Final Report

Probabilistic Modeling of Energy Use and Indoor Air Quality in Historic Buildings

Amanda L. Webb, Ph.D
Department of Civil and Architectural Engineering and Construction Management
University of Cincinnati
Cincinnati, OH 45221
webb2al@uc.edu

Thomas E. Boothby, Ph.D., P.E., R.A.
Department of Architectural Engineering
The Pennsylvania State University
104 Engineering Unit A
University Park, PA 16802

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Executive Summary

Existing guidance on historic preservation and energy conservation recommends evaluating a building's "inherent energy efficient features" (IEEFs) before planning or implementing any retrofits. The U.S. Secretary of the Interior's *Guidelines for Preserving, Rehabilitating, Restoring and Reconstructing Historic Buildings* advises that "prior to retrofitting historic buildings to make them more energy efficient, the first step should always be to identify and evaluate existing historic features to assess their inherent energy-conserving potential." Related guidance, such as the U.S. National Parks Service's *Preservation Brief 3: Improving Energy Efficiency in Historic Buildings*, echoes this advice. However, this guidance is primarily qualitative; current guidance lists potential IEEFs – e.g., shutters, storm windows, uninsulated mass walls, operable windows – but does not provide a quantitative procedure for evaluating them. This is a major limitation, given that retrofit decisions are typically made on the basis of quantitative metrics, such as estimated energy savings and economic payback.

The objective of this study is to develop a quantitative methodology to identify and evaluate the IEEFs in an historic building. A new analysis method has been developed combining building energy simulation with regionalized sensitivity analysis and machine learning techniques – classification trees and random forests – to determine which features or combinations of features in a building result in energy-efficient performance. This report provides an overview of the method, and then a demonstration using a case study historic building on the Penn State University campus. In the case study, 13 energy retrofit measures are evaluated; these include several potential IEEFs – such as natural ventilation via operable windows, thermally massive walls, and shading from surrounding landscape – as well as other common energy retrofits – such as reduced infiltration via air sealing, and attic insulation. The results of the study suggest that the IEEFs have minimal influence on reducing annual energy consumption. While these results are limited to this case study building, this new method could be widely applied to aid retrofit decision-making in any historic building. By identifying the tradeoffs between various retrofit measures, this method helps the design team find an appropriate balance between energy efficiency and conservation goals. Overall, this study suggests that the IEEF concept may need to be revised in order to make a better argument for preserving these features, and the report concludes with a discussion of possible directions for revising this concept.

Introduction

There is a longstanding claim among preservationists that older buildings contain "inherent energy efficient features" (IEEFs). Variously referred to as "inherent energy-saving features," "inherent energy conserving features," and "inherently sustainable features," this concept has been central to preservationists' approach to energy efficiency in older and historic buildings. IEEFs are the starting point for discussing energy efficiency in canonical preservation texts in the U.S. – e.g., Weeks and Grimmer (1995); Grimmer et al. (2013); Hensley and Aguilar (2011) – and also show up in guidance documents from abroad (Franzen 2014).

These documents all convey a similar message: before retrofitting an historic building, consider IEEFs. As described in *The Secretary of the Interior's Standards for the Treatment of Historic Properties*, the task is as follows: "prior to retrofitting historic buildings to make them more energy efficient, the first step should always be to identify and evaluate existing historic features to assess their inherent energy-conserving potential" (Weeks and Grimmer 1995). *The Secretary of the Interior's Guidelines on Sustainability for Rehabilitating Historic Buildings* goes one step further and suggests also recovering lost features, advising that "The key to a successful rehabilitation project is to identify and understand any lost original and existing energy-efficient aspects of the historic building" (Grimmer et al. 2013).

This approach, in addition to serving as a way to achieve energy savings, has two potential benefits. First, ensuring that IEEFs operate as intended may eliminate the need for further retrofits, thereby protecting the building's historic fabric and visual appearance from potential damage. As Smith (1981) writes in a discussion on the benefits of IEEFs, "If the attributes of historic buildings are considered and allowed to function as they were intended, a great deal of energy may be saved without any retrofitting." Second, IEEFs may have interactive effects – either positive or negative – with other energy efficiency measures. A given IEEF may adversely impact other energy efficiency measures, or may be able to operate in concert with them, producing greater combined energy savings. In addition to operating a building's IEEFs as intended, The Secretary of the Interior's *Guidelines on Sustainability for Rehabilitating Historic Buildings* notes that "It is equally important that [IEEFs] function effectively together with any new measures undertaken to further improve energy efficiency" (Grimmer et al. 2013).

In sum, IEEFs have been a key conceptual tool in the approach to reconciling historic preservation and energy efficiency. They promise to save energy while simultaneously protecting a building's historic significance (i.e., its historic fabric and visual character), and facilitating the successful use of new retrofit measures.

Yet, a clear definition of IEEFs remains elusive. IEEFs are primarily discussed in descriptive terms, usually by listing a large set of building features. Shutters, storm windows, blinds, curtains, awnings, porches, operable windows, interior courtyards, clerestories, cupolas, vents, roof monitors, skylights, light wells, overhangs, thermally massive walls, low window-to-wall ratio, building orientation, and landscape features have all been included on lists of IEEFs (Hensley and Aguilar 2011; Grimmer et al. 2013; A. W. Smith 1981). These features have been interpreted as "inherently energy efficient" because of a belief that "historic building construction methods and materials often maximized natural sources of heat, light and ventilation to respond to local climatic conditions" (Hensley and Aguilar 2011). This post-hoc interpretation of environmental design principles in historic buildings emerges, in part, by looking at historical patterns of energy consumption. This line of thinking is summarized by Burns (1982) in a detailed review of IEEFs in older homes: "Historically, energy has been difficult to obtain, produce, and control and its resulting value demanded that it be used efficiently."

This existing logic behind IEEFs, however, makes it difficult for them to deliver on their promise in any given building. There are two major barriers. The first barrier is that the existing logic seems to imply that everything that is part of the original design of the building is an IEEF (or potential IEEF). While this is consistent with preservation objectives, which aim to protect historic fabric and visual appearance, it can be an overwhelming and untenable starting point for an analysis seeking to identify and evaluate IEEFs. The second (and more critical) barrier is that the existing logic is entirely qualitative. Evaluating whether or not a given IEEF is, in fact, "energy efficient" is a quantitative problem for which an appropriate point of reference must be determined (i.e., energy efficient compared to what?). Since building owners and project design teams make decisions about energy retrofits largely using quantitative data, assessment tools, and performance metrics, IEEFs must be understood quantitatively in order to be viable contenders for preservation during a retrofit process.

The objective of this study is to develop a quantitative methodology to identify and evaluate the IEEFs in an historic building. A methodology meeting this objective must: (1) characterize "energy efficient" behavior, and (2) identify which features in the building are most important in producing those behaviors. In this study, a novel probabilistic simulation method has been developed to identify which features and/or proposed retrofits in the building are most important to producing energy efficient behavior. The method developed here uses regionalized sensitivity analysis and tree-based models – classification trees and random forests – and is demonstrated via application to a case study historic building. The results of the study are discussed in terms of their broader implications for the approach to energy efficiency in historic buildings.

Methods

Regionlized sensitivity analysis

Broadly speaking, sensitivity analysis (SA) is a class of methods that examines how variation (or uncertainty) in the output of a model can be can be apportioned to different sources of variation (or uncertainty) in the model inputs (also referred to as predictors or factors) (Saltelli et al. 2004). In scope, these methods can be local, in which only a single input factor is varied or factors are varied one at a time while all others are kept constant, or they can be global, in which input factors are varied while all other factors are also varied. The former allows only a single point (or several points) in the input space to be explored, while the latter allows for exploration of the full input space. Global methods include regression-based techniques using standardized regression coefficients, screening techniques like the Morris method, or meta-modeling, in which a non-parametric model is used to evaluate sensitivity (Iooss and Lemaître 2015; Tian 2013).

In contrast to global SA, regionalized sensitivity analysis (RSA) examines how variation in model inputs influence model output *in a particular region of interest*. Like global methods, input factors are varied simultaneously in RSA, but unlike global methods, the model output is categorized into two classes: those that fall within the region of interest (behavioral), and those that do not (non-behavioral). Saltelli et al. (2004) describe the steps in an RSA as follows:

- For each of the p predictors, $X_1, X_2, \ldots, X_p$, define an input range that captures its uncertainty.
- Conduct a sufficiently large number of Monte Carlo simulations, N, in which the p predictors are varied simultaneously over their respective ranges. The output from each simulation, $Y_1, Y_2, \ldots, Y_n$, will be associated with a vector of predictor values.
- Classify each of the simulation vectors as either behavioral, B, or non-behavioral, $\bar{B}$, based on their output. This defines, for each predictor X_i, two subsets: $(X_i|B)$ of m elements and $(X_i|\bar{B})$ of n elements, where $m + n = N$.

