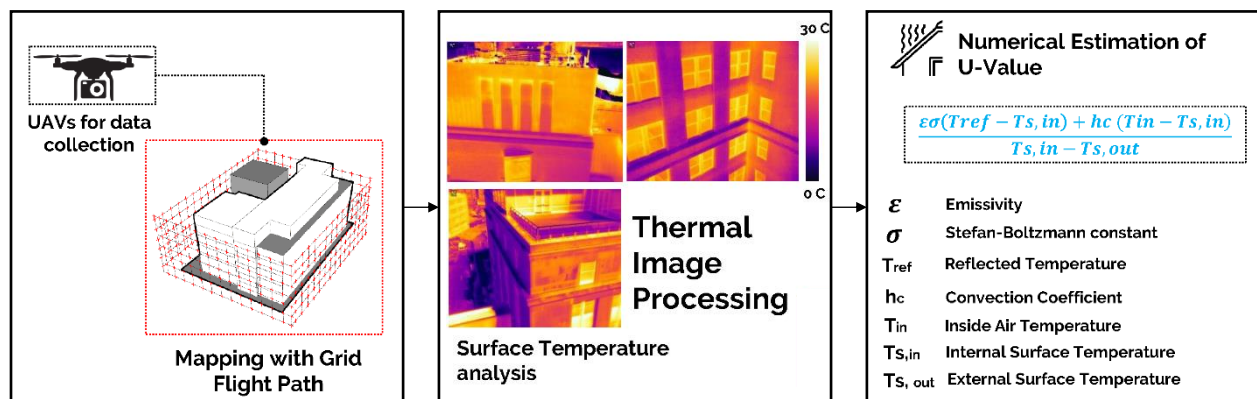


Figure 9-1: Schematic diagram illustrating the analysis framework and methods used for aerial thermography, data collection, processing and calculation of envelope thermal properties.

9.1.2. Calibration: ensuring diversity in ensemble models

Chapter 7 discussed that the ensemble-baseline could not simulate the impact of lighting upgrades accurately; illustrating that even 100 unique high-ranking solutions from the optimization routine did not include enough diversity. Future work must investigate mechanisms that ensure that the solutions selected for the ensemble-baseline represent an appropriate spread. Recent work (Brown & Mueller, 2018) has looked at possible metrics for quantifying diversity in parametric design and has proposed measuring diversity based on a design set's characteristics, as illustrated in **Figure 9-2**, rather than its performance. This could help identify solutions that are not only unique, but diverse enough to simulate a more reliable range of results for future scenario evaluations, especially when only a few of several inter-dependent building characteristics are upgraded.

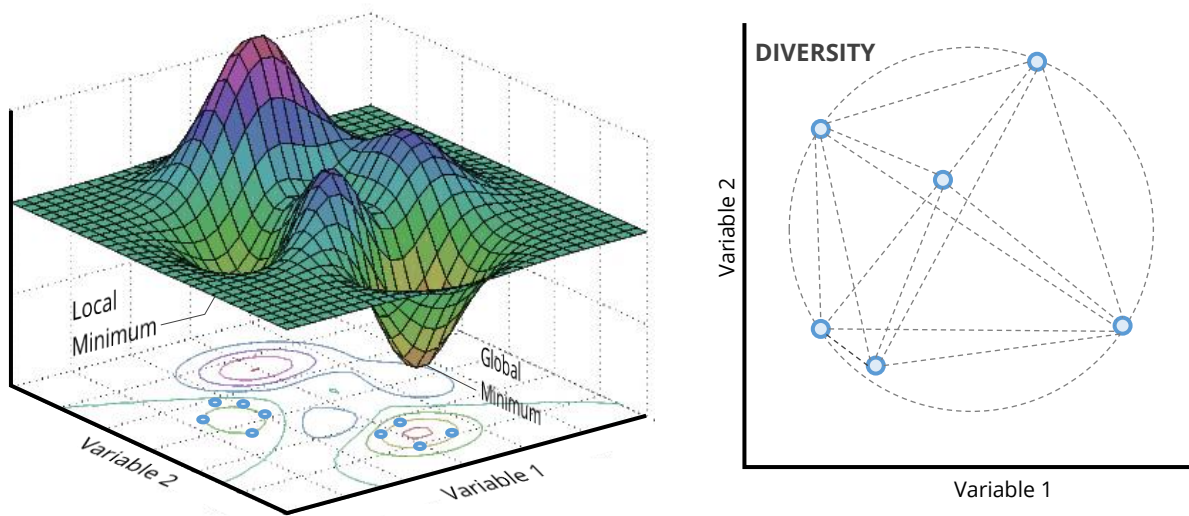


Figure 9-2: Schematic diagram illustrating the measurement of the diversity of a set of designs. The distance between parametric design solutions represent their dissimilarity or variation.

