Probabilistic Reliability Assessment and Case Studies for Predicted Energy Savings in Residential Buildings

Piljae Im[a,*], Roderick Jackson[b], Yeonjin Bae[a], Jin Dong[a], Borui Cui[a]

[a]Building Technologies Research & Integration Center (BTRIC), Oak Ridge National Laboratory,
One Bethel Valley Road, Oak Ridge, TN USA 37831
[b]National Renewable Energy Laboratory, Golden, CO 80401

Abstract

This study aims to (1) investigate the key influential parameters (KIPs) in estimating the uncertainty of energy savings using a residential building energy simulation model and (2) perform uncertainty quantification for energy savings for several different scenarios. The proposed methodology was successfully applied to the calculation of uncertainties associated with residential energy retrofits using two test houses designed for pre- and post-retrofit cases. Uncertainties were determined using basic parameters that might be supplied to an energy model and then reevaluated based on an audit of the KIPs identified, resulting in substantially reduced uncertainty. Of four different scenarios, the most uncertain scenario estimated the annual energy savings from the retrofit would be between 18% and 51% at a 95% confidence level, and the least uncertain scenario estimated the annual savings would be between 26% and 40% at a 95% confidence level. The actual measured annual savings from the two test houses was 28%, which shows an agreement with the uncertainty analysis.

Keywords: Uncertainty quantification, sensitivity analysis, building energy modeling, retrofit

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1. Introduction

1.1. Background

Retrofitting existing building is urgent given the increasing need to improve the energy

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∗Corresponding author
Email address: imp1@ornl.gov (Piljae Im)

energy efficiency by implementing the most optimal mix of technologies at a reasonable investment. Energy retrofits of existing buildings are important because buildings tend to undergo system degradation, changes in use and unexpected problems over time. Historically, the energy savings potential of proposed energy efficiency measures (EEMs) in existing residential buildings has been estimated based on building energy modeling, rule-of-thumb calculations, or simply “rough estimates” based on experience. Of these, savings estimated from hourly building energy simulation is considered the most rigorous methodology and is used by energy savings programs with whole-building performance goals, retrofit and new construction contractors, and building energy research programs (e.g., The Department of Energy’s (DOE’s) Building America program [2]). However, these applications typically depend on deterministic simulation results and do not integrate any type of uncertainty analysis or risk assessment.

The **simulation models** used in these applications assess the performance of buildings based on **numerous assumptions and uncertainties** in input parameters for building components, occupancy behaviors, and weather [3], so the simulated energy consumption has a significant level of uncertainty. Two major resources of uncertainty are (1) the physical properties of the building components, system parameters, and operational scenarios and (2) questions regarding the accuracy of the simulation models themselves due to the lack of detailed information or expertise [4]. For example, the on-site performance of heating, ventilation, and air-conditioning (HVAC) systems may vary beyond the nameplate efficiency, depending on the local conditions and usage. The modeler must make assumptions for the energy simulation models and the assumptions, in many cases, can be too optimistic and thus lead to an overstatement of performance as predicted by the energy simulation. With deterministic simulation analysis, the uncertainties cannot be assessed, and the estimated energy savings often are not close to the measured savings because of the uncertainties in these input parameters [5].

Moreover, the current lack of understanding regarding energy savings uncertainty, sensitivity, and risk associated with different packages of retrofit measures hampers energy efficiency investments, increases total cost, and limits the ability to develop robust deep energy retrofit packages. Because the **required rate of return for investors is a function of the uncertainty of future payback from energy savings**, uncertainty increases the rate of return to a level where fewer efficiency investments can surpass the resulting hurdle. Further- more, because lenders, energy efficiency programs, and investors often reduce the expected savings from energy efficiency measures (EEMs) to account for the uncertainty of savings, the perceived profitability of energy efficiency packages is decreased. In these cases, packages with greater energy savings are often not chosen, because the ratio of perceived benefits to costs no longer exceeds the required threshold.

A quantitative risk analysis is needed to support investment decisions in building retrofits to assuage investors' doubts regarding risks. In fact, the lack of a quantitative risk analysis has been referenced as "the most glaring deficiency in the energy efficiency business [6]". While **actuarial** approaches have been suggested [6,7,8], these methods rely on a sufficient amount of available data for the different types of end-users and different types of EEMs. Because of the more recent focus by DOE's Office of Building Technologies on promoting building retrofits, **there is not a sufficient amount of data available**, and the data deficiency may continue for the near future.

Existing buildings come with nuances associated with how buildings and their components are actually operated and these are often difficult to represent in building energy models. As an attempt to address this discrepancy in energy savings predictions, baseline simulation results are often calibrated with a pre- retrofit building's energy use and then used to predict energy savings by modifying the calibrated simulation results with the proposed EEMs. The baseline (energy) use pattern before the installation of EEMs is studied to determine the relationship between energy use and production. Following EEM installation, this baseline relationship is used to estimate how much energy would have been used if there had been no EEMs (called the "adjusted-baseline energy"). The saving, or 'avoided energy use' is the difference between the adjusted-baseline energy and the energy that was actually metered during the reporting period [9].

Although calibrated simulations can reduce the error and uncertainty in energy savings prediction, there remain many sources of uncertainty, such as the thermal characteristics of the EEMs, construction workmanship, and occupant behavior changes after retrofit. In addition, the process of calibrating the simulation with measured data requires a great amount of time and effort, de- pending on the available building and system data, complexity of the simulation model, and experience of the building energy modeler. Therefore, clear actions to identify and reduce the uncertainty of energy savings from energy efficiency investments have been limited.

1.2. Literature Review on Uncertainty Analysis in Building Energy Consumption and Savings

The effects of uncertainty can greatly limit the accuracy of model output irrespective of the quality of the underlying model. The Efficiency Valuation Organization, through the International Performance of Measurement and Verification Protocol [10], defines three types of uncertainty in performing building energy simulation analysis: modeling, sampling and measurement that, should be applicable to any energy efficiency project [9]. Modeling uncertainty refers to errors in mathematical modeling due to inappropriate functional form, inclusion of irrelevant variables, exclusion of relevant variables, and so on. Sampling uncertainty refers to error that occurs when only a portion of the population of actual values is measured, or a biased sampling approach is used. Measurement uncertainty refers to errors arising from sensor inaccuracy, data tracking errors, drift since calibration, imprecise measurements, and so on.

To overcome the shortcomings of the traditional simulation approach, there has been increasing effort recently to apply uncertainty analysis and quantification of energy savings from building retrofit cases [1,4,11,12,13]. The typical candidates for uncertainty parameters are building construction material thermal properties [14,15,16], HVAC equipment system properties [17,18,19], parameters related to occupant behavior (e.g., thermostat set point temperature, lighting and plug power density, schedules, domestic hot water [DHW] usage) [16], annual price change rates [11,12], risk preferences [4], and future climate data [13].

Instead of deterministic solutions, probabilistic solution/distribution can enable greater confidence in results with respect to the propagation of errors and underlying complex interactions among factors. Probabilistic outputs can be straightforwardly translated to quantify risks of underperformance associated with retrofit interventions [1]. In general, the first step of this probabilistic simulation approach addressing parameter uncertainty is to choose a limited number of input parameters, which will have uncertain ranges instead of a single value. There are multiple resources that define the probabilistic distribution of input parameters, yet much more effort would be needed to develop a whole set of databases for this distribution. Different probabilistic distributions such as uniform [1,16,20], normal [4,21], triangular [5,17], and log-normal [14,22] might be required for each type of input parameter. The energy model output under specific known conditions and for a chosen set of calibration parameters, despite being deterministic, is assumed to follow a normal distribution [1]. This procedure might be the most critical process in estimating the uncertainty of energy consumption and savings, since a wrong assumption regarding the probabilistic distribution for some influential input parameter can impact the energy consumption to a large extent.

Typical hourly building energy simulation software requires several thousand input parameters; therefore, it is nearly impossible to define uncertainty ranges for all input parameters. In addition, not all input parameter values would be uncertain in a building simulation or result in significant output sensitivity. Even when a limited number of input parameters are given a probabilistic distribution instead of a single input value, the number of all possible combinations of the selected input parameters could still be immense. Therefore, relevant sampling techniques such as the Monte Carlo method [5,14,15,17,22] and Latin hypercube sampling (LHS) [1,16,22,23] are frequently adopted (Morris method [20]). Model simulations for each sampled input file are run to generate the probabilistic distribution of energy consumption.

These types of uncertainty analysis studies in buildings have been performed mostly in academic research, and the techniques and methodologies proposed from these studies have **not been yet implemented widely in industry**. This is partially because of the absence of easy-to-use tools, excessive simulation run times, insufficient information for the distribution of key influential input parameters, and unawareness of the uncertainty techniques one the part of most people in the industry. If those problems were resolved by developing an easy-to-use tool and building an extensive database for key influential parameter (KIP) distribution, the new uncertainty analysis technique would have great potential in the residential retrofit market, and could change stakeholders' views of residential retrofit projects.

