Testing a Streamlined Project Evaluation Tool for Risk-Conscious Decision Making: The Chicago Loop Energy Efficiency Retrofit Initiative

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ABSTRACT

The goals of the Chicago Loop Energy Efficiency Retrofit Initiative are to (1) develop a scalable, normative assessment tool to help overcome current barriers to widespread adoption of building energy-efficiency measures; and (2) test and adapt the tool in a real-world environment. To achieve these goals, a core project team consisting of Argonne National Laboratory, the Georgia Institute of Technology, Sieben Energy Associates, and Skidmore Owing and Merrill is building, testing, and ultimately deploying a user-friendly decision-making tool for energy-efficiency retrofits. Our approach, based on normative energy modeling, is computationally efficient and does not require modeling expertise. The final tool will allow users to evaluate retrofits in large portfolios of buildings while greatly alleviating burdens in data collection, model construction, and computation.

In this paper, we describe results from a portion of the project: the sensitivity and comparative analyses that were conducted to advance the application of normative energy modeling to inform energy-efficiency retrofit investments. The sensitivity analysis was important to our subsequent streamlining of the input data requirements for the model. The comparative analysis focused on demonstrating the efficacy of our approach compared with traditional energy assessment methods, such as audits and modeling.

Introduction

Commercial buildings represent nearly one-half of building energy consumption and, when placed in a larger context, almost one-fifth of U.S. energy consumption (DOE, 2010). Moreover, existing commercial buildings make up the vast majority of the commercial building stock, representing 71.6 billion square feet, compared with 1.6 billion square feet of floor area for new construction (EIA, 2003). With increasing pressure to reduce carbon dioxide (CO_2) emissions and increase energy efficiency, existing commercial buildings are naturally a prime target. The Better Buildings Initiative, as announced by President Obama in February 2011, reinforces the urgency of achieving energy savings by targeting a 20% reduction in commercial building energy consumption by 2020. President Obama's plan outlines a number of initiatives designed to attain the reduction though retrofitting; these initiatives include financing opportunities, tax incentives, competitive grants, public recognition, and workforce training (White House, 2011).

A multitude of similar initiatives and goals are also in place at the local level. For instance, the Chicago Climate Action Plan is designed to reduce energy consumption and CO_2 emissions. The Action Plan includes five strategies, one of which targets energy-efficient buildings. In Chicago, buildings generate approximately 70% of the City's total CO_2 emissions. The target of the Action Plan is to retrofit 50% of existing commercial and residential buildings by 2020, potentially reducing energy consumption by 30% and preventing 1.3 million metric tons of CO_2 emissions (Chicago Climate Action Plan, undated). To achieve these goals, approximately 9,200 buildings will need to be retrofitted (Chicago Climate Action Plan, undated).

At both the national and local levels, energy-efficiency goals have been established, and a number of mechanisms, including modeling and assessment tools, have been developed and/or improved to better achieve these goals. Nevertheless, a number of market barriers and unknowns remain. One perceived market barrier is the time, capabilities, and resources needed to evaluate the effectiveness of retrofits using the conventional approach of energy audits and dynamic simulation models (Menassa, 2011; Almeida et al., 2012). Other key barriers to widespread investment in energy-efficiency projects include capital constraints, performance risk, and performance uncertainty (Zero Energy Commercial Buildings Consortium 2011; Mills, 2003). Currently, subjective assessments and expert judgment are used to estimate the risk of underperformance of energy-efficiency measures (EEMs). Ideally, even with subjective assessments, all building owners and operators would have the time, resources, and interest to employ expert modelers; but of course, this is not the reality. In addition, given the complexity of buildings and the number of different factors that impact energy use, we believe that these subjective methods cannot accurately characterize retrofit costs, benefits, and risks. As an example, most models require user expertise and do not address the uncertainty associated with an EEM. As a consequence, the decision maker (e.g., commercial building owner and/or manager) often lacks sufficient energy-savings information and/or confidence in the energy-savings information generated by these models to make an informed decision; often, this uncertainty results in inaction, instead of investment in the retrofit. To meet aggressive energy-efficiency goals, decision makers will need more objective analytical tools and/or supplemental tools designed to overcome the gaps associated with readily available assessment tools on the market today.