9.1.3. Implementation: interactive evolutionary frameworks

The primary objective of the work presented in this dissertation is the development, and implementation of portfolio-wide energy performance planning systems that allows owners and administrators to assess, plan and track the effectiveness of their energy policies on an ongoing basis. A proof-of-concept working prototype of a web-based user interface was recently developed (S. Nagpal et al. 2019) with the aim of helping building-portfolio owners manage their building energy-use over time and to track their performance vis-à-vis a set of earlier defined targets.

This framework, illustrated in **Figure 9-3**, collected and displayed information on the historic energy use breakdown, and predicted potential changes in energy use with future changes. For such frameworks to be truly useful, future versions of such a tool must also allow users to select potential upgrades, run the energy models in the background, and present in real-time the predicted energy-use and greenhouse-emissions impact of evaluated upgrades on building and portfolio energy use.

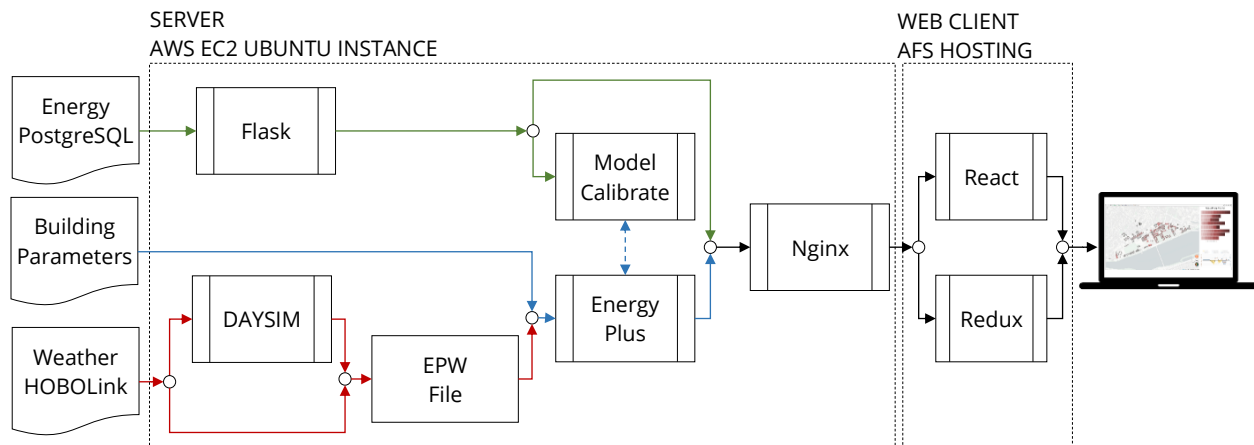


Figure 9-3: Schematic diagram illustrating the flow of information protocols and libraries employed to collect measured energy use and weather data, to develop and auto-calibrate urban building energy models, and to deliver processed data to a web client. Links to all protocols and libraries are included in the References.

9.2. Concluding Remarks

The amount of data that is getting collected from building systems connected to the internet, the extent to which analytical processes interact with technology, and the computational power that is available for exploration of design strategies – is not only unprecedented, but also rapidly increasing. Machine Learning algorithms can analyze large amounts of data, automate otherwise effort-intensive processes, and find patterns to help make better and faster decisions. This thesis attempts to capitalize on these advancements as we look to find ways to decarbonize our existing building stock.

The procedures outlined in this dissertation have helped to set up a “living energy model” for the campus of the Massachusetts Institute of Technology. This work should empower owners, administrators, facility managers or any stakeholders - of other institutional, commercial, industrial or any building-portfolios - in a single campus or across multiple geographies - to develop similar platforms that can assess, plan and track the effectiveness of their building energy use, operating energy costs, and greenhouse-gas emission reduction strategies on an ongoing basis.

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