This portion of the RSA process is also known as Monte Carlo filtering, and a diagram is provided in Figure 1.

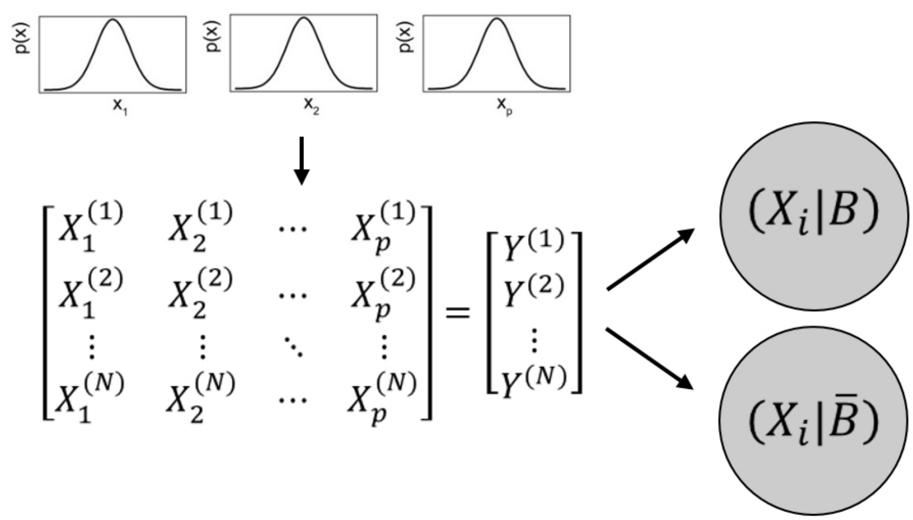

Figure 1: Conceptual diagram of the Monte Carlo filtering process

Once the predictor space has been divided into behavioral and non-behavioral sets, some form of analysis must be applied to the two sets to assess whether a given factor is important in producing behavioral realizations of the model. Traditionally, the two-sample Kolmogorov-Smirnov test has been used to evaluate factor importance in RSA. However, this test is univariate and therefore cannot detect higher-order interactions with other variables, and also intended for application to continuous variables only, severely limiting the applicability of this test to building energy simulation applications. Instead, classification trees and random forests are used here to assess the importance of each of the model factors in producing behavioral realizations. The use of tree-based models in this application is a form of sensitivity analysis via meta-modeling.

Decision trees and random forests

Decision trees are a class of predictive models that divide the predictor space into distinct and non-overlapping rectangular regions based on a series of splitting rules, and fit a simple model (e.g., a constant) in each region (Hastie, Tibshirani, and Friedman 2009; James et al. 2013). Trees can be used to predict a continuous response (regression trees), or a categorical one (classification trees). In both types of trees, the predictor space – i.e., the set of all possible values for predictor variables $X_1, X_2, \dots, X_p$– is divided using a top-down, greedy method known as recursive binary splitting. The splitting method begins at the top of the tree, considering all possible predictor variables and all possible cutpoints for each predictor. The predictor X_j and cutpoint s that minimize the given splitting criterion are selected, and the predictor space is split into two regions: $\{X|X_j < s\}$ and $\{X|X_j \geq s\}$. This binary splitting process is then repeated for each new region independently, until a stopping criterion is reached. Regions that cannot be split further are known as terminal nodes or leaves, and splitting points within the tree are known as internal nodes. Note that the model may reach the stopping criterion before all of the variables are used.

As outlined by Breiman et al. (1984), there are three key elements involved in the construction of a tree: (1) the selection of the splits; (2) the stopping criterion; (3) the assignment of a response value to each terminal node. For more details on classification and regression trees, see Hastie, Tibshirani, and Friedman (2009) and James et al. (2013), upon which this discussion is largely based.

Figure 2 provides a graphical depiction of the results of a simple tree-based model using two predictor variables. In this example, the first split is made using variable X_1 at cutpoint s_1, dividing the predictor space into region $R_1 = \{X|X_1 < s_1\}$ and $R_2 + R_3 = \{X|X_1 \geq s_1\}$; the second split is made using variable X_2 at cutpoint s_2, further dividing region $R_2 + R_3$ into regions $R_2 = \{X|X_1 \geq s_1, X_2 < s_2\}$ and $R_3 = \{X|X_1 \geq s_1, X_2 \geq s_2\}$. The predicted value for each observation falling into region R_1 is the mean value (or majority class, for classification trees) for that region, and likewise for regions R_2 and R_3.

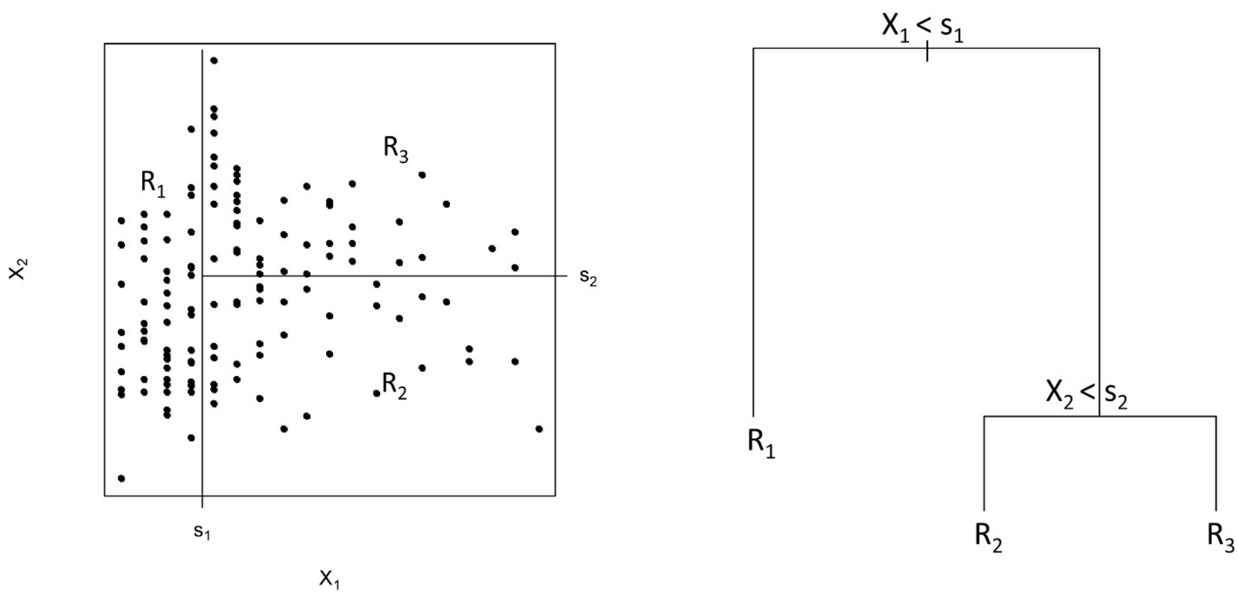

Figure 2: Partition plot of the predictor space (left) and corresponding classification tree (right). Figure adapted from James et al. (2013).

In RSA applications, a binary classification tree is used to divide the predictor space into behavioral and non-behavioral regions (nodes). The behavioral nodes describe the combinations of predictors and their ranges that produce behavioral realizations of the model. Variables towards the top of the tree (i.e., those used in the earliest splits) make the greatest contribution to reduction in deviance, and are therefore interpreted as being more important to producing behavioral realizations (Mishra, Deeds, and RamaRao 2003).

Overall, there are a number of advantages to tree-based methods: (1) they are model-independent (i.e., nonparametric); (2) they can easily handle both continuous and categorical predictors; (3) they detect and capture complex, non-linear interactions, thereby uncovering structure in the data; (4) and they are conceptually simple, with a straightforward interpretation and graphical display. However, the major drawback to decision trees is that they have high variance, meaning that they are sensitive to fluctuations in the training data. This means that small changes in the Monte Carlo data can produce different trees and, in the context of RSA, different rankings of predictor importance. Often, a pruning method is used to create a smaller tree with lower variance, but slightly higher bias (James et al. 2013), although this does not fully resolve the inherent instability of a single decision tree. Random forests provide one useful solution.