Given the urgency of achieving the national and local goals, Argonne and the project partners have been developing a normative energy model, similar to those used for benchmarking in Europe (Roulet and Anderson, 2006; van Dijk, 2009). Defined simply, a normative model, as it relates to buildings, is a set of modeling rules that produces a standard measure for energy performance; when calibrated, it can accurately represent the building as-operated and accurately evaluate EEM options. By seeking engagement with Chicago Loop stakeholders and building owners, the project partners intend to not only design, test, calibrate, and validate the model, but also develop a tool that end users (i.e., building owners and/or operators interested in energy efficiency) find useful. The City intends to achieve its energy-efficiency goals by implementing an infrastructure bank and assembling a group of independent parties that offer a full spectrum of resources. The primary focus of the Chicago Loop Energy Efficiency Retrofit Initiative is to research and develop a credible, easy-to-use tool for estimating energy savings that will help engage and aid decision makers in making energy-efficiency investments, both at the individual building and the policy and planning levels. This research component will proceed in parallel with other retrofit initiatives in Chicago, all designed to work toward greater energy efficiency in the built environment. This paper highlights the sensitivity and comparative analyses portions of the Chicago Loop Energy Efficiency Retrofit Initiative.

Methodology

Normative Energy Modeling

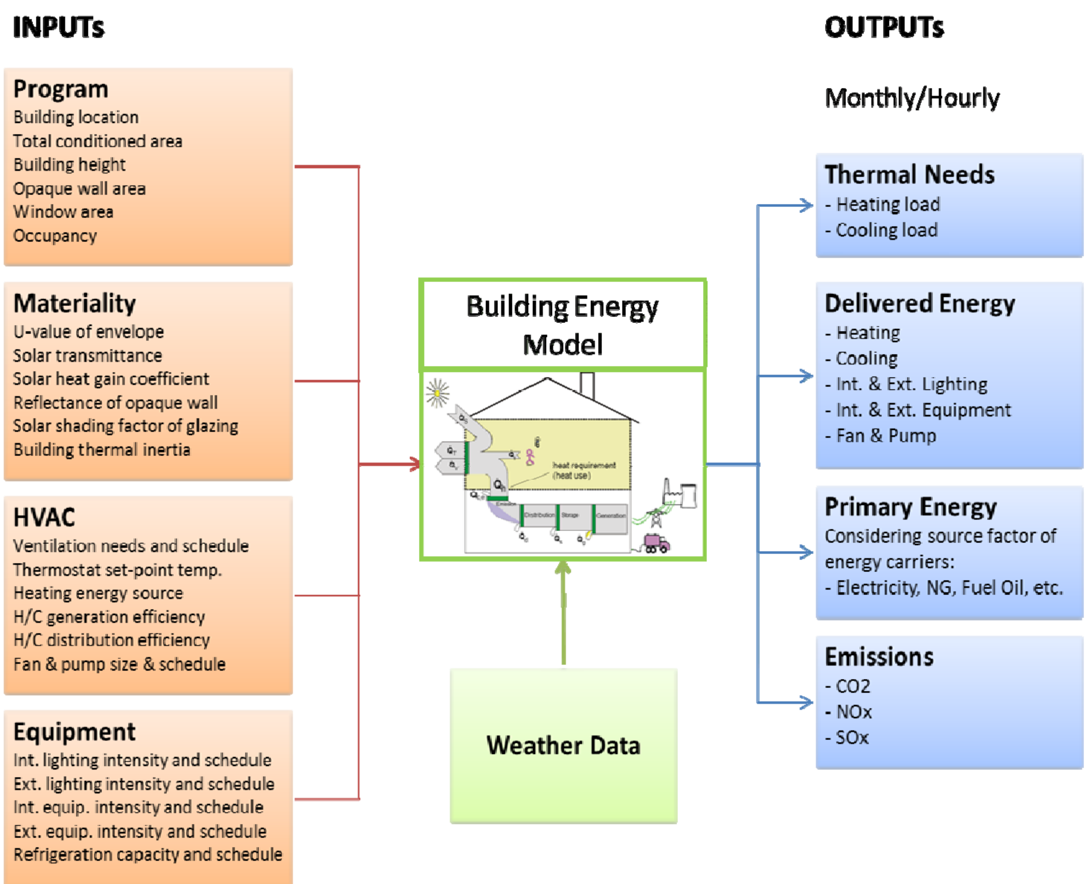
To evaluate energy savings from the implementation of EEMs, we deploy normative energy calculations derived from the European Committee for Standardization and the International Organization for Standardization and translated by the Georgia Institute of Technology into an Energy Performance Standard Calculation Toolkit (Lee et al., 2011). The toolkit calculates thermal energy demands for heating and cooling using a monthly, quasi-steady-state method. Thermal energy demand accounts for heat losses by transmission and ventilation, heat gains from solar and internal sources, and the effect of thermal inertia driven by building mass (Heo et al., 2012). The total thermal energy demand can be used to assess the energy efficiency of the architectural design. The toolkit also calculates energy consumption by the end users: heating, cooling, ventilation, lighting, plug loads, pumps, and domestic hot water systems. The calculation takes into account heating and cooling losses through the distribution and heating and cooling system to determine the energy use of each fuel type. From the calculated delivered energy, the toolkit derives primary energy and CO_2 emissions by (1) considering the specific details of the energy supply utilities and network and (2) tracking the generation and emission efficiency of the local mix of utilities. Figure 1 shows the current model inputs and outputs; in the future, infiltration will be added to the figure.