Achieving that goal requires a focus on computation-based uncertainty quantification (UQ), which had its start in in the building simulation research domain in the early 2000s [24,25,26]. Uncertainty analysis provides a reliable way to quantify properly how uncertainties in the input reflect on output. In addition, we will investigate sensitivity analysis (SA) to attribute a value to the relative importance of the different input parameters.

1.3. Study Objective

This study aims to develop a practical and comprehensive methodology that can be used in the residential retrofit market to analyze energy savings potential and the associated risk. As a complement to data-driven statistical methods of quantifying uncertainty, this paper will use a probabilistic analysis of modeled energy savings to evaluate EEMs. Although this method has been demonstrated in many academic environments, we propose to use "real-world" data to ground- truth this approach to provide a level of "certainty" to UQ. As a demonstration of the benefit and application of UQ and SA in residential buildings, this study will have two primary outcomes:

I. Identification of KIPs for a common residential building type in a mixed-humid climate.

An analytical elucidation of KIPs can provide a consistent, rigorous framework for building modelers as they develop and subsequently calibrate building models. Additionally, building auditors can use KIPs to prioritize the parameters to measure during their limited available time in a building. Furthermore, KIPs can be used by contractors seeking to identify which retrofit measures have the most impact on predicted building energy consumption and energy savings. Building energy research programs that seek to improve the consistency and reliability of building-energy-modeled energy consumption and savings (e.g., Building America) can also prioritize research investments in projects that will have the largest impact with regard to uncertainty minimization.

II. **Quantification of building energy consumption and projected energy savings from a specific retrofit package.**

An analytical estimation of energy consumption and energy savings uncertainty will provide investors (e.g., contractors, energy service companies, and financial institutions) with increased transparency and credibility of predicted outcomes.

As a final outcome to demonstrate the application of this research in real-world environments, this paper also includes a case study comparing the energy savings uncertainty associated with the fidelity of input parameters. For the demonstration, two occupancy emulated test houses designed for pre- and post-retrofit buildings were used to ensure a fair comparison. The two buildings shared the same floor plan, occupancy schedules, and other operational conditions, but the post retrofit house was designed with various EEMs. Furthermore, energy savings uncertainties associated with different levels of building audit are demonstrated. To achieve these outcomes, this study is divided into the following tasks:

- *Task 1. Investigate potential KIPs (pKIPs) in building energy modeling and their probabilistic distributions from literature review.*
- *Task 2. Develop EnergyPlus Models for two target houses (pre and post retrofit houses).*
- *Task 3. Perform sensitivity analyses of the pKIPs for a pair of case study residential buildings' energy use and savings to select KIPs for the selected houses*
- *Task 4. Perform UQ of the energy consumption and savings for two houses using KIPs that were selected in Task 3 to provide an expected probabilistic distribution of energy savings.*

1.4. Limitations of the study

The limitations of the study are as follows.

- The study did not consider model form uncertainty.
- Weather uncertainty regarding micro-climate weather differences and annual weather

variation was not considered. Instead, an actual weather file was used to eliminate the uncertainty in weather variations.

- The study used two research houses, and the results may not be suitable for other houses in different climate zones. But the overall methodology described in this paper can be applied to similar studies.

2. Methodology

This chapter discusses the detailed methodology for each task defined in Section1.3.

2.1. Task 1. Investigate pKIPs in building energy modeling and their probabilistic distributions from literature review.

The first task for the study is to review existing literature and other resources to find the pKIPs and their estimated ranges. pKIPs are the building simulation input parameters expected to contribute significantly to variability in simulated energy consumption and savings predictions. This study uses the EnergyPlus building energy simulation engine as a main tool. A typical input file for EnergyPlus requires several thousand input parameter values. Investigation of pKIPs will reduce the number of input parameters for which probabilistic distributions are needed. Previous studies were the main source of information for defining the probabilistic distribution of each pKIPs, but other resources such as a national database and personal communication with domain experts was also if no previous studies for specific input parameters were available.

2.2. Task 2. Development of EnergyPlus Models for two target houses (pre- and post-retrofit houses)

Two Campbell Creek unoccupied (but occupancy-simulated) research houses in Knoxville, Tennessee, were chosen to be modeled and were used for the uncertainty analysis. Although the two homes have the same design and identical occupancy schedules and are located side-by-side, one of the homes (CC2) is a “retrofit” version of the first home (CC1). CC1 and CC2 have been operated in the same location and on the same operating schedule for more than 3 years, and their hourly end-use energy consumption has been monitored.

Many studies in uncertainty analysis have investigated the methodology of uncertainty analysis, but often the results have not been compared with a real- world example to see if the proposed methodology would be valid. This is partially because it would be hard to obtain extensive data from an existing house. Even if some measured energy data from existing houses were available, there are too many uncertainties in input parameters (e.g., building occupancy behavior, operating schedules). So even if the UQ showed reasonable agreement with the measured energy data, it would be hard to know if the agreement was actually based on a correct assumption of the probabilistic distribution for each input parameters, or just correct by chance. Since the target houses in this study have such limited uncertainty because of extensive energy use measurements, detailed building information, and emulated occupancy, it is possible to validate the uncertainty distributions of energy consumption and savings with a reasonable distribution of input parameters as well as measured energy data.

2.3. *Task 3. Perform sensitivity analyses of the pKIPs using EnergyPlus models to select KIPs.*

The pKIPs identified in Task 1 are generic KIPs found in several studies and not necessarily KIPs for the selected two houses. SAs were performed to identify the real KIPs for the two houses in this task. The main UQ tool used throughout this study is the Georgia Tech Uncertainty and Risk Analysis Workbench (GURA-W) [27].

SA refers to the probability distribution of the most important parameters that generated the variation [16]. SA is important to reduce the dimension of the unknown parameter space in building energy models when detailed information through a building audit is not achievable [28]. Not all the aspects modeled have the same level of importance, and not all the inputs make the same contribution to error propagation. Therefore, uncertainty analysis must be coupled with SA to attribute a value to the relative importance of the different input parameters [29]. Changing the input of the parameters and showing the effect on the outcome of a model provides a “what-if analysis” [23].

SA is a post-processing task in GURA-W that is conducted after all input files and corresponding output files (i.e., annual energy consumption) are generated. Global sensitivity analysis (GSA) is used to study the impact of variations in input variables on the variation of a model output. Here, we briefly introduce the required mathematical formulation and definitions for GSA. We start by defining the variance by sum of squares (SS) for each parameter.

$$SS_k = \sum_{k=1}^{m_0} (\hat{y}_{k,full} - \bar{y})^2 - \sum_{k=1}^{m_0} (\hat{y}_{k,reduced} - \bar{y})^2 \tag{1}$$

where m_0 is total number of parameter, $\hat{y}_{k,full}$ represents the model with all parameters, $\hat{y}_{k,reduced}$ represents the model without parameter k, and $\bar{y}$ represents the sample mean.

SS_k is the variation (uncertainty) of output explained from the variation of the parameter k, which can be decomposed as

$$SS_k = \sum_{k=1}^{m_0} SS_k + SS_{Error} \tag{2}$$

with sensitivity index (SI)

$$SI_k = \frac{SS_k}{SS_{Total}} \tag{3}$$

By performing GSA for energy consumption and savings, it is possible to choose KIPs from the list of pKIPs. To rank the output sensitivities to the different pKIPs, an SI was used. The SI of parameter k, SI_k, is defined as the ratio of SS_k to SS_{Total}, where SS_k is the uncertainty in the output that can be attributed to the uncertainty of parameter k, and SS_{Total} is the total uncertainty of the model output. An increased SI_k is reflective of a higher relative impact of the input parameter on the variation of the model output (e.g., energy consumption and savings). The highly ranked pKIPs were selected as KIPs and used in Task 4 for further UQ analysis.

Because the a priori uncertainty distribution for each KIP has a large impact on the overall uncertainty analysis, a priori uncertainty distribution was assessed with realistic uncertainty distribution for each KIP. The SA was performed using more realistic uncertainty distribution for each KIP whose typical range was defined in the previous section. High ranked pKIPs from the SA will be selected for use as KIPs in Task 4.

2.4. Task 4. Perform UQ of the energy consumption and savings for two houses using KIPs that were selected in Task 3 to provide an expected probabilistic distribution of energy savings

Based on the selected KIPs in task 3, an uncertainty assessment for predicted energy savings was performed. For the analysis, four different scenarios were defined to represent several possible cases for which different levels of building information are available when the UQ analysis is performed.