Random forests are a method for reducing the variance of decision trees by growing an ensemble of individual trees and then aggregating them. Bootstrapping is used to take repeated samples from the training data, and a single decision tree is grown (unpruned) on each bootstrapped sample. On average, each of the bootstrapped samples uses about two-thirds of the total training data. The remaining observations – referred to as “out-of-bag” (OOB) – can be used to provide a valid estimate of test error for the model (James et al. 2013). The overall prediction for outcome Y is the average of the predictions of all of the individual trees (for regression trees), or the most commonly occurring class (“majority vote”) among the individual trees (for classification trees).

While random forests reduce variance compared to single trees, it comes at a loss of interpretability since there is no longer a single tree. However, permutation importance, which measures how much the model prediction accuracy decreases when one predictor variable is randomly permuted, and the other variables remain the same, can be interpreted as factor importance (Liaw and Wiener 2002). In this study, both classification trees and random forests are used and presented for comparison.

Application to building energy simulation

Tian (2013) outlines the general steps for applying sensitivity analysis with building energy simulation tools as follows:

1. Define probability distributions for input factors
2. Create building energy models based on probability distributions
3. Run energy models
4. Collect simulation results

5. Run sensitivity analysis
6. Present sensitivity analysis results

Figure 3 illustrates the process used in this study to couple Monte Carlo simulations with regionalized sensitivity analysis.

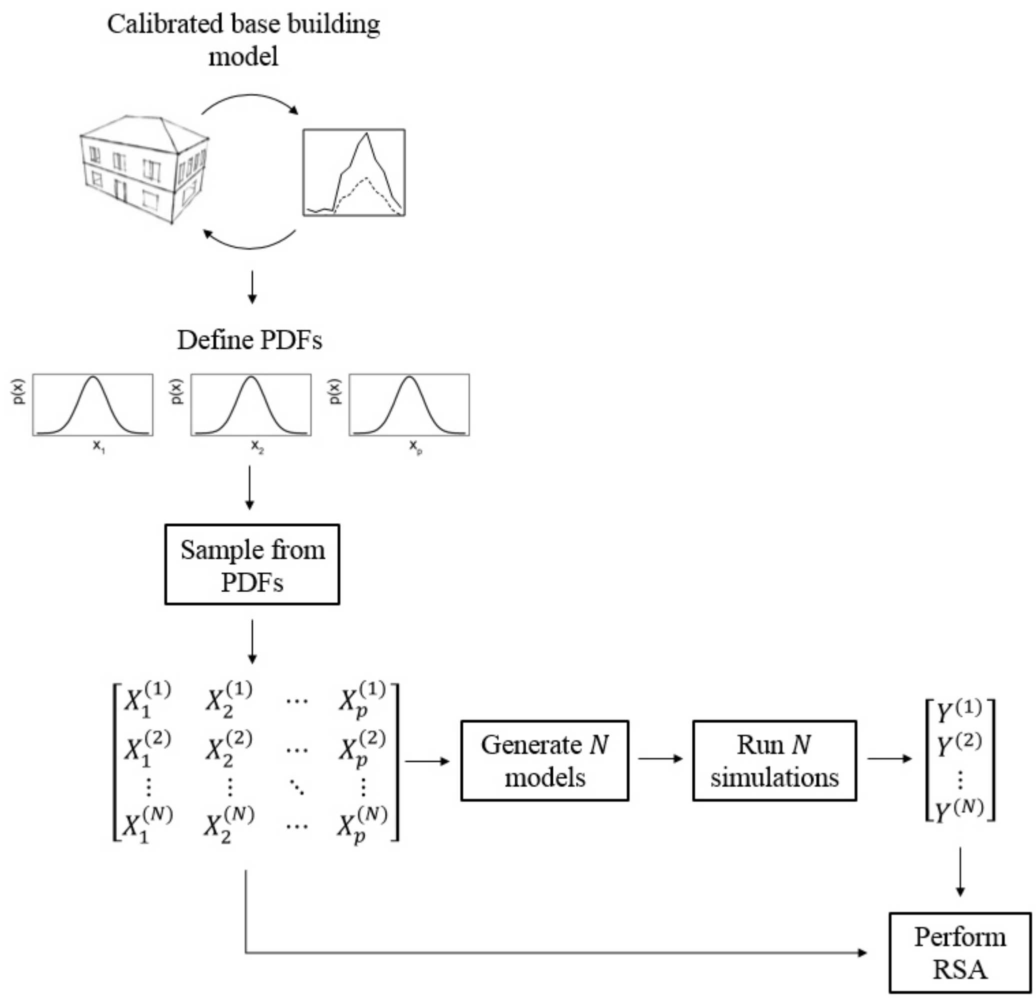

Figure 3: Diagram of process coupling Monte Carlo simulations with regionalized sensitivity analysis

Probability density functions (PDFs) were defined for each of the p variables of interest in the study. Using the **randtoolbox** package (Dutang and Savicky 2015) in the statistical computing software R (R Core Team 2014), sobol sequences were used to sample from these PDFs and produce an $N \ x \ p$ input matrix. Sobol sequences have been shown previously to provide efficient sampling of the parameter space in building energy simulation applications (Burhenne 2011). The energy simulations for this study were performed using the software EnergyPlus (U.S. Department of Energy 2016), and the eppy package (Philip 2016) in the Python programming language was used to automatically generate N models with input parameters corresponding to each vector in the input matrix. The N simulations were manually divided into batches and run on multiple computers. A Python script was used to compile the output from the N simulations into a single file, which was combined into a single file in the statistical computing software R. The RSA was then conducted in R using the **tree** package (Ripley 2016) for producing classification trees, the **randomForest** package (Liaw and Wiener 2002) for building the random forests, and the **party** package (Hothorn, Hornik, and Zeileis 2006) for building conditional inference trees and forests.

Results and Discussion

Building description

The RSA method with classification trees and random forests is demonstrated here via application to an historic building on the Penn State University Park campus. The Old Botany building was designed in 1887 by Frederick L. Olds, the University's first official architect, as part of Penn State's initial building program (Paris 1998). Olds designed and built seven new instructional buildings and six faculty cottages during this period, spanning 1887 to 1893, and Old Botany is the oldest of these and one of only five that remain today (Paris 1998). Construction on Old Botany was completed in 1888 and included the building itself in addition to an attached greenhouse, conservatory and power plant. The building originally housed instructional and laboratory space for the botany department. In 1929 the botany department moved out, and the building has housed a succession of various programs since: zoology until 1940, Reserve Officer Training Corps (ROTC) until 1946, veterans administration until the 1950s, and music until the 1960s (Grant 1977); the building is currently home to the Department of Asian Studies.

Figure 4 depicts the building and accompanying structures as originally constructed (Special Collections Library, Pennsylvania State University c1889). Olds designed the building in the

Richardsonian Romanesque style. This is evident in the building's three part massing: a random ashlar stone first floor, a brick second floor, and a slate hipped roof (Paris 1998). The main façade of the building faces southeast, and a door on the southwest façade leads to the attached conservatory; the building has fenestration on all four facades. Eyelid dormers project from the hipped roof, which is topped with a terra cotta crest on its ridge.

As it stands today, the exterior of the building itself has remained largely unaltered, making the Old Botany building the oldest building on the Penn State campus that retains its original appearance (National Register Nomination #81000538 1981). The building interior layout and site, however, have changed somewhat Formal botanical gardens and a nearby row of evergreen trees dubbed the "Ghost Walk" predated the building and surrounded it from its original construction, but the latter was cut down in 1929 (Grant 1977) and the former was gone by the late 1930s. The greenhouse was torn town in 1940, and the conservatory and power plant are no longer extant. Three trees flanking the building date to around its original construction, and today are marked with plaques: two Japanese maple trees – one on the southwest, which died in 1981, and one on the northeast sides of the building – and an umbrella pine. The building interior was originally composed of open classroom spaces on the second floor, but these spaces have all been reconfigured to smaller rooms, and overcrowding was an issue in the building as early as 1915 (Grant 1977).