The normative energy modeling approach provides several benefits over traditional methods:

- Alleviates some of the subjectivities and modeling biases in the analysis;
- Requires considerably fewer data (only tens of inputs instead of the hundreds required in typical dynamic simulations); and
- Because of the reduced date requirements, is less labor and computationally resource intensive and therefore more cost effective.

The normative model can be implemented in a spreadsheet so computation of a single set of inputs is instantaneous. Computation of tens of thousands of input combinations can be accomplished in a few minutes, as opposed to the hours or days that would be required for such analysis using typical dynamic simulations. These features combine to offer an adaptable, scalable method for evaluating the energy savings resulting from EEMs for individual buildings or portfolios of buildings. In addition, because the energy calculations are computationally efficient, they are more amenable to the use of stochastic processes to evaluate uncertainty. We adopt the Bayesian calibration approach to propagate uncertainties in the model.

Figure 1. Inputs and Outputs of the Building Energy Model



Bayesian Calibration

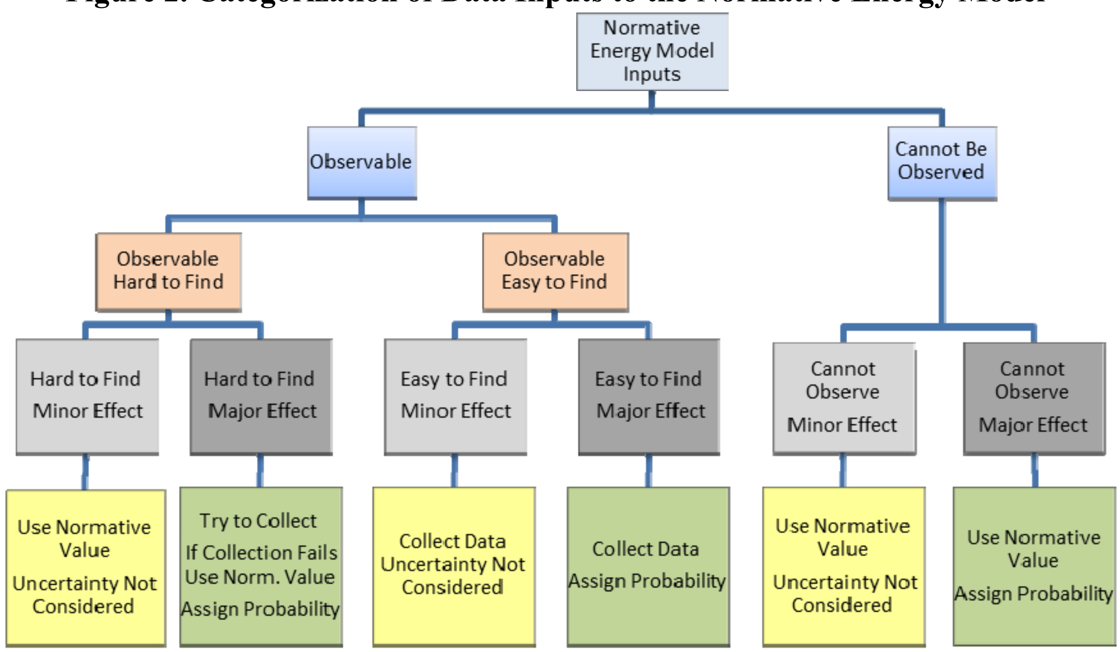
We apply Bayesian calibration to the normative model so that the resulting model can reliably represent a building as operated. The Bayesian approach treats our degree-of-belief on true values about calibration parameters as prior probability distributions and updates our prior beliefs given the measured data under the mathematical formulation of Bayesian calibration. Following the mathematical formulation developed by Kennedy and O'Hagan (2001), Heo et al. (2012) introduced the use of the Bayesian approach to calibrate normative models and the applicability of normative models enhanced by Bayesian calibration in the context of retrofit applications. The calibration module requires three types of inputs: (1) prior density functions of calibration parameters, (2) monthly utility data, and (3) model outcomes exploring the space of calibration parameters. These space-filling data are used to evaluate how closely testing calibration parameter values match actual monthly energy data. Prior density functions are derived by collecting expert knowledge from technical reports, industry reports, and standards. As a result, the module provides posterior distributions of calibration parameters refined from the prior distributions. The calibration results will reliably assess feasible EEMs by testing their effects over all plausible baseline scenarios. In addition, the calibrated model will generate probabilistic outcomes of retrofit performance that will inform decision makers about the risks associated with testing EEMs.