- *Scenario 1:* Basic building information
- *Scenario 2:* Scenario 1 + blower door test
- *Scenario 3:* Scenario 2 + duct leakage test
- *Scenario 4:* Comprehensive audit

For each scenario, different a priori input parameter distributions were defined for the CC1 and CC2 models, and the uncertainty distributions of energy consumption and energy savings were generated. In addition, a GSA was performed to investigate the changes in the sensitivity rankings for KIPs.

3. PROBABILITY DISTRIBUTION OF KIPS

Defining the range of KIPs is probably the most important task in uncertainty studies. It is also the most challenging task because of the lack of available information, especially for residential buildings, and because of discrepancies regarding the estimated ranges among various sources. After all, the estimated range would impact the sensitivity of the KIPs to a considerable degree, and faulty assumptions in the estimated range could result in a misleading selection of KIPs in energy consumption and savings. There is a relatively large amount of information on the uncertainties in building thermal properties [25,30]; whereas information related to uncertainties regarding human behavior [1,31] and HVAC systems [32] is limited, and even the existing information shows large variations.

Table 1 shows the pKIPs identified with the estimated ranges for typical existing residential buildings. The pKIPs were selected by literature review and domain experts' judgment, and the estimated ranges were selected from the literature. For lighting and miscellaneous electrical loads (MELs) and power density, two parameters were taken from commercial buildings and were shown to provide a reference for a typical range (±%) for residential buildings. The estimated ranges for the HVAC-related pKIPs were defined mostly by personal communication with building equipment experts.

Table 1 pKIPs for existing residential buildings with probabilistic distribution

	General KIPs	Unit	Min	Max	Mid	Mean	Std. Dev.	Source
1	Heating set point	T (°C)				21	2	[31,33]
2	Cooling set point	T (°C)				24	2	[31,33]
3	Number of occupants	#				1.67	0.39	[33]
4	Occupant sensible heat fraction	%	50	68	59			[34]
5	Occupant fraction radiant	%	30	40	35			[34]
6	Heating system efficiency	Multiplier	0.9	1.05	1			[32]c)
7	Cooling system efficiency	Multiplier	0.9	1.05	1			[32]c)
8	Window U-value	W/m^{2}K				2.26	0.07	[33]
9	SHGC	SHGCa)	0.39	0.41	0.42			[35]
10	Wall U-value	W/m^{2}K				0.59	0.07	[33]
11a	Infiltration (general)	ACHb)	0.2	1.2	0.45			[36]d)
11b	Infiltration (ENERGY STAR certified home)	ACHb)	0.1	0.8	0.2			[36]d)
12	Lighting power density	W/m^2	11	15	13			[1]
13	MELs power density	W/m^2	12	22	15			[1]
14	TPe)-roof deck	W/mK				0.53	0.07	[25]
15	TP-asphalt shingle	W/m^{2}K				0.0409		[25]
16	TP-felt paper	W/mK				0.036		[25]
17	TP-sheathing	W/mK	0.12	0.15	0.135			[25]
18	TP-38mm x 89mm	W/mK				0.151	0.042	[25]
19	TP-organic insulation (foam)	W/mK				0.054	0.022	[25]
20	TP-inorganic insulation (fiberglass)	W/mK				0.039	0.014	[25]
21	Electric water heater efficiency	Multiplier	0.98	1.02	1			[37]
22	Electric water heater set point	T (°C)			48.8		2	Subject judgment
23	Schedules: occupancy, lighting, plug, and HVAC schedules	Schedules						Fixed

a) SHGC: solar heat gain coefficient, b) ACH: air changes per hour, c) No duct leakage counted, d) Approximation from the reference, e) TP: thermal performance

4. Description of the Research Houses and the Modeling

pKIPs need to be ranked to identify the parameters more sensitive to energy consumption and/or savings so that a limited number of pKIPs is used for the UQ to reduce computational time while providing reasonable results. The first phase of this task was to build initial building simulation models using EnergyPlus to be used for the SA and UQ. Building characteristics for the two houses are shown in Table 2.

Table 2 Building characteristics for CC1 and CC2

	CC1 (Builder House)	**CC2 (Retrofit House)**
HERS rating	101	68
Foundation	Slab insulated with 25.4 mm extruded polystyrene (XPS), 610 mm in horizontal; RSI-0.9 m$_2$K/W except side adjacent to garage	Slab insulated with 25.4 mm extruded polystyrene (XPS), 610 mm in horizontal; RSI-0.9 m$_2$KW except side adjacent to garage
Walls	38 by 89 mm frame, insulation RSI-2.3 m$_2$K/W, framing factor of 0.23, vinyl siding with solar absorptance of 0.8	38 by 89 mm frame, insulation RSI-2.3 m$_2$K/W, framing factor of 0.23, vinyl siding with solar absorptance of 0.8
Windows	U-factor = 3.29 W/m$_2$K and SHGC = 0.58, no overhangs	U-factor = 1.93 W/m$_2$K and SHGC = 0.35
Doors	3 doors, one solid insulated to garage U-value = 1.65 W/m$_2$K, one half-view front door, one full-view patio door to the back	3 doors, one solid insulated to garage U-value = 1.65 W/m$_2$K, one half-view front door, one full-view patio door to the back
Roof	Attic floor (RSI-4.5 m$_2$K/W), framing fraction of 0.05	Cathedralized, sealed attic with no ventilation, open-cell spray foam and fiberglass insulation, RSI-5.3 m$_2$K/W with flash and spider
Roofing	0.75 solar absorptance, composition shingles on oriented strand board (OSB), vented attic	0.75 solar absorptance, composition shingles on OSB with foam/spider, no ventilation in attic
Infiltration	ACH50 = 5.7	ACH50 = 3.4
Heating and cooling	2 ducted heat pump units (1 per each floor), 1.5 ton and 2.5 ton, 4 ton total capacity, 3.8 SCOP$_C$, 2.3 COP$_H$	Up to 6.0 SCOP$_C$, 3.8 COP$_H$, variable-speed, ducted 3 ton heat pump
Mechanical ventilation	Bathroom exhaust	Energy recovery ventilator. exhausting two baths and laundry and supplying to foyer
Duct location	Outside conditioned space, duct insulation is SIR-1.1 m$_2$K/W, supply area 43.7 m$_2$, return area 17.5 m$_2$, duct air leakage = 7.8% (by floor area)	Supply and return ducts are inside conditioned space, duct air leakage = 2.5%, SIR-1.1 m$_2$K/W, supply area 43.7 m$_2$, return area 17.5 m$_2$
Air handler location	Attic and garage	Inside, conditioned attic
Water heater	Electric, 189 L capacity, EF = 0.86, usage = 227 L/day, set temp = 49$_o$C	Hybrid electric heat pump water heater, 189 L capacity, EF =2.4, usage = 227 L/day, set temp = 49°C
Lighting	100% incandescent	100% fluorescent
Energy Star	None	All Energy Star appliances

Unpredictable occupancy behavior (i.e. occupancy schedules) can have a significant influence on energy consumption and the uncertainty associated with the occupancy prevents from estimation of energy consumption with high accuracy. The research houses were unoccupied, but the occupancy emulator was installed to capture realistic behavior for a family, and to eliminate occupancy driven uncertainty, the occupancy impact on the house was emulated. In other words, both CC1 and CC2 houses are outfitted with automated controls that manage the opening/closing of the refrigerator door, use of the oven, operation of the clothes washer and dryer, and shower usage. These automatic controls achieve an occupancy pattern that is consistent with typical energy usage patterns of American households [2]. The simulated occupancy provides stable behavioral patterns. This means the data set is free from behavioral factors, making it easier to compare results for different houses [38].

Although detailed building information and measured data are available, including blower door and duct blast test data for the houses, the initial EnergyPlus models were developed assuming only limited building information available. These initial models were used as Scenario 1 of the four scenarios in Task 4, the scenario in which the modeler does not have enough information about the building for high-level analysis (i.e., maximum uncertainty in input parameters). More highly tuned models with detailed building and measured data (i.e., less uncertainty in input parameters) were developed for use in Scenarios 2, 3, and 4. Further details regarding the different models are discussed in Chapter 5.

A calibrated building energy model for the CC1 house, as shown in Figure 1a, was developed using the building characteristics collected from architectural drawings and field measurements. Figure 2 presents a 3D rendering of the building energy model for CC1.

(a) CC1 (b) CC2

Figure 1 Photo of CC1 (left) and CC2 (right)

Figure 2 3D rendering of CC1 EnergyPlus model

Because of the occupancy simulation of the house, it is possible to isolate one of the largest uncertainties in building energy use (the other one is weather uncertainty) so that different scenarios could be explored for UQ. The CC2 house, as shown in Figure 1b, is the post-retrofit house based on CC1. The model was created by modifying the parameters in the CC1 model, i.e. the building envelope and HVAC system.