The building itself has a gross square footage of 5,275 ft^2 and includes a basement, two main floors, and an attic (3,462 ft^2 for first and second floors only) (Special Collections Library, Pennsylvania State University 1944). The floor to ceiling heights for the first and second floors are 12 feet and 13 feet, respectively, and 6.26 feet (average) for the basement. The foundation walls are 24 inch thick rubblestone, 16 inch thick stone on the first floor, and 12 – 16 inch thick brick on the second floor (Special Collections Library, Pennsylvania State University 1944). The building is heated with cast iron radiators connected to the campus central steam system. The building has no central ventilation or cooling system; portable or window-mounted units in each room are used to provide cooling.

Figure 4: Photograph showing a view of Old Botany from the southeast (circa 1889).

Almost a decade of monthly utility data for the Old Botany building were obtained from Penn State's Office of Physical Plant in order to understand the building's current energy performance. Figure 5 plots the building's monthly electricity consumption and Figure 6 plots monthly steam consumption from 2007 to 2014 (partial year data only available for 2014).

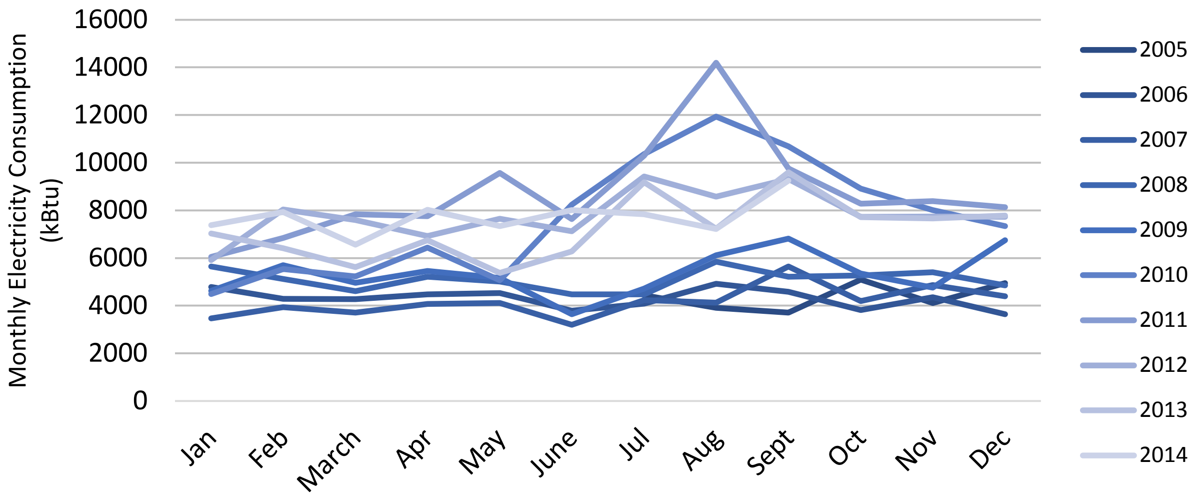

Figure 5: Monthly electricity utility data for Old Botany building

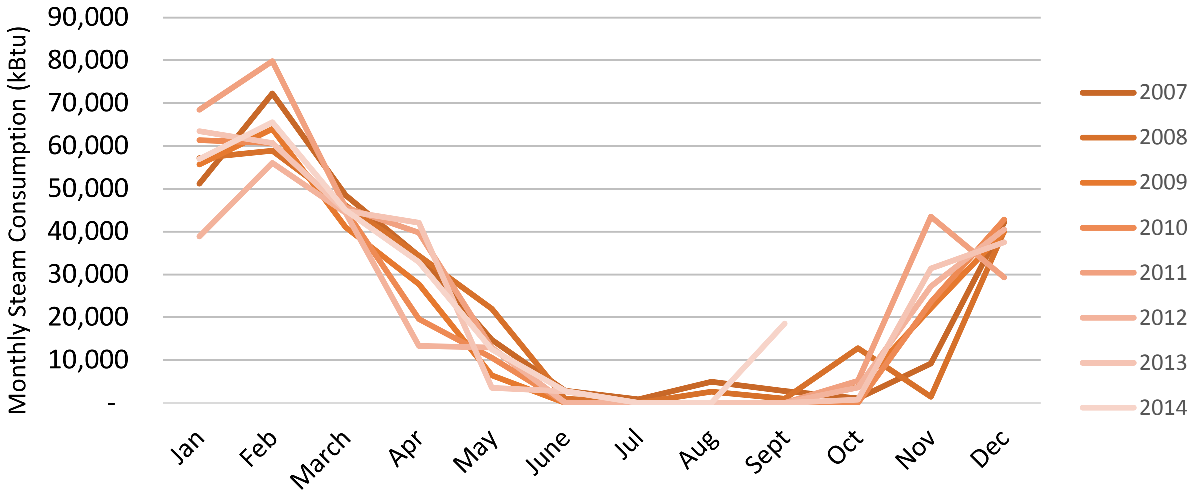

Figure 6: Monthly steam utility data for Old Botany building

The data indicates that the building's energy consumption is dominated by its steam use, which accounts for 78% of total annual energy use, on average. Space heating is the only major steam end use in the building, and this is reflected in the very low base load and strong seasonal dependence in Figure 6. Electricity end uses include lights, plug loads (e.g., computers and other office equipment), and the portable and window-mounted air conditioning units. While Figure 5 shows a moderate seasonal peak in July and August, especially in more recent years, the data suggest that space cooling is a relatively small end use compared to the base electric loads.

The building's average annual energy use intensity (EUI) is 67.1 kBtu/ft^2-yr. Without controlling for any other factors, this EUI is slightly below average compared to the rest of the U.S. commercial building stock for a building of its type, size, and vintage. According to the 2003 CBECS, the category mean EUI for office buildings is 92.9 kBtu/ft^2-yr, for buildings 5,001 to 10,000 square feet is 78.3 kBtu/ft^2-yr, and for buildings constructed prior to 1920 is 80.2 kBtu/ft^2-yr (U.S. Energy Information Administration 2003); this can be compared to Griffith et al. (2007) who suggest that some of the most high performance commercial buildings have an EUI ranging between around 25 and 40 kBtu/ft^2-yr.

While the Old Botany building had been regarded as a potential candidate for demolition in the past, it was designated a campus landmark by 1970 (Grant 1977). In 1981, the Old Campus area of Penn State was added to the National Register of Historic Places as a national historic district under the name “Farmers’ High School,” and the Old Botany building is listed as one of 36 contributing resources (National Register Nomination #81000538 1981). The nomination form emphasizes Old Botany’s modesty, stating that the building’s “…enduring character derives from its simplicity,” and describing it as “an unassuming version of the Romanesque Revival style” with “quiet and tasteful detailing” (National Register Nomination #81000538 1981). Several features of the building are highlighted in the nomination, including the segmented arches, the eyelid dormers, the exterior wall materials, the terra cotta roof crest, and the large semicircular window on the northeast façade.

Model description

The building was modeled using the simulation software EnergyPlus version 8.5.0, developed by the U.S. Department of Energy (2016). The base building was modeled with three zones: two occupied, conditioned zones, and an unconditioned attic. The basement was not modeled; the ground condition was modeled as an adiabatic slab surface. The stone and brick walls were modeled with typical stone and brick properties based on those found in the ASHRAE Handbook of Fundamentals (ASHRAE 2013). Brick was modeled with a conductivity of 0.89 W/m-K, a density of 1920 kg/m^3, and a specific heat of 790 K/kg-K; stone was modeled with a conductivity of 3.17 W/m-K, a density of 2560 kg/m^3, and a specific heat of 790 K/kg-K. Windows were modeled as typical single pane, with a U-value of 5.63 W/m^2-K and a Solar Heat Gain Coefficient of 0.819. These envelope material properties fall generally within the range of those determined experimentally by Baker (2011) and Rhee-Duverne and Baker (2013). The infiltration rate was 0.001777 m3/s-m^2, which is the approximate upper standard deviation value for masonry construction from Persily (1999), adjusted to 4 Pa. Internal gains were modeled as follows, per the typical office building assumptions in Deru et al. (2011): lights: 16.89 W/m^2; electric plug loads: 10.76 W/m^2; people 18.58 m^2/person. EnergyPlus is not able to model district steam systems, therefore the heating system was modeled as an “ideal” steam boiler with 100% efficiency connected to steam baseboard radiators. No central ventilation system was modeled; window air conditioning units were modeled in each of the two occupied zones. Equipment sizing was performed using the 99% heating and 1% cooling design day data for Altoona, PA.