Sensitivity Analysis

During our initial trial in applying normative energy modeling for retrofit analysis of large office buildings in Chicago, we had difficulty obtaining values for some of the model inputs. To address this issue, we conducted a sensitivity analysis to streamline the data requirements. The intent of the analysis was to characterize each of data input types according to its difficulty of observation, difficulty to find, and effect on the results and uncertainty of the results. Figure 2 illustrates these categories.

Sensitivity analysis is the study of how uncertainty in a model output can be apportioned to uncertainty in the various inputs (Saltelli et al., 2008). Such investigations are useful for analyzing computer models that support decision making (by making results more credible), for increasing understanding of input/output relationships in the model (by helping to better inform measurement of model inputs), and for improving model development (by helping to streamline or find errors in a model). In our project, an understanding of the relationship between input uncertainty and output uncertainty is crucial to assessing which input parameters must be known accurately to reduce output uncertainty and which can be set to fixed values, or removed from the model altogether, without increasing the uncertainty of the output.

Figure 2. Categorization of Data Inputs to the Normative Energy Model



Consider a system that has an output value y for a set of input values x_i, i.e., $y = f(x_1,x_2,\ldots,x_i,\ldots)$. Using traditional sensitivity analysis, we calculate the sensitivity, S_i, of the model output y to a given input x_i as the partial derivative of the output to input as:

$$S_i = \frac{\partial y(x_1, x_2, \cdots, x_i, \cdots)}{\partial x_i} \tag{1}$$

The partial derivative in Equation (1) could be computed analytically or numerically. Unfortunately, the value obtained from this equation in complex models is often dependent on the exact values for all input variables that are used in its computation. Global sensitivity analysis replaces the local variation computed by Equation (1) with a global computation of variations that evaluate the relationship between input and output uncertainties over the whole range of possible model input values. Indeed, in global sensitivity analysis, partial derivatives are replaced with ratios of variances, and Equation (1) is replaced by a statistical generalization:

$$S_i = \frac{V\left(E(y|x_i)\right)}{V(y)} = \frac{\text{Variance over } x_i \ \left(\text{Mean(vary all but } x_i)\right)}{\text{Total Variance in } y}, \tag{2}$$

where S_i, y, and x_i are as defined above. For this project, we applied global sensitivity analysis by characterizing the uncertainty in inputs using probability distributions; computed the output distribution by using Monte Carlo methods; and then evaluated the variances of Equation (2) using the Saltelli algorithm (Saltelli et. al., 2008).

The sensitivity analysis was conducted for eight existing high-rise office buildings in Chicago, as well as the DOE large office reference building. The buildings used in the model are typical of a high-rise office building in the downtown Chicago Loop. On average, the buildings are 40 stories tall with a conditioned floor area of 75,300 m^2 (810,000 ft^2). The older buildings use gas for space heating and domestic hot water heating, while the newer buildings use electricity. Most of the buildings are either glass or stone panel curtain walls. In comparison, the DOE large office reference building has 12 stories, 46,000 m^2 of floor space, and concrete walls.

Tables 1 and 2 summarize the results of the sensitivity analysis. Table 1 lists the average and total sensitivity, $S_{i,}$, for each of the 21 inputs that had an average sensitivity of at least 0.1%. The total sum column is the sum of the S_i for all nine buildings. The average column lists the average over the nine buildings. The highest-ranking column lists the highest that the input ever ranked among all nine buildings. A ranking of 1 means that input had the highest sensitivity index, a ranking of 2 means the second highest, etc. The priority column shows how we categorized the importance of the input for data collection.