The daily calibration results, as shown in Figure 3, demonstrate the good match of the modeled energy use of CC1 with the measured data (i.e., 0.4% difference in annual energy use, 0.4% of normalized mean bias error, and 11.8% of coefficient of variation of the root mean square error, and meets the calibration requirements of ASHRAE Guideline 14). Note that it was assumed no CC2 measured building energy data would available to demonstrate the typical procedure for estimating the energy saving from a retrofit project. Therefore, the performance of the CC2 model was not calibrated.

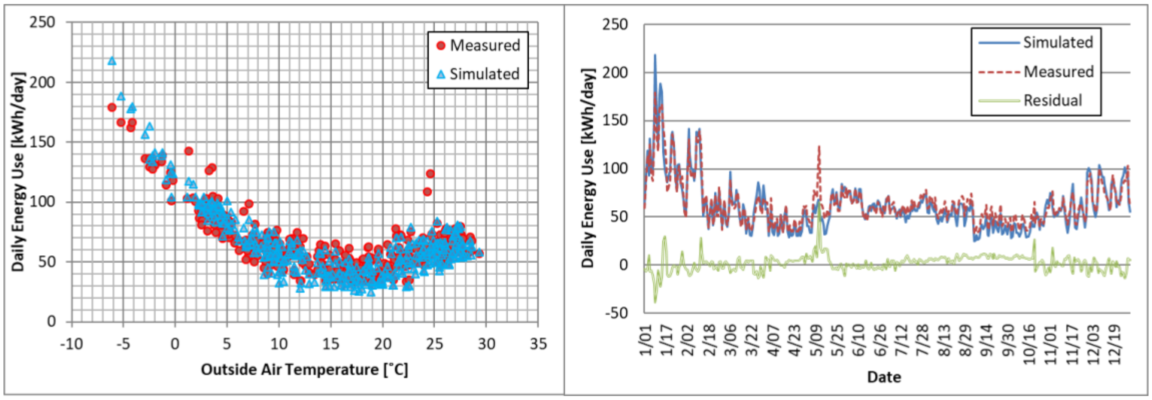


Figure 3 Daily calibration results: Scattered plot for total energy use (left) and time series plot for total energy use (right)

5. Global Sensitivity Analysis for pKIPs

With the initial CC1 and CC2 energy models and pKIPs, GSAs for energy consumption and savings were performed using a realistic uncertainty distribution. The typical ranges of the KIPs were defined in the previous section.

5.1. CC1 and CC2 Consumption Sensitivity Analysis

In this section, the distribution of the pKIPs for CC1 and CC2 is defined with realistic ranges instead of an equal uncertainty distribution applied to all parameters. The estimated range for each pKIP (i.e., standard deviation, min/max values) has a high impact on the uncertainty of the energy consumption and savings. For example, a 1% standard deviation for the building infiltration rate could result in low sensitivity on the total energy savings (low-ranked pKIPs), while a 10% standard deviation for the same parameter would result in higher-ranked pKIPs.

Normal distribution and triangular distribution, which is a bounded continuous distribution with minimum, medium, and maximum values, are selected for input parameters. Table 3 shows the type of distribution; standard deviation (for normal distribution); and minimum, medium, and maximum values (for triangular distribution) for each KIP. The standard deviation and min/max values were determined based on literature review and domain experts' educated judgment. The current version of EnergyPlus cannot model the residential duct model in the attic, and degraded heating/cooling COPs were implemented to consider the total cooling/heating energy penalty due to the duct leakage. To estimate the duct leakage impact on total energy use, the duct model included in DOE's BeOpt was used. First, CC1 was separately modeled using BeOpt and calibrated with the measured data. The initial model was developed with no duct model, and then duct leakage rates of 7.5%, 15%, and 30% were applied to assess the impact on the total energy, cooling, and heating energy uses.

Table 4 shows the simulation results and the degraded heating and cooling COPs for each duct leakage rate. As shown, as the duct leakage rate increases, the total cooling, and heating energy increase proportionally. To consider the duct leakage in the EnergyPlus CC1 model used in GURA-W, the original heating and cooling COP values were degraded to increase the heating and cooling energy uses. Assuming the duct leakage could vary from 0 to 30% (7.5% median) in CC1, the cooling and heating COP ranges were defined as in Table 4. As the CC2 ductwork was installed in the conditioned zone, no duct leakage penalty was assumed. Therefore, the uncertainty ranges in heating/cooling COPs were much less than in CC1 COPs.

Table 3 KIPs and their ranges

Component	EnergyPlus Input Parameters	Distribution	Normal	Triangular		
			Standard deviation (%)	Min.	Med.	Max.
Wall/roof/foundation	Conductivity	Normal	5			
	Density	Normal	1			
	Specific heat	Normal	12			
	Thermal absorptance	Normal	2			
	Solar absorptance	Normal	4			
	Visible absorptance	Normal	4			
Window	U factor	Normal	5			
	Solar heat gain coefficient	Normal	1			
	Visible transmittance	Normal	1			
Lighting	Watts per zone floor area	Normal	10			
Equipment	Watts per zone floor area	Normal	10			
Infiltration	Air changes per hours	Normal	10			
Ground temperature	Monthly average temperature	Normal	5			
Fan	Fan efficiency	Normal	4			
	Pressure rise	Normal	4			
	Motor efficiency	Normal	2			
Cooling coil	Rated total cooling capacity	Normal	5			
	Rated COP (CC1: Duct in unconditioned)	Triangular		2.16	2.8	3.26
	Rated COP (CC2: Duct in conditioned)	Triangular		3.15	3.5	3.61
	Rated air flow rate	Normal	5			
Heating coil	Rated total heating capacity	Normal	5			
	Rated COP (CC1: Duct in unconditioned)	Triangular		1.89	2.7	3.26
	Rated COP (CC2: Duct in conditioned)	Triangular		3.24	3.6	3.71
	Rated air flow rate	Normal	5			
Heat pump water heater	Rated heating capacity	Normal	5			
	Rated COP (Multiplier)	Triangular		0.9	1	1.03
Electric water heater	Heater thermal efficiency (Multiplier)	Triangular		0.98	1	1.02
Occupants	Number of people	Normal	10			

** Mean values of the input parameters with normal distribution are the calibrated model input values*

Table 4 Duct leakage rate, corresponding energy differences, and cooling and heating COP

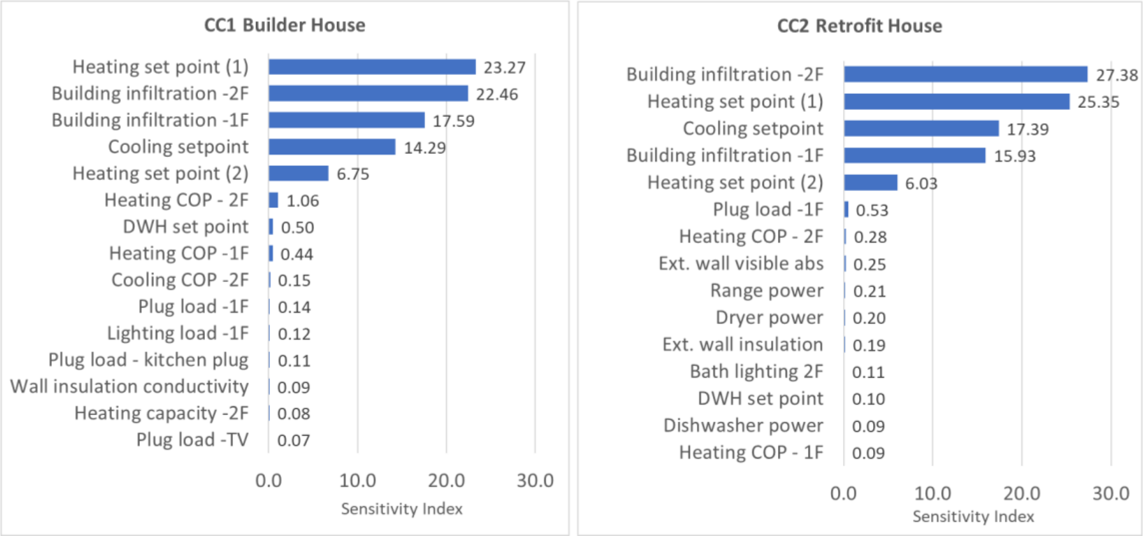
Duct Leakage	Total (MMBtu)	% Diff	Cooling (MMBtu)	% Diff	Heating (MMBtu)	% Diff	Corresponding Cooling COP	Corresponding Heating COP
None	238.1	-	13.1	-	52.6	-	3.1	3.1
7.5%	248.4	4%	14.5	11%	59.3	13%	2.8	2.7
15%	253.8	7%	15.2	16%	63.3	20%	2.7	2.5
30%	266.6	12%	16.8	28%	72.8	38%	2.4	2.1

**Duct in unconditioned attic, duct insulation: RSI-1.1 m^{2}K/W*

Figure 4 shows the 15 pKIPs with the highest SIs for CC1 and CC2 energy use. Within these parameters, there are 11 common parameters. Compared with the earlier analysis with equally distributed pKIPs, the heating/cooling set point still has the highest SI, followed by the infiltration rates for both houses. The DHW set point temperature also has a higher SI, but it is relatively lower compared with the previous analysis with uniform distributions. Six CC1 input parameters and five CC2 input parameters have SIs ≥ 1 (Table 5). However, 80 to 90% of the output uncertainty can be attributed to the combination of heating/cooling set points and infiltration rate.