While the Monte Carlo simulations were performed using Typical Meteorological Year (TMY) weather data for State College (averaged data from the years 1991-2005), actual meteorological year (AMY) data was used to evaluate model calibration. AMY data for the weather station KUNV (University Park Airport, State College, PA) was obtained for the period July 1, 2013 through June 30, 2014 from Weather Analytics (http://www.weatheranalytics.com/wa/). The energy simulation was run using this weather file, and the results were compared to the measured utility data for the same period of time. The monthly values were adjusted for utility billing period start and end dates, which started on roughly the 25th of each month for electricity, and on roughly the 15th of each month for steam. The results are plotted in Figures 7 and 8.

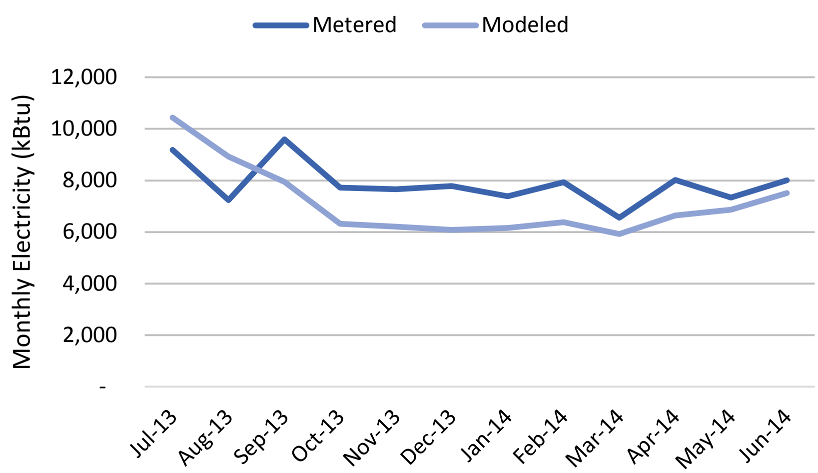

Figure 7: Metered vs. modeled monthly electricity consumption

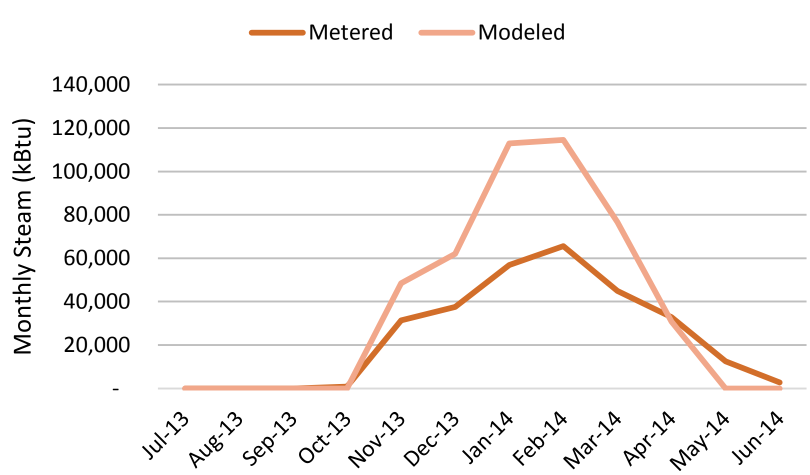

Figure 8: Metered vs. modeled monthly steam consumption

According to ASHRAE Guideline 14 (ASHRAE 2002), the simulation model shall have a normalized mean bias error (NMBE) of ±5% and a coefficient of variation of the root mean square error CV(RMSE) of 15% relative to monthly calibration data in order for the model to be considered acceptably calibrated. Table 1 gives these statistics for the model of the Old Botany building.

Table 1: Calibration metrics for model of Old Botany building

Metric	Electricity	Steam	Total
CV(RMSE)	16.7%	105.9%	77.3%
NMBE	9.6%	-56.1%	-39.8%

The table indicates that the current model does not meet the criteria for calibration. Due to time constraints on the project, additional measured data from the building was not collected. Future work will collect additional measured data from the building (e.g., measured air leakage) to develop a better calibrated model; the model described here is used in this study for demonstration purposes.

For this study, 13 energy retrofit measures were selected for analysis. These measures were selected based on: (1) lists of common energy retrofit measures recommendations for commercial buildings given in standards and guides such as ASHRAE Standard 100, *Energy Efficiency in Existing Buildings* (ASHRAE 2015), CEN EN 16247-2,Energy Audits – Part 2: Buildings (CEN 2014), and the U.S. DOE Advanced Energy Retrofit Guide for Office Buildings (Liu et al. 2011); (2) energy retrofit measures recommended for historic buildings in the guidance documents listed in Webb (2017); (3) archival research on the Old Botany building. To reiterate the recommendation cited in the introduction, "the key to a successful rehabilitation project is to understand and identify the existing energy-efficient aspects of the historic building" (Hensley and Aguilar 2011) and historic drawings, descriptions, and photographs of the Old Botany building were used to qualitatively identify characteristic features of the building that may serve an energy conservation function. Based on the features commonly listed as IEEFs (Hensley and Aguilar 2011; Grimmer et al. 2013; A. W. Smith 1981) and the archival research on Old Botany, the features listed in Table 2 were qualitatively identified as potential IEEFs:

Table 2: List of potential inherent energy efficient features for the Old Botany building

Feature	Rationale
Thermal mass	The building has 16 inch thick stone walls on the first floor, and 12 – 16 inch thick brick walls on the second floor
Landscape features	Historic photographs of the building show the growth of major landscape features over time; three trees flanking the building play a potentially important role in providing exterior solar shading: (1) a japanese maple on the southwest façade; (2) a japanese maple on the northeast façade; (3) an umbrella pine on the northeast façade.
Operable interior blinds	Historic photographs of the building show active use of interior blinds; this is evident in both interior and exterior photographs In addition, Penn State's 2012 Building Energy Report Smart Energy Tip for Old Botany recommends keeping blinds closed in the summer to reduce solar gain (Penn State Office of Physical Plant 2012)
Daylighting	The building has a compact footprint with ample fenestration on all facades, suggesting that daylight will penetrate into most of the floorplate.
Operable windows	Historic photographs of the building show active use of operable windows, especially in the spring and summer

The list of retrofit measures evaluated in this study, along with a description of their corresponding probability distribution functions, are listed in Table 3. The following variables in Table 3 correspond to the potential inherent energy efficient features in Table 2 as follows: thermal mass - variable X_1; landscape features - variables X_6, X_7, X_8; daylighting - variable X_{10}; operable interior blinds - variable X_{11}; operable windows - variable X_{12}. This list of retrofits evaluated in this study is not intended to be exhaustive or definitive. For any given building, the list of relevant retrofit measures is typically specific to that building, and the measures evaluated here are intended to be broadly representative. The ranges for the probability distributions for each of the retrofit measures were determined from a variety of sources. For each measure, one end of the probability distribution – either the maximum value, or the minimum value, depending on the measure – represents the "base" building, i.e., the current performance as-is. The other end of the distribution represents the maximum value, or "max tech," for that given measure. Similar to the use of the term in Griffith et al. (Griffith et al. 2007), the "max tech" value in this study simply represents a high-performance scenario, not the maximum physically possible value.

Table 3: Evaluated retrofit measures and corresponding probability distributions

Variable	Measure description	Distribution	Range	Unit
X1	Increase interior wall R-value	Uniform	[0.001, 5.08]	W/m^2-K
X2	Increase roof (attic floor) R-value	Uniform	[0.18, 8.26]	W/m^2-K
X3	Decrease window SHGC	Uniform	[0.35, 0.819]	-
X4	Decrease window U-factor	Uniform	[1.42, 5.778]	W/m^2-K
X5	Reduce infiltration rate	Uniform	[0.0002956, 0.001777]	m^3/s-m2
X6	Exterior shading - east japanese maple tree	Uniform	[0.0,1.0]	-
X7	Exterior shading - west japanese maple tree	Uniform	[0.0,1.0]	-
X8	Exterior shading – east umbrella pine	Uniform	[0.0,1.0]	-
X9	Reduce interior lighting power density	Uniform	[8.8, 16.89]	W/m^2
X10	Daylight control of interior lighting	Uniform	[0, 0.99]	-
X11	Operate interior shades to reduce solar gain	Discrete Uniform	[0, 1]	-
X12	Operate windows to provide natural ventilation	Uniform	[0, 1]	-
X13	Increase fraction of roof area covered in PV panels	Uniform	[0.0, 1.0]	-

In this study, 50% energy savings over the “base” case model was used as the behavioral threshold; in terms of EUI, this corresponded to $Y < 42.4$ kBtu/ft2-yr. While a variety of behavioral thresholds could be relevant in a building energy simulation context – e.g., the threshold could be set based on benchmarking target, net zero energy, or any other criteria meaningful for a given project – energy savings of 50% compared to the building’s current performance is generally considered to qualify as a “deep” energy retrofit (Zhivov et al. 2016; Liu et al. 2011), and was used because it is generally representative of an ambitious energy savings target.