Table 1. Global Sensitivity Analysis Summary Results

Input	Si Sum	Si Ave (%)	Highest Ranking	Priority
Plugload - Occ [W/m^2]	3.042	33.8	1	High
Int. Light Power Dens [W/m^2]	1.478	16.4	1	High
Qinf@75Pa m^3/h/m^2	1.010	11.2	1	High
Cool Sys MPLV	0.896	10.0	1	High
Heat T Set - Occ [C]	0.546	6.1	2	High-Med
Heat Sys Eff [kW/kW]	0.351	8.8	1	High-Med
Env. Heat Cap [J/m^{2}K]	0.244	3.0	4	Low
Total Floor Area [m^2]	0.229	2.5	3	Low
Cool Sys COP [kW/kW]	0.187	2.3	6	Low
Wall U [W/m^{2}K]	0.155	2.2	3	Low
Plugload - Unocc [W/m^2]	0.171	2.4	4	Low
HVAC Heat Sys Loss	0.160	2.3	11	Low
Window U [W/m^{2}K]	0.093	1.0	7	Low
Window Area Mult	0.081	1.3	8	Low
Cool T Set - Occ [C]	0.063	1.0	7	Low
HVAC Waste Factor	0.059	2.9	10	Low
Height [m]	0.047	0.8	8	Unimportant
Heat T Set- Unocc [C]	0.043	4.3	7	Low
Occ Dens [m^2/person]	0.013	0.2	8	Unimportant
DHW Demand [m^3/yr]	0.010	0.5	10	Unimportant
Occ Heat Gain - Occ [W/per]	0.001	0.1	12	Unimportant

Table 2 is a summary of how each input ranked among all the buildings. For example, the first row of the table shows that the plug load input had the highest sensitivity index for five buildings, the second highest for one building, the ninth highest for one building, the twelfth highest for one building, and the fifteenth highest for one building. For the nine office buildings that were analyzed, the normative model is clearly most sensitive to plug loads, lighting loads, infiltration, and the cooling system mean partial load value (MPLV = SEER/EER). These four inputs all have average sensitivity indices greater than 10% and have the highest S_i sums as well.

There is also a medium sensitivity to heating system efficiency and heating set point temperatures for occupied conditions. Table 2 shows that sensitivity to heating system efficiency is high only for a few buildings and is quite low for most others. Inspection of the full records shows that the high sensitivity values occur, as expected, for buildings with low-efficiency boilers. The sensitivity to all other inputs would best be characterized as low or unimportant.

On the basis of these results, we streamlined the data requirements for the normative energy model, incorporating normative values for the low or unimportant parameters that can be used if the actual building data cannot be found.

Table 2. Global Sensitivity Analysis Rankings

	Rankings														
Input	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Plugload - Occ [W/m^2]	5	1	0	0	0	0	0	0	1	0	0	1	0	0	1
Int. Light Power Dens [W/m^2]	1	3	2	0	1	0	0	0	0	1	0	0	0	1	0
Qinf@75Pa m^3/h/m^2	2	0	1	0	2	1	0	0	1	0	2	0	0	0	0
Cool Sys MPLV	0	2	4	0	1	0	0	1	0	0	1	0	0	0	0
Heat T Set - Occ [C]	0	2	0	1	0	1	0	1	3	1	0	0	0	0	0
Heat Sys Eff [kW/kW]	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1
Env. Heat Cap [J/m^{2}K]	0	1	0	1	1	2	2	0	0	0	1	0	0	0	0
Tot Flr Area [m^2]	0	0	1	1	0	0	1	0	2	3	0	0	1	0	0
Cool Sys COP [kW/kW]	0	0	0	2	2	1	0	1	0	0	0	0	0	1	1
Wall U [W/m^{2}K]	0	0	0	1	0	0	0	0	0	0	2	1	1	1	1
Plugload - Unocc [W/m^2]	0	0	0	3	1	1	0	1	0	0	0	0	0	0	1
HVAC Heat Sys Loss	0	0	0	0	0	2	1	0	0	0	0	0	2	1	1
Window U [W/m^{2}K]	0	0	0	0	0	0	1	1	2	0	2	1	0	1	1
Window Area Mult	0	0	0	0	0	0	0	2	0	0	0	1	3	0	0
Cool T Set - Occ [C]	0	0	0	0	0	0	3	1	0	1	0	1	0	0	0
HVAC Waste Factor	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
Height [m]	0	0	0	0	0	0	0	0	0	1	0	2	1	1	1
Heat T Set- Unocc [C]	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Occ Dens [m^2/person]	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1
Wall Area Mult	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Occ Heat Gain - Occ [W/per]	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
DHW Demand [m^3/yr]	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0