Table 5 Eight highly sensitive KIPs for CC1 and CC2 house energy use

KIPs for CC1 and CC2
Heating set point
Cooling set point
Building infiltration rate
DWH set point
Heating COP
Wall insulation conductivity
Cooling COP
Lighting/plug power density



** Heating set point (1) and (2) are the heating set points from Jan to Mar, and October through December, respectively.*
***1F represents the first floor and 2F represents the second floor.*

Figure 4 Sensitivity index for CC1 and CC2 energy consumption

5.2. Energy Savings Sensitivity Analysis

In a similar fashion to the uniform distribution case, using the 200 runs each for CC1 and CC2, the annual energy savings were estimated and a GSA was performed to identify KIPs.

Shown in Figure 5 are the 15 pKIPs with the highest SIs. Energy savings are most sensitive to the infiltration rate of the pre-and post-retrofit cases, CC1 and CC2, respectively, followed by the heating and cooling equipment effective COP. Unlike in the SA of energy consumption, the sensitivity of energy savings to the heating and cooling set points is small and no longer ranks in the 15 input parameters to which the output is most sensitive. This is a result of the assumption that heating and cooling set points are common to both CC1 and CC2. Therefore, even though there remains an un- certainty distribution for the input parameter, in computing the energy savings for CC2 compared with CC1, the same value is sampled for both simulations. This method of computing the uncertainty of energy savings results in a smaller contribution of "common parameters" to the energy savings uncertainty. Consequently, most of the KIPs correspond to input parameters that were impacted by the retrofit measures.

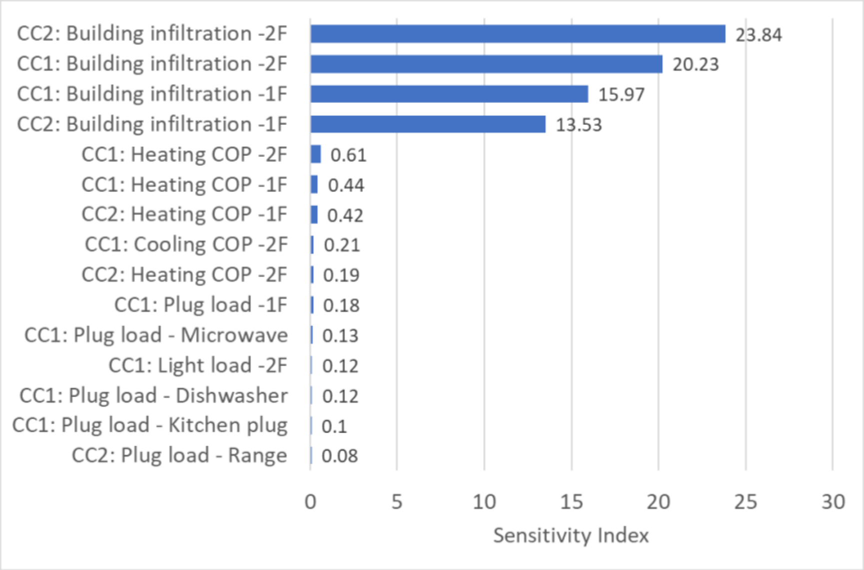


Figure 5 Sensitivity index for energy savings

6. Uncertainty Quantification

Based on the KIPs identified in Chapter 3, an uncertainty assessment for predicted energy savings was performed. For the analysis, four different scenarios were defined to represent possible real-world scenarios in which differing levels of building information are available to building modelers.

I. **Scenario 1: Basic building information.** There is limited building information, and the modeler has to assume typical building characteristics with estimated ranges based on building age and geographic location. As a result, there is large uncertainty in input parameters. This scenario has the most uncertainty among the four cases, but the effort and expense required to collect the data required for the simulation are minimal. This could be similar to an "online-screening assessment."

II. **Scenario 2: Basic information + blower door test.** In addition to basic building information, a blower door test (or tracer gas test) is conducted to estimate the infiltration rate of the house. In this scenario, the uncertainty of the building air-change-per-hour (ACH) input parameter would be reduced (i.e., a narrow range of distribution).

III. **Scenario 3: Scenario 2 + duct leakage test.** In this scenario, a duct blaster test is performed to estimate the duct leakage rate and thereby reduce the uncertainty of this influential KIP in energy savings estimation.

IV. **Scenario 4: Comprehensive audit.** This scenario has the least uncertainty in the KIPs. The cooling/heating thermostat set point temperatures are identified, and the lighting/plug power density is identified from the comprehensive audit. This scenario has the least uncertainty among the four cases, but it requires the maximum amount of time and expense to gather precise data for building energy modeling.

Tables 6 and 7 show the KIP distribution for CC1 and CC2 per scenario, respectively. For the UQ analysis, the parameters were selected using LHS method, and 400 simulation runs were performed for each scenario (200 for CC1 and 200 for CC2).

Table 6 KIPs and their ranges for four scenarios for CC1

	Scenario 1: Basic building information				Scenario 2: Scenario 1 + blower door test				Scenario 3: Scenario 1 + blower door + duct blast test				Scenario 4: Comprehensive audit			
Model parameter	**Base**	**Min**	**Max**	**Std. Dev**	**Base**	**Min**	**Max**	**Std. Dev**	**Base**	**Min**	**Max**	**Std. Dev**	**Base**	**Min**	**Max**	**Std. Dev**
Heating set point (°C)	21			2	21			2	21			2	21			1%
Cooling set point (°C)	24			2	24			2	24			2	24			1%
Building infiltration (ACH)	0.45	0.2	1.2		0.39			5%	0.39			5%	0.39			5%
DHW set point temp. (°C)	48.8			2	48.8			2	48.8			2	48.8			1%
Heating system efficiency (COP)	2.7	1.89	3.26		2.7	1.89	3.26		2.5			2%	2.5			2%
Cooling system efficiency (COP)	2.8	2.16	3.26		2.8	2.16	3.26		2.7			2%	2.7			2%
Plug power density	1			10%	1			10%	1			10%	1			1%
Lighting power density	1			10%	1			10%	1			10%	1			1%
Ext. wall insulation	1			5%	1			5%	1			5%	1			1%

Table 7 KIPs and their ranges for four scenarios for CC2

	Scenario 1: Basic building information				Scenario 2: Scenario 1 + blower door test				Scenario 3: Scenario 1 + blower door + duct blast test				Scenario 4: Comprehensive audit			
Model parameter	**Base**	**Min**	**Max**	**Std. Dev**	**Base**	**Min**	**Max**	**Std. Dev**	**Base**	**Min**	**Max**	**Std. Dev**	**Base**	**Min**	**Max**	**Std. Dev**
Heating set point (°C)	21			2	21			2	21			2	21			1%
Cooling set point (°C)	24			2	24			2	24			2	24			1%
Building infiltration (ACH)	0.1	0.2	0.8		0.1	0.2	0.5		0.1	0.2	0.5		0.1	0.2	0.5	
DHW set point temp. (°C)	48.8			2	48.8			2	48.8			2	48.8			1%
Heating system efficiency (COP)	3.1	3.6	3.78		3.1	3.6	3.78		3.1	3.6	3.78		3.1	3.6	3.78	
Cooling system efficiency (COP)	3.1	3.6	3.78		3.1	3.6	3.78		3.1	3.6	3.78		3.1	3.6	3.78	
Plug power density	1			10%	1			10%	1			10%	1			10%
Lighting power density	1			10%	1			10%	1			10%	1			10%
Ext. wall insulation	1			5%	1			5%	1			5%	1			1%

6.1. SCENARIO 1: BASIC BUILDING INFORMATION

Similar to an “online-screening assessment,” Scenario 1 is based on typical building characteristics with estimated ranges based on building age and geographic location.

For CC1, the air infiltration leakage rate was assumed based on the Lawrence Berkeley National Laboratory (LBNL) Residential Diagnostics Database [36], and the cooling and heating COP values and related ranges were assumed based on discussion with domain experts. The typical duct leakage rate for the building was also assumed based on the LBNL Residential Diagnostics Database. Heating and cooling set point and DHW set point were assumed to have a 2°C standard deviation.