Two response variables were examined for the sake of comparison: total annual site energy consumption and net annual site energy consumption, which accounts for any energy produced on-site. The behavioral threshold was the same in both cases. This resulted in 2151 simulations in the behavioral set and 2848 simulations in the non-behavioral set for total site energy, and 2944 simulations in the behavioral set and 2056 simulations in the non-behavioral set for net site energy. A histogram of the simulation results is shown in Figure 9 for each of these response variables; the red vertical line indicates the behavioral threshold.

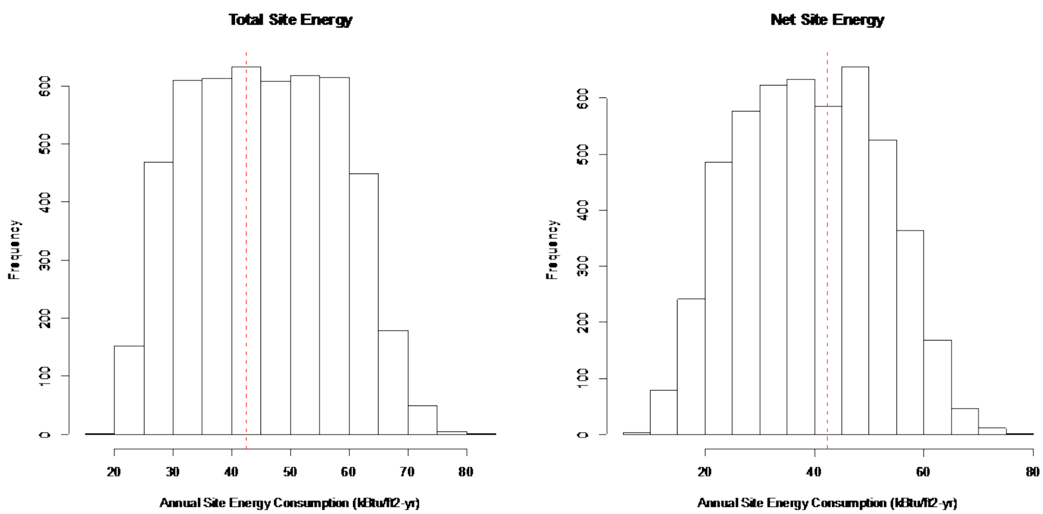

Figure 9: Histogram of Monte Carlo simulations for total site energy (left) and net site energy (right)

Model results – Total site energy

A random forest model was fit to the data from the Monte Carlo simulation, using total site energy as the response variable. The overall OOB error rate was 3.96%, and the class errors are shown in Table 4.

Table 4: Random forest model classification errors for total site energy

	OOB Predicted		
Actual	B	$\bar{B}$	Class error (%)
B	2062	89	4.1%
$\bar{B}$	109	2740	3.8%

The permutation importance (unscaled) for each variable is shown in Table 5. Since variable importance has been shown to be biased when predictors are of varying types and numbers of categories (Strobl et al. 2007), variable importance was also evaluated using a forest of conditional inference trees via the **party** package in R (Strobl et al. 2007, 2008). The permutation importance scores using the **randomForest** package and **party** package are generally in agreement with one another. The results indicate that X_5 (reduced infiltration) is by far the most important variable. Variable X_1 (interior wall insulation) could also be considered important, but much less than X_5. The importance measure for all other variables is effectively zero.

Table 5: Random forest variable importance measures for total site energy

		Permutation importance	
Variable	Description	randomForest	party
X_1	Interior wall insulation	0.028	0.035
X_2	Attic insulation	0.002	0.003
X_3	Window SHGC	0.000	0.001
X_4	Window U-factor	0.007	0.010
X_5	Reduced infiltration	0.379	0.409
X_6	Exterior shading – Tree 1	0.000	0.000
X_7	Exterior shading – Tree 2	-0.001	0.000
X_8	Exterior shading – Tree 3	0.000	0.000
X_9	Reduced lighting power density	0.001	0.001
X_{10}	Daylight harvesting	0.003	0.004
X_{11}	Operable interior blinds	0.000	0.000
X_{12}	Operable windows	0.000	0.000
X_{13}	Photovoltaics	0.000	0.000

As previously mentioned, compared to classification trees, random forests have reduced variance, but achieve this at the expense of some interpretability. Despite its limitations, plotting a single classification tree can be instructive. While this tree should not be taken as "exact", it can indicate approximate cutpoints for each of the variables. A single (unpruned) classification tree was fit to the entire set of Monte Carlo simulations and is shown in Figure 10. The resulting tree has eight terminal nodes – four behavioral (B) and four non-behavioral (B_bar) – and three variables are used in the model, X_5 (reduced infiltration), X_1 (interior wall insulation), X_4 (window U-factor). Since only these three variables enter the tree, only these three variables are important to producing energy-efficient behavior. Since X_5 (reduced infiltration) enters the model first, it is the most important of the three variables; X_1 (interior wall insulation) and X_4 (window U-factor) enter the tree at roughly the same point and are therefore of equal secondary importance. This matches the results of the random forest model importance measures

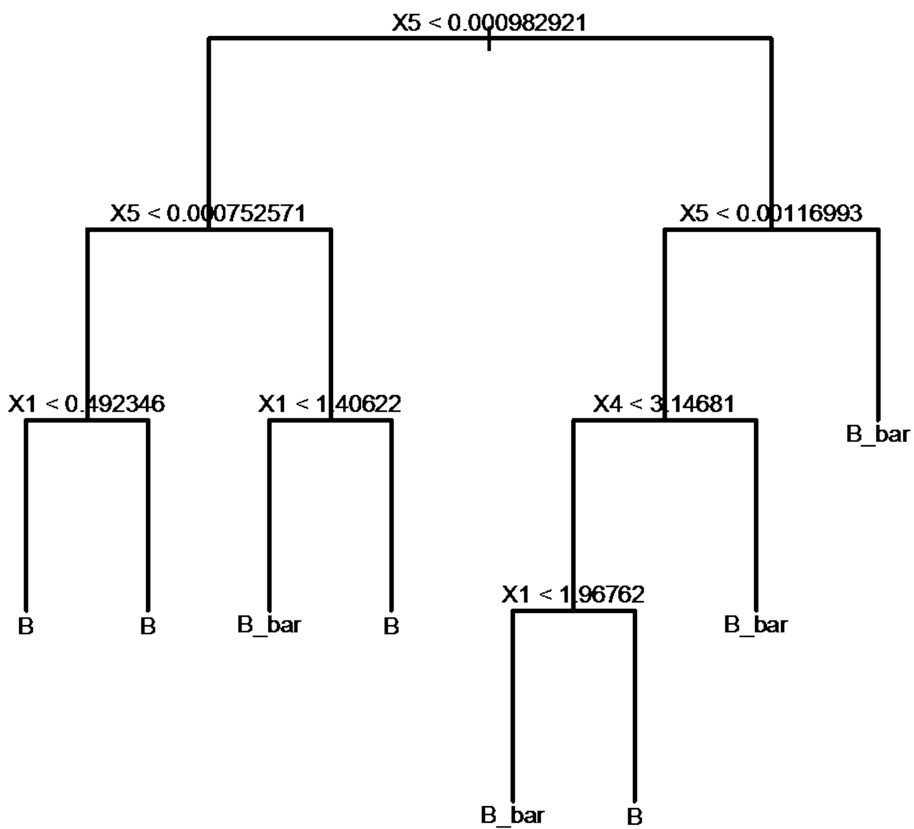

Figure 10: Unpruned classification tree for total site energy

Table 6 provides additional detail on each of the terminal nodes, indicating the split conditions, the fitted (predicted) value at each node, and the fitted probabilities for each response level. What is particularly useful, conceptually, about using a single classification tree (rather than a random forest) to understand the Monte Carlo simulations is that the behavioral terminal nodes can be interpreted as four unique behavioral regions within the sample space. Effectively, each of the behavioral terminal nodes identifies a different “pathway” to achieving the desired energy efficiency goal. Node 8, for example, identifies a behavioral region in the sample space with very low infiltration rates (X_5 < 0.00075 m^3/s-m2) and minimal improvement to wall insulation (X_1 < 0.49 W/m^2-K). In contrast, Node 11 identifies a behavioral region with only moderately low infiltration rates (0.00075 < X_5 < 0.00098 m^3/s-m2) but greater improvements to wall insulation (X_1 > 1.41 W/m^2-K).