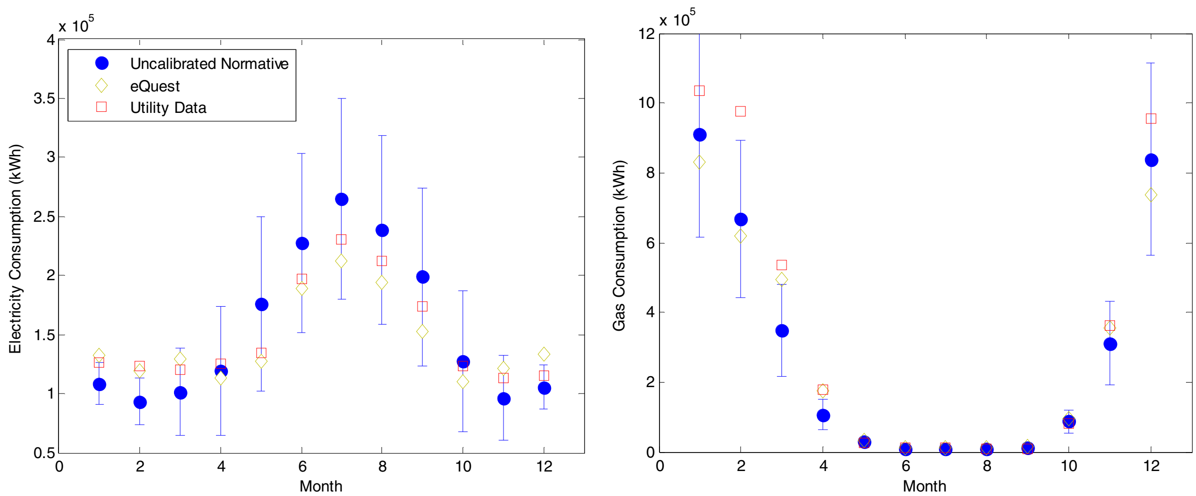
Comparative Analysis

To support the utility of the normative-energy-model-based approach to retrofit analysis, we compare the results of traditional energy audits and simulations of actual buildings with the results that would be obtained using our methodology. A first case study is illustrative of the comparative analysis approach and results. The test case building has the following characteristics:

- Mixed-use, including office, retail, and medical;
- Approximately 350,000 ft^2;
- Curtain wall, concrete building with dark window glazing;
- 28 floors;
- Built in 1971; and
- Located in the Chicago Loop.

Information available from the baseline/comparitive energy assessment includes monthly gas and electricity bill data, a calibrated eQuest model, and associated building parameter data prepared by a professional energy consulting firm. The electricity bill data do not include electricity consumption from tenant space, which the consulting firm estimated to account for 90% of the total building lighting and plug loads. On the basis of the available information, we constructed a normative model of the test building and compared energy consumption values predicted by the uncalibrated normative model with those from the calibrated eQuest model and actual energy consumption values from the utility bills in 2008, as shown in Figure 3. We used Actual Meteorological Years (AMY) weather data to compare the two different baseline models and calibrate the normative model given the measured energy uses under the same weather conditions. Overall, the energy data are in good alignment, although there are some discrepancies. Without calibration, the normative model overpredicts electricity consumption during the summer and underpredicts consumption during the winter, compared with actual energy use. The eQuest model used in the baseline/comparitive underpredicts gas consumption during the winter, even after calibration.

Figure 3. Comparison of Energy Consumption Values for the Un-calibrated Normative Model, the Calibrated eQuest Model, and Utility Data – Electricity Consumption (left) and Gas Consumption (right)