CC2 KIPs (Table 7) were also defined based on assumptions similar to those shown in Table 6, with the exception of the building infiltration rate and heating/cooling COP. Since the ducts in CC2 are located in the conditioned zone, it was assumed that duct leakage has a limited impact on the cooling/heating energy; therefore, the heating/cooling COP value was not adjusted as were those for CC1. Consequently, the COP uncertainty range of CC2 was smaller than that of CC1.

The uncertainty of energy consumption was quantified as shown in Table 8 and Figure 9. The average energy consumption for CC1 and CC2 was estimated as 26,908 and 17,469 kWh, with standard deviations of 12.6% and 11.9%, respectively. In other words, at a 95% confidence level, it is expected that CC1 would use approximately 20,311 ~ 34,030 kWh annually with the given distribution of KIPs, and CC2 would use approximately 13,309 ~ 21,629 kWh annually.

The uncertainty of the annual energy savings of CC2 with respect to CC1 was quantified in the same manner. CC2 is projected to use 35% less energy than CC1 with an 8% standard deviation. In other words, CC2 is expected to save 18 to 52% compared with CC1 at a 95% confidence level. Given that the measured energy savings for CC1 relative to CC2 in 2011 was about 35%, it seems this UQ estimated the right range of energy savings.

A GSA for the energy savings was also performed to understand the relative importance of the KIPs assessed. As shown in Figure 5, the infiltration in CC1 and CC2 accounts for most of energy savings uncertainty. Since the sensitivity of the energy savings to the building infiltration rate was so high (almost 70%), the uncertainty caused by the remaining KIPs was relatively small. Based on these results, it is expected that reducing the uncertainty of the building infiltration would significantly reduce the overall energy savings uncertainty.

6.2. SCENARIO 2: BLOWER DOOR TEST + BASIC BUILDING INFORMATION

In Scenario 2, a blower door test (or tracer gas test) was conducted to estimate the infiltration rate in CC1. Measuring the infiltration rate reduced the uncertainty of the building ACH input parameter of CC1 substantially compared with Scenario 1. The actual blower door test for CC1 shows the $ACH_{natural}$ was about 0.39. Since this blower door test was performed only once, it is assumed there would still be uncertainty in this estimated ACH, and a 5% standard deviation was assumed as an uncertainty.

As shown in Table 8, the average energy consumption for CC1 and CC2 was estimated as 23,618 kWh and 16,022 kWh with standard deviations of 8.8% and 10.5%, respectively. In other words, at a 95% confidence level, it was expected that CC1 would use about 19,462 ~ 27,774 kWh annually with the given distribution of KIPs, and CC2 would use about 12,641 ~ 19,402 kWh annually. It was observed that average CC1 energy use was reduced by about 12.2%, as the measured building infiltration rate was lower than the initial assumption. The standard deviation was also reduced from 12.6 to 8.8% as the uncertainty of building infiltration rate for CC1 was reduced.

The uncertainty of the annual savings was quantified in the same manner, and the analysis shows that CC2 would use 32% less energy than CC1 with a 4.3% standard deviation (Figure 9). In other words, a 24 to 41% savings is expected at a 95% confidence level. As discussed earlier, the uncertainty in this scenario was significantly lower than in Scenario 1 because the sensitivity of the energy savings in Scenario 1 was largely driven by building infiltration. Measuring this input parameter in CC1 makes the impact on overall uncertainty clear. The uncertainty was not reduced further, because there still remained uncertainty regarding the post-retrofit (CC2) building infiltration. This uncertainty was not adjusted because we assumed a scenario in which estimated energy savings are provided before the retrofit is completed, so the actual building infiltration of the post-retrofit building is uncertain.

After the UQ was done, the GSA for the savings was performed to identify highly ranked KIPs. Figure 6 shows the ranking for the savings SI of CC1 and CC2. CC1 infiltration shows a lower SI (6th and 12th), as the ACH number for CC1 was estimated according to the blower door test and the uncertainty range was narrowed, whereas CC1 infiltration had the highest SI in Scenario 1. CC1 duct leakage uncertainty still has a high SI, as no duct leakage test was associated with this test (high uncertainty remains for the duct leakage rate).

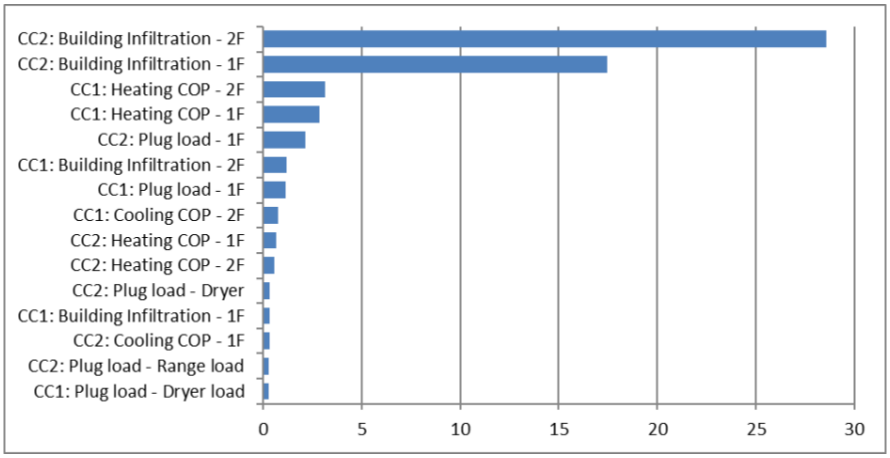


Figure 6 Scenario 2: Sensitivity analysis for energy savings

6.3. SCENARIO 3: DUCT BLASTER TEST

In Scenario 3, a duct blaster test was conducted to estimate the duct leakage rate in CC1 in addition to basic building information with a known building infiltration rate. The current version of GURA-W and EnergyPlus cannot effectively model the duct leakage impact on the energy use of a residential building. Therefore, the duct leakage impact on total cooling and heating energy was investigated using BeOpt and was integrated with the model by reducing the heating and cooling performance values accordingly. The field test for CC1 revealed that the duct leakage rate is about 15%, and this leakage rate was integrated into the model. As shown in Table 4, the heating and cooling COP values for CC1 in scenario 1 were reduced to correspond to 15% duct leakage. There is still some uncertainty (i.e., 2% standard deviation) in heating/cooling COP because of the uncertainty regarding the performance of the HVAC unit itself.

The UQ analysis (Figure 9) shows that knowing the duct leakage rate reduced the uncertainty slightly compared with Scenario 2. The average energy consumption for CC1 and CC2 (Table 8) was estimated as 23,841 kWh and 16,028 kWh with standard deviations of 8.5 and 10.1%, respectively. In other words, at a 95% confidence level, it is expected that CC1 would use about 19,768 kWh to 27,913 kWh annually with the given distribution of KIPs, whereas CC2 would use about 12,792 ~ 19,263 kWh annually. It was observed that the average CC1 energy use was similar in scenario 2, and the standard deviation was reduced from 8.8 to 8.5% as the uncertainty regarding the duct leakage rate for CC1 was reduced. However, it was shown that the measurement of duct leakage for CC1 (i.e., a narrower distribution of heating and cooling COP values) did greatly reduce the uncertainty for CC1 energy use. This could be attributed to the fact that in Scenario 2, although the blower door test reduced the uncertainty for the building infiltration rate, the uncertainty of the heating/cooling set point temperature in CC1 was still high. (The sum of SIs for the heating/cooling set point was about 80). Therefore, the duct leakage and corresponding COP input parameter did not impact energy consumption substantially.

In scenario 3, CC2 would consume 33% less energy than CC1 with a 3.5% standard deviation. In other words, it is expected to use 26 to 40% less energy at a 95% confidence level. In contrast to energy consumption, for which the uncertainty for each building was impacted very little by the reduction in duct leakage uncertainty, the percentage reduction in the uncertainty of energy savings was larger (from 4.3 to 3.5%). Although the heating and cooling COP and duct leakage had low SIs for CC1 energy consumption, the indices were higher (Figure 7) for the energy savings analysis. Hence, reducing the uncertainty in these parameters reduced the uncertainty in energy savings much more than it reduced the uncertainty in energy consumption.

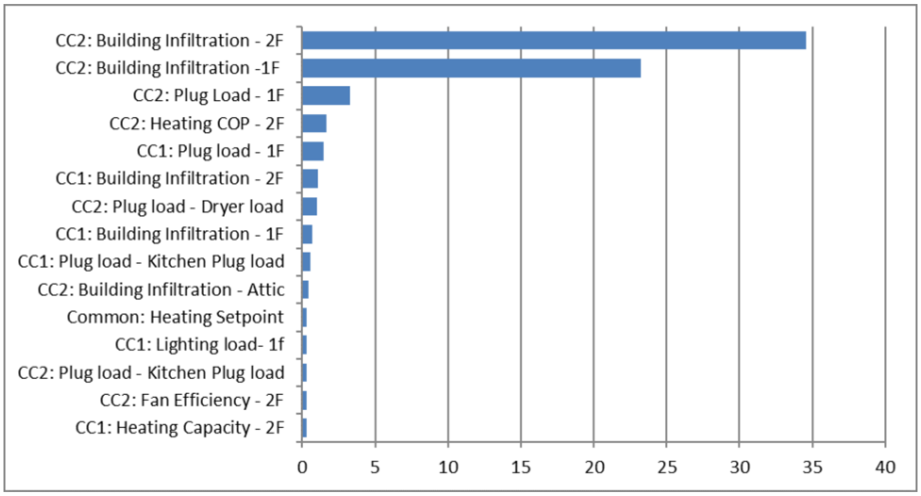


Figure 7 Scenario 3: Sensitivity analysis for energy savings

6.4. SCENARIO 4: COMPREHENSIVE AUDIT

In Scenario 4, the uncertainties regarding the remaining KIPs in CC1 were reduced by performing a comprehensive audit. This scenario is the most time-consuming and costly scenario, as detailed building information should be obtained for it through measurement, visual inspection, and a series of interviews with occupants. The audit procedure revealed the heating/cooling thermostat set point, which is the most highly sensitive input parameter in energy use, and lighting and plug load density (W/m2). The KIPs that remained the same in CC2 after the retrofit (e.g., wall R-value, heating/cooling set point, DHW set point) had reduced uncertainty.

As the uncertainties in the KIPs in CC1 energy consumption were reduced, the energy consumption uncertainty was significantly reduced as well (Figure 9). The standard deviation for CC1 energy use was reduced from 8.5 to 1.4%. Since CC2 still had relatively high uncertainties for some KIPs that corresponded to EEMs (e.g., building infiltration rate, heating/cooling COP, lighting/plug load), the standard deviation for CC1 energy consumption was reduced by less than the CC1 energy use was reduced. The standard deviation for CC2 was reduced from 10.1 to 4.9%. Interestingly enough, even with the large reduction in energy use uncertainty in CC1 and CC2, the energy savings uncertainties from Scenario 3 to Scenario 4 were almost the same (about 3.5% standard deviation with 33% average savings).

As shown in the SA of energy savings for Scenario 3 (Figure 7), the uncertainty sensitivity in savings was mostly due to the uncertainty for building infiltration in CC2, which could not be precisely estimated before the retrofit was completed. Therefore, even with reduced uncertainties for relatively insensitive KIPs, the energy savings uncertainty could not be reduced by a large degree. As shown in Figure 8, most of ranked KIPs were from CC2. As these KIPs correspond to EEMs in CC2, there were relatively high uncertainties for their performance (i.e., further reduction in uncertainties is difficult).

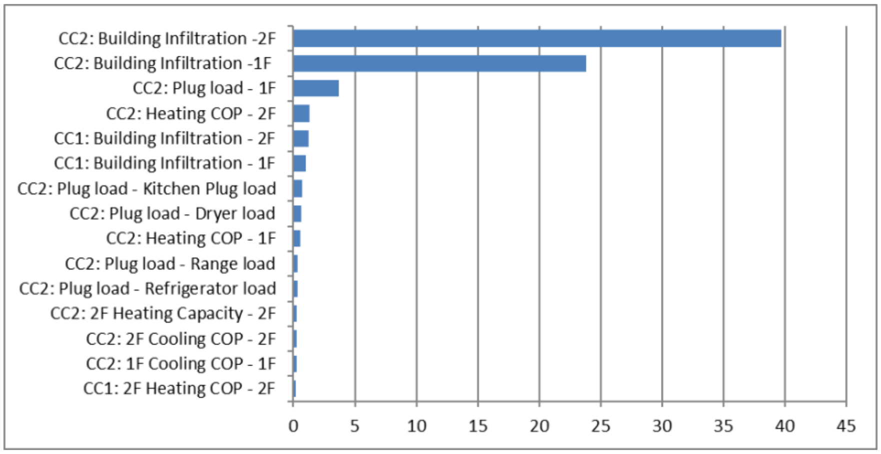


Figure 8 Scenario 4: Sensitivity analysis for energy savings

Table 8 and Figure 9 shows the summary results from the uncertainty analyses for the four scenarios. Of four different scenarios, the most uncertain scenario estimated the energy savings from the retrofit would be between 18 and 51% at a 95% confidence level, and the least uncertain scenario estimated the savings would be between 26 and 40% at a 95% confidence level. Further reduction of the savings uncertainty would also be possible by ensuring enhanced performance of the retrofit house envelope and HVAC systems based on a form of commissioning, or third-party retrofit certification program.

Table 8 Summary table for the four scenarios

	Scenario 1			**Scenario 2**			**Scenario 3**			**Scenario 4**		
	CC1 Use	**CC2 Use**	**Savings**	**CC1 Use**	**CC2 Use**	**Savings**	**CC1 Use**	**CC2 Use**	**Savings**	**CC1 Use**	**CC2 Use**	**Savings**
Average	26,908	17,469	34.5%	23,618	16,022	32.1%	23,841	16,028	32.8%	23,587	15,797	33.0%
SD	3,351	2,080	8.3%	2,078	1,690	4.3%	2,036	1,618	3.5%	339	769	3.5%
SD (%)	12.5	11.9	24.1	8.8	10.5	13.4	8.5	10.1	10.6	1.4	4.9	10.5
Upper (95%)	33,611	21,629	51.2%	27,774	19,402	40.7%	27,913	19,263	39.7%	24,265	17,336	40.0%
Lower (95%)	20,205	13,309	17.9%	19,462	12,641	23.5%	19,768	12,792	25.8%	22,908	14,259	26.0%
Min	20,474	13,183	8.0%	18,984	12,582	19.4%	19,024	12,602	21.3%	22,614	14,017	23.8%
Max	37,840	25,088	53.1%	29,160	21,557	41.0%	30,693	22,223	41.5%	24,327	17,871	40.2%

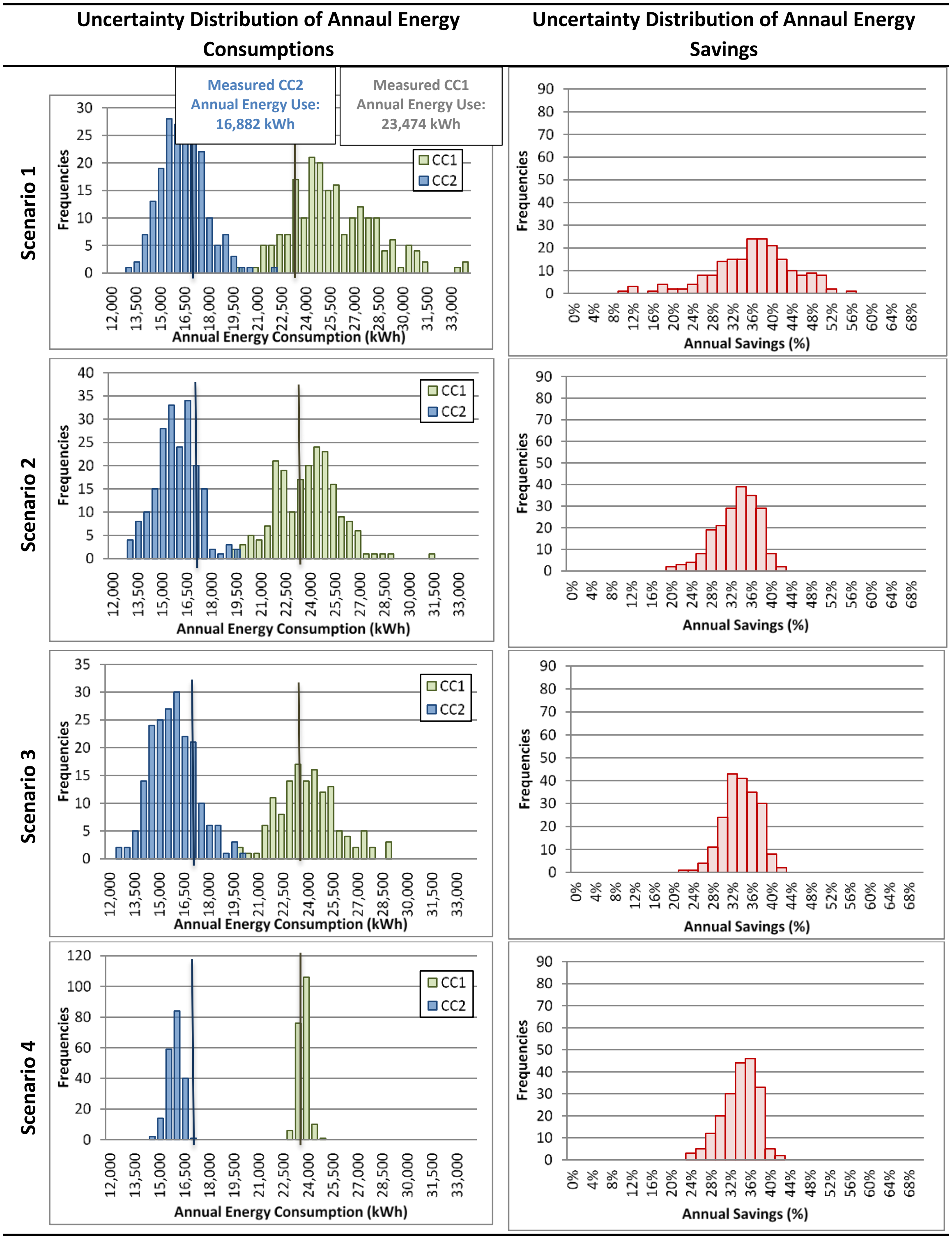


Figure 9 Uncertainty distribution for energy consumption and savings.

Major findings, lessons, and insights from the study are described as follows. From the literature review and resources, commonly selected KIPs were identified for residential buildings. The KIPs from previous studies are mainly for energy consumption, not savings. This study looks at energy consumption and energy savings, and it found that high-ranked KIPs for energy consumption are not necessarily high-ranked KIPs for energy savings. If some KIPs' values in a pre-retrofit house remain the same in a post-retrofit house, it is most likely that those KIPs would have little or no influence on energy savings, although the uncertainty for the same KIPs can have a high impact on energy consumption. For example, heating and cooling set point temperatures, which may not change between pre- and post-retrofit scenarios, have the highest rankings for energy consumption in this study; but they show no important impact on energy savings. Therefore, the focus on how to reduce output uncertainty by managing the uncertainty of KIPs should be based on the purpose of the modeling. If the modeling is for estimating energy savings, identifying heating and cooling set point temperatures should not be the main focus, as these KIPs would have very low impact on energy savings, but would be important in estimating energy consumption. Focusing on them would be equivalent to a Type III error, where the right answer is given to the wrong question.

The highly ranked KIPs for energy consumption in both CC1 and CC2 were heating and cooling set point temperatures, building infiltration rate, DHW set point temperature, heating and cooling equipment efficiency, duct leakage rate (if ductwork is installed in an unconditioned zone), wall R-value, and lighting/plug power density. Different houses in different climate zones would have different lists of highly ranked KIPs. Further research would be required to generalize the list of KIPs in energy consumption and savings.

Highly ranked KIPs for energy savings included building infiltration rate for both pre- and post-retrofit houses, heating and cooling COP, duct leakage rate, and the pre-retrofit house lighting and plug loads. Because the uncertainty in the duct leakage rate for ducts in an unconditioned zone shows a high impact on energy savings, uncertainty analysis tools and building energy simulation softwares for residential buildings should consider incorporating a duct model. Without a duct model, it is hard to estimate the energy savings due to sealed ducts, installation of ducts in conditioned zones, and so on.

There was a significant difference in the uncertainty ranges for heating/cooling COPs and duct leakage rates for CC1 and CC2 because CC1 has its ductwork in a vented attic, whereas CC2 ductwork is in a conditioned attic. This indicates that installing of ducts in conditioned zones reduces the uncertainty in energy consumption and savings prediction because of reduced uncertainty in total heating/cooling system efficiency.

Although a comprehensive audit to verify all KIP uncertainty would be beneficial to reduce the uncertainty in predicted energy savings, the audit procedure could be time consuming. Identifying only highly sensitive KIPs such as the building infiltration rate and duct leakage rate can still reasonably estimate the uncertainty in building energy savings without a comprehensive audit.

Figure 10 and 11 show that, even with the large reduction in energy use uncertainty in CC1 and CC2 based on the comprehensive audit, the energy savings uncertainties between scenario 3 (performing blower door test + duct leakage test) and scenario 4 (comprehensive audit) were almost the same (about a 3.5% standard deviation with 33% average savings). As shown in the SA of energy savings in Figure 7, (basic building information + a blower door test + a duct blaster test) for CC1, the uncertainty sensitivity in savings is mostly due to the uncertainty in building infiltration in CC2, which cannot be precisely estimated before a retrofit is completed. Therefore, with reduced uncertainties in relatively insensitive KIPs, the energy savings uncertainty cannot be reduced to a large degree. Based on this analysis, a suggested approach to minimizing energy savings uncertainty would include a pre-retrofit audit with a blower door test to estimate air infiltration, along with a form of retro-commissioning or third-party retrofit certification program to ensure the enhanced performance of the retrofit house envelope and HVAC systems.

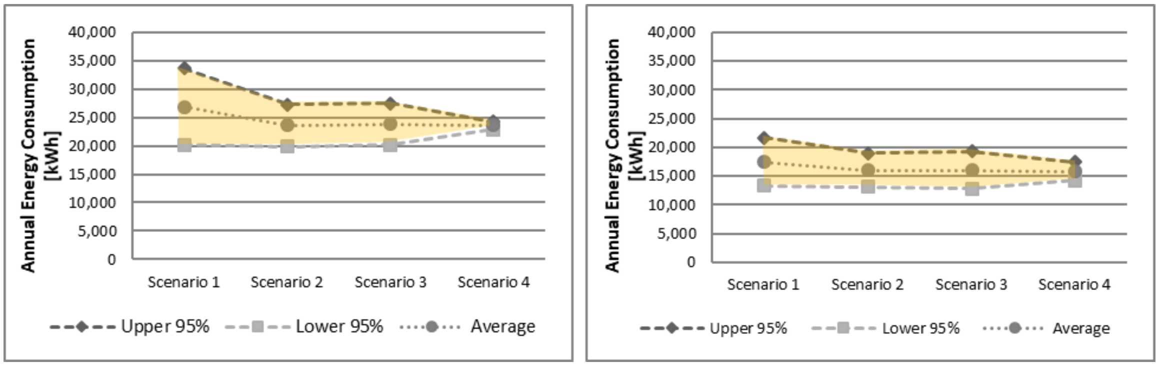


Figure 10 CC1 and CC2 energy consumption and uncertainty changes by scenario

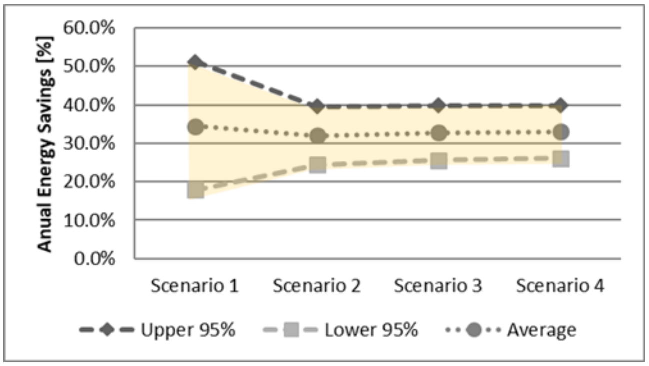


Figure 11Energy savings and uncertainty changes by scenario.

7. Conclusions

This study (1) investigated the KIPs in estimating the uncertainty of energy savings using a residential building energy simulation model and (2) performed UQ for energy savings for several different scenarios. The project's methodology was successfully applied to the calculation of uncertainties associated with residential energy retrofits using two test houses designated CC1 and CC2. Uncertainties were determined using basic parameters that might be supplied to an energy model. They were then re-evaluated based on an audit of the KIPs identified by this technology, resulting in substantially reduced uncertainty.

Further Research Several future research topics were identified from the current study to enhance the results and apply the results in practice.

I. It is recommended that similar studies be conducted in numerous climate zones in the United States. Such research could reveal how the SIs and rankings for KIPs would vary per climate zone. Possible reasons for the discrepancies could be investigated, and climate-specific KIPs and their range/distribution for residential buildings could be developed.
II. Development of a national database for KIP distribution for residential buildings would be a top priority.
III. Currently, there is no easy-to-use, computationally efficient UQ tool that can be connected to multiple building simulation engines. Such a tool could expedite the use of UQ analysis in industry and academia and make possible more effective strategies and planning in energy savings analysis by implementing a type of risk assessment.
IV. This study explores an implementation of UQ analysis using an hourly simulation tool and two occupancy-simulated research houses that have limited uncertainty in occupancy behavior. The study would need to be expanded to more houses with real occupancy to validate the UQ analysis results.

V. This UQ analysis assumes there will be no changes in thermostat set point temperature and lighting/equipment operation schedules before and after the retrofit. Further behavior changes as a result of the building retrofit could be explored in future research. In addition, the impact of weather uncertainty (i.e., variation of annual weather) should be included.

Acknowledgment

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