Table 6: Terminal nodes for classification tree in Figure 10

			Fitted probabilities	
Node	Split conditions	Fitted value	B	$\bar{B}$
8	X5 < 0.00098; X5 < 0.00075; X1 < 0.49	B	0.78	0.22
9	X5 < 0.00098; X5 < 0.00075; X1 > 0.49	B	0.99	0.01
10	X5 < 0.00098; X5 > 0.00075; X1 < 1.41	$\bar{B}$	0.26	0.74
11	X5 < 0.00098; X5 > 0.00075; X1 > 1.41	B	0.85	0.15
24	X5 > 0.00098; X5 < 0.001; X4 < 3.15; X1 < 1.97	$\bar{B}$	0.06	0.94
25	X5 > 0.00098; X5 < 0.001; X4 < 3.15; X1 > 1.97	B	0.56	0.44
13	X5 > 0.00098; X5 < 0.001; X4 > 3.15	$\bar{B}$	0.07	0.93
7	X5 > 0.00098; X5 > 0.001	$\bar{B}$	0.00	1.00

Model results – Net site energy

A random forest model was fit to the Monte Carlo simulation data using net site energy as the response variable. The overall OOB error rate was 4.62%, and the class errors are shown in Table 7.

Table 7: Random forest model classification errors for net site energy

	OOB Predicted		
Actual	B	$\bar{B}$	Class error (%)
B	2836	108	3.7%
$\bar{B}$	123	1933	6.0%

The permutation importance (unscaled) for each variable is shown in Table 8 using net site energy as the response variable. As with total site energy, variable importance here has also been computed using conditional inference trees, and, again, both types of permutation importance values are generally in agreement with one another. Again, the results indicate that X_5 (reduced infiltration) is by far the most important variable, and variables X_1 (interior wall insulation) and X_{13} (photovoltaics) could both also be considered important, but, again, much less than X_5. The importance measure for all other variables is effectively zero.

Table 8: Random forest variable importance measures for net site energy

		Permutation importance	
Variable	Description	randomForest	party
X_1	Interior wall insulation	0.020	0.025
X_2	Attic insulation	0.001	0.001
X_3	Window SHGC	0.000	0.000
X_4	Window U-factor	0.007	0.008
X_5	Reduced infiltration	0.336	0.370
X_6	Exterior shading – Tree 1	0.000	0.000
X_7	Exterior shading – Tree 2	0.000	0.000
X_8	Exterior shading – Tree 3	0.002	0.000
X_9	Reduced lighting power density	0.000	0.000
X_{10}	Daylight harvesting	0.002	0.002
X_{11}	Operable interior blinds	0.000	0.001
X_{12}	Operable windows	0.000	0.000
X_{13}	Photovoltaics	0.036	0.043

A single (unpruned) classification tree was fit to the entire set of Monte Carlo simulations for net site energy and is shown in Figure 11. The resulting tree has eleven terminal nodes – five behavioral (B) and six non-behavioral (B_bar) – and three variables are used in the model, X_5 (reduced infiltration), X_1 (interior wall insulation), X_{13} (photovoltaics). Since only these three variables enter the tree, only these three variables are important to producing energy-efficient behavior. Since X_5 (reduced infiltration) enters the model first, it is the most important of the three variables; X_1 (interior wall insulation) and X_{13} (photovoltaics) enter the tree at roughly the same point and are therefore of equal secondary importance. This matches the results of the random forest model importance measures.

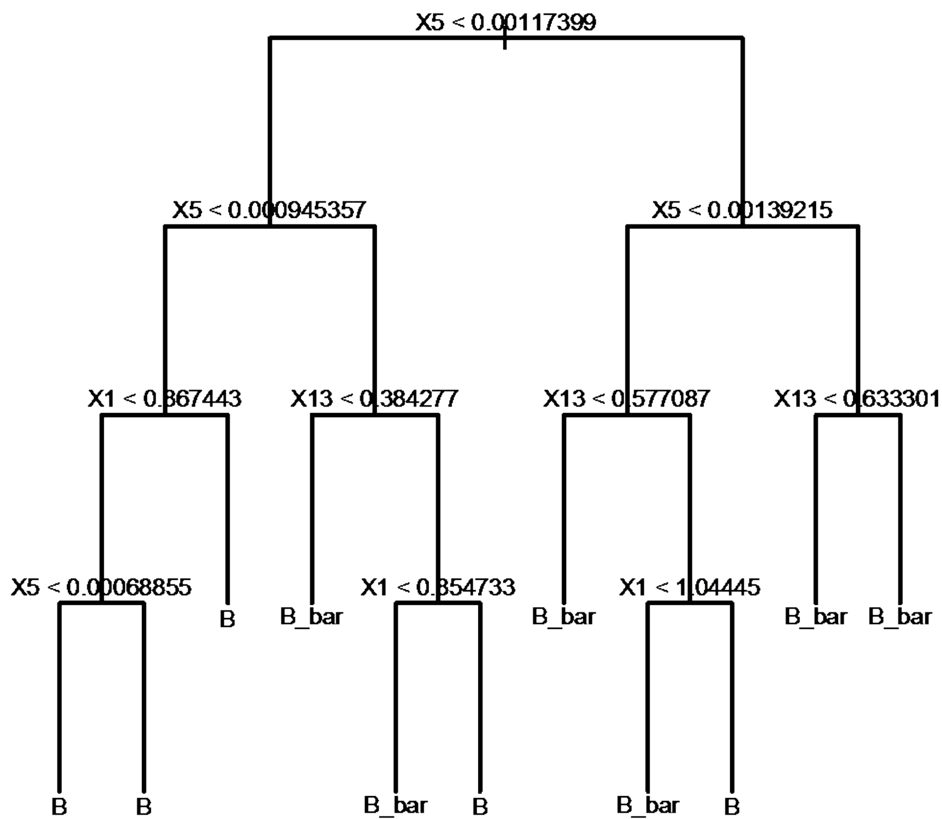

Figure 11: Unpruned classification tree for net site energy

Table 9, lists each of the terminal nodes, indicating the split conditions, the fitted (predicted) value at each node, and the fitted probabilities for each response level. Again, the behavioral terminal nodes can be viewed as a method for identifying different “pathways” to achieving behavioral outcomes. Compared to the total site energy classification tree in Figure 10, the inclusion of variable X_{13} in the model adds “pathways” with different sets of tradeoffs. Node 23, for example, has moderately low infiltration rates (0.0009 > X_5 < 0.001 m^3/s-m2), moderate improvements in wall insulation (X_1 > 0.85 W/m^2-K), and a moderate fraction of the roof area covered in photovoltaics (X_{13} > 0.38 % of roof area). Node 27 has slightly higher infiltration rates, but trades off for a slightly greater improvement in wall insulation and a much higher fraction of roof area covered in photovoltaics.

Table 9: Terminal nodes for classification tree in Figure 11

			Fitted probabilities	
Node	Split conditions	Fitted value	B	$\bar{B}$
16	X5 < 0.001; X5 < 0.0009; X1 < 0.87; X5 < 0.0007	B	0.99	0.01
17	X5 < 0.001; X5 < 0.0009; X1 < 0.87; X5 > 0.0007	B	0.71	0.29
9	X5 < 0.001; X5 < 0.0009; X1 > 0.87	B	1.00	0.00
10	X5 < 0.001; X5 > 0.0009; X13 < 0.38	$\bar{B}$	0.44	0.56
22	X5 < 0.001; X5 > 0.0009; X13 > 0.38; X1 < 0.85	$\bar{B}$	0.43	0.57
23	X5 < 0.001; X5 > 0.0009; X13 > 0.38; X1 > 0.85	B	0.95	0.05
12	X5 > 0.001; X5 < 0.0014; X13 < 0.58	$\bar{B}$	0.11	0.89
26	X5 > 0.001; X5 < 0.0014; X13 > 0.58; X1 < 1.04	$\bar{B}$	0.11	0.89
27	X5 > 0.001; X5 < 0.0014; X13 > 0.58; X1 > 1.04	B	0.72	0.28
14	X5 > 0.001; X5 > 0.0014; X13 < 0.63	$\bar{B}$	0.00	1.00
15	X5 > 0.001; X5 > 0.0014; X13 > 0.63	$\bar{B}$	0.07	0.93

Discussion

In many ways, the analysis results are not surprising, and match our intuition. Old Botany is an envelope-dominated building, with a large exterior envelope area relative to its floor area and comparatively low internal loads. Space heating is the dominant energy end use, and, given this, the most important retrofit measures for improving energy performance are likely to be ones that reduce heating loads, like air sealing to reduce infiltration rates and adding insulation to increase wall R-value.

The benefit of the simulation results is that they give us quantitative insight beyond our intuition. The method developed and presented in this study, using Monte Carlo simulations and RSA with classification trees and random forests, allows us to efficiently explore the entire sample space and identify entire regions likely to produce the behaviors of interest. In doing so, this method captures the full value of a given retrofit measure, as its interactions with other parameters are accounted for. Compared to simply plotting the Monte Carlo simulations, the RSA adds helpful structure to our exploration of the sample space. The method used here also has distinct advantages over the typical one-at-a-time experimental design currently common in practice. If simulated one-at-a-time, the results would indicate that reducing infiltration rates will, by far, lead to the greatest energy savings, followed distantly by adding wall insulation, and adding PV panels to the roof (if net site energy is used as the response variable). While this allows us to explore individual points in the sample space, it does not tell us which ranges and combinations of these retrofit measures produce the behaviors of interest, a major limitation from a design and decision-making perspective.

Crucially, the method developed in this study allows us to identify different "pathways" to the behavior of interest, via the behavioral nodes of the classification trees. Conceptually, this is an especially valuable way to understand energy simulation results in the context of historic preservation. Recall that the purpose of this study is to identify and understand the IEEFs in an historic building. The method developed here identifies not just individual features, but combinations of features representing entire regions in the sample space, which can be viewed as "pathways" to achieving energy efficiency. This is a helpful way to frame the retrofit problem, since one or more of these "pathways" may be preferential from a pure preservation perspective.

While the results may not be surprising, they may be disappointing from a preservation perspective. In the case study presented here, the analysis results indicated that the features that we qualitatively identified as potential IEEFs – e.g., thermal mass, landscape features, operable windows (see Table 2 and Table 3) – are not, in fact, particularly energy efficient compared to other potential retrofits. Rather than preserving the building's thermally massive walls as-is, increasing the wall R-value by adding insulation (variable X_1) was shown to be important in producing energy-efficient behavior. Similarly, preserving or reinstating landscape features (variable X_6, X_7, X_8), utilizing daylighting control (variable X_{10}), operating interior blinds to reduce solar heat gain (variable X_{11}), and using operable windows for natural ventilation (variable X_{12}) were all shown to be unimportant in producing energy efficient behavior. Given this, it may not make sense to call these features “inherently energy efficient”.

More broadly, the results of this study suggest that the IEEF concept is not useful in its current form. The present study highlights the incompleteness and imprecision of the IEEF concept, largely due to its focus on energy. Total site energy consumption and net site energy consumption were used as the metrics of interest in this study because they most obviously capture the “energy-efficient” assertion of the IEEF concept. If the purpose of the IEEF concept is to best capture the potential benefits of a particular feature of interest, energy consumption may simply not be the right metric to use; in a heating-dominated building like Old Botany, under a different response variable, such as electricity consumption or cooling load, the results of the analysis may be very different. Changing the metric used, however, doesn’t change the actual energy use profile of the building, it only narrows the lens of the analysis. Developing a preservation argument around “energy efficiency” (or any energy-related metric) is perhaps bound to be problematic because energy efficiency is a moving target; what may have helped historic buildings qualify as “energy efficient” in the early days of energy conservation may no longer, as codes become more stringent, technologies become more efficient, and the energy performance of the building stock, as a whole, improves.

An improved approach to preservation and energy efficiency would clarify the IEEF concept by expanding it beyond energy or even energy-related metrics. Consider that many of the features often cited as IEEFs – e.g., shutters, blinds, awnings, operable windows – require daily or seasonal operation by building occupants. This suggests that the benefits of these features are not purely a result of their form and fabric, but tied to a larger set of behaviors. Similarly, the benefits of these features are not merely energy-related, as they also serve social, cultural, and physiological functions, e.g, thermal “delight” (Heschong 1979). Winter (2016) examines this idea, suggesting that we should understand IEEFs not only in terms of energy or thermal comfort, but as “bundles of materialities and practices.” Stated more explicitly, “the current focus on the fabric of buildings and architectural design needs to form part of a more expansive discussion, one that seeks to sustain low carbon comfort practices” (Winter 2016).

Conclusions

This study began by highlighting the importance of the IEEF concept in the approach to energy efficiency in historic buildings. The objective of this study was to develop a quantitative methodology to identify and evaluate IEEFs in an historic building. In order to meet this objective, a novel method was developed using building energy simulation and regionalized sensitivity analysis. While the conclusions about the value of specific retrofit measures cannot be generalized beyond the specific case study building used here, they suggest that features commonly viewed as IEEFs may not significantly contribute to energy efficient performance, when considered along with other common retrofit measures.

The results of this study have important implications for how we perform energy simulations and make decisions about energy retrofits in historic buildings. The proposed method was cited as being particularly beneficial in an historic preservation context, since it identifies different "pathways" to energy efficiency. But the method can also be usefully applied to exploring the sample space for energy retrofits in non-historic buildings. Any meaningful behavioral/non-behavioral threshold could be selected – 50% energy savings over the base case was used here, but a benchmarking target, net zero energy, or any other criteria meaningful for a given project could be used – and the threshold could even be based on multiple simulation output variables (e.g., energy consumption and thermal comfort conditions).

The results of this study also have implications for the prevailing narrative about preservation and energy efficiency. The greatest shortcoming of the current concept of IEEFs is, perhaps, that it places too much emphasis on energy. While this may seem strange, even the early discussions on preservation and energy conservation acknowledged that "not every old building is energy conservative," and that the reasons behind the design of a specific building may be entirely unrelated to saving energy (Sande 1981). They recognized that some older buildings may never be as efficient as newer buildings using modern energy conservation technologies (Sawhill 1981; Quivic 1981), but at the time did not have widespread access to performance-based tools such as building energy simulation, which could have helped quantify and clarify the IEEF concept (Smith and Elefante 2009).

As noted in the introduction, IEEFs have been a key and commonly used conceptual tool in reconciling preservation and energy efficiency since the emergence of the first building energy conservation codes in the late 1970s. While the dominance of the IEEF concept may seem innocuous, it propagates potential misunderstandings about the contribution of these features to a building's overall energy efficiency. This is misleading in the sense that it shields us from deeper insight and therefore (potentially) better solutions to the problem of energy efficiency in historic buildings. As Meir and Roaf (2006) write: "…the automatic justification for their existence and continued use, based on their perceived climatic advantages alone is also dangerous because it denies us the benefits of re-interpreting (understanding) rather than re-using (copying) the technology. It also relies on the veracity of those perceptions of performance". A more reliable, robust, and useful understanding of IEEFs would require evidence over perception or belief, and, further, would cast the value of IEEFs in a framework that includes not just energy and not just the fabric of the building, but wider social, cultural, and physiological dimensions.

Acknowledgments

This report is primarily based on the 2017 doctoral dissertation of the first author, "Evaluating the Energy Performance of Historic and Traditionally Constructed Buildings." Readers interested in additional detail on the technical aspects of the methods presented here are referred to that work. The authors gratefully acknowledge the assistance of the National Center for Preservation Technology and Training and their sponsorship of this project. The authors also acknowledge access to the Old Botany building and utility data provided by the Penn State University Office of Physical Plant, particularly Paul Moser, Superintendent of Steam Services and Mike Prinkey, Senior Energy Program Manager.

The results of this study were presented by the first author at the Association for Preservation Technology 2017 Annual Conference in Ottawa, Canada. A literature review conducted as part of this study was published by the first author in the following article: Webb, Amanda L. 2017. "Energy Retrofits in Historic and Traditional Buildings: A Review of Problems and Methods." *Renewable and Sustainable Energy Reviews* 77:748–59. Subsequent journal publications from the present study are currently in preparation.

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