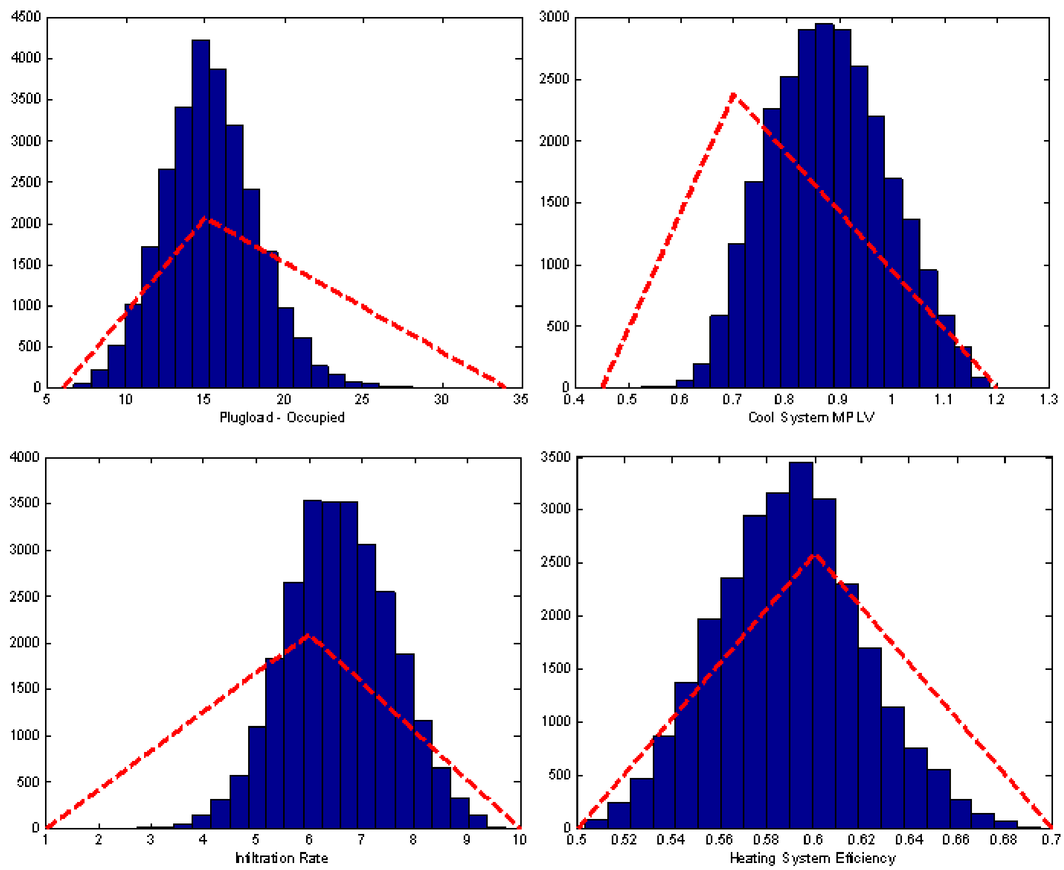
Before calibration, we quantified uncertainty in model parameters for the test building and applied the Morris method to identify the dominant parameters with respect to their effect on (1) gas consumption or (2) electricity consumption. On the basis of the ranking of model parameters shown in Table 3, we selected the top four parameters for calibration: (1) Plug Load – Occupied, (2) Cooling System MPLV, (3) Infiltration Rate, and (4) Heating System Efficiency.

Table 3. Ranking of Model Parameters in Terms of Gas and Electricity Consumption

Rank	Gas Consumption	Electricity Consumption
1	Infiltration Rate	Plugload-Occupied
2	Plugload-Occupied	Cooling System MPLV
3	Heating System Efficiency	Cooling System Efficiency
4	Heating Set-point Temperature	Lighting Power Density
5	Heating System Loss Factor	Fraction of Tenant Plugload

Figure 4 exhibits probability distributions (blue histogram) for the four calibration parameters updated from the prior probability distributions (derived from the literature study [red line]). For the Plug Load – Occupied parameter, the expected value does not change substantially from our prior estimate, but the magnitude of uncertainty is greatly reduced. For the Cooling System MPLV parameter, the expected value changes from 0.7 to 0.9. For Infiltration Rate, the results indicate that the building envelope is likely to be leakier than expected. For Heating System Efficiency, the posterior distribution does not change much from the prior distribution.

Figure 4. Calibration Results of the Four Parameters (prior – red line, posterior – blue histogram)



We validated the calibrated normative model by comparing the probability distributions of predictions against measured energy consumption, as shown in Figure 5. The calibrated model results in much narrower confidence intervals of predictions than the un-calibrated model (shown in Figure 3). This comparison demonstrates that Bayesian calibration enhances the reliability of the baseline model by helping to assure its accuracy and reduce its uncertainty. While the calibrated normative model quite closely replicates actual energy consumption, it still results in a discrepancy between predicted electricity consumption and actual consumption during the winter. This discrepancy can be attributed to the inability of the monthly normative model to capture cooling loads that occur during peak hours during the winter and the intermittent season. More case studies are necessary to validate the normative model across various buildings and enhance the capabilities of the model.

Figure 5. Energy Consumption Predicted by the Calibrated Normative Model Compared with the eQuest Model and Utility Data

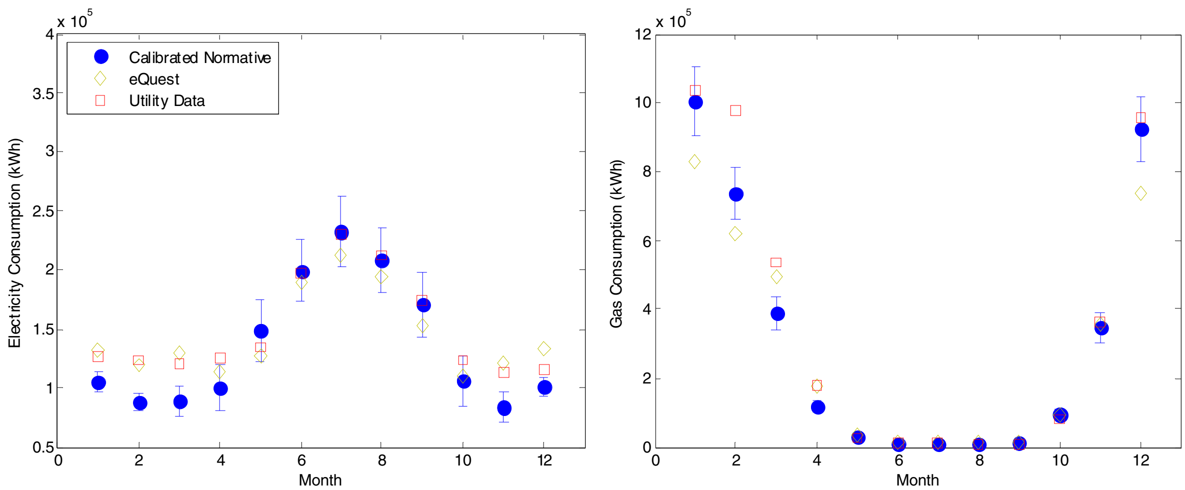
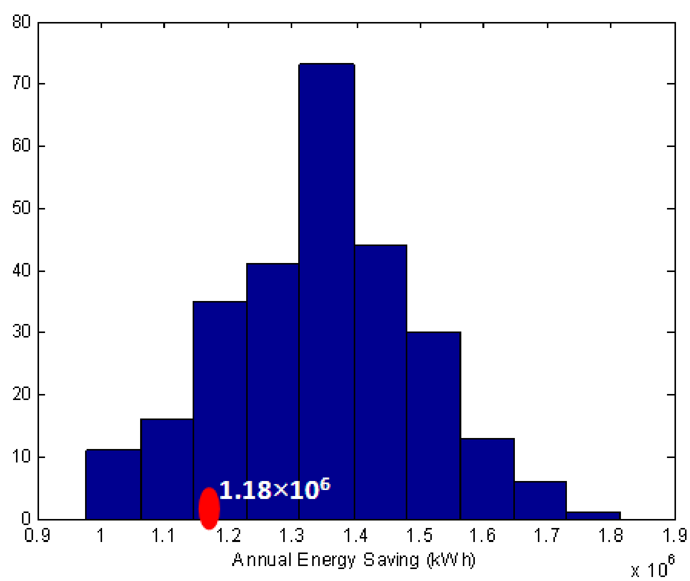


Figure 6. Probability Distribution of Annual Energy Savings Compared with a Single Estimate from the Audit Project



We evaluated the same EEM as the audit project: upgrading a boiler from 60% to 95% efficiency (note, this EEM was evaluated in the eQuest model, so we use the same values for comparison). We used Typical Meteorological Year (TMY) data to obtain energy savings over time because TMY data represent average weather conditions on the basis of 30-year historical data. In our analysis framework, we propagated uncertainty in calibration parameters and additional uncertainty from the retrofit option (ranging between 0.90 and 0.97 with the base of 0.95) by using Latin Hypercube Sampling. By subtracting post-retrofit energy consumption values from baseline values, we obtained probabilistic outcomes of annual energy savings, as shown in Figure 6. The proposed methodology yields a plausible range of annual savings and their likelihoods, while the typical audit project results in only a single value, even after labor-intensive audit and modeling. This more robust information helps support risk-conscious decision making by explicitly translating probabilistic outcomes into a single measure according to decision makers' objectives and risk attitude.

Conclusion

The sensitivity and comparative assessments described in this paper demonstrate the utility and efficiency of normative energy modeling approaches for building energy assessment and predictions of energy savings offered by EEMs. Ultimately, the goal is to develop a user-friendly decision-making tool designed to effectively inform retrofits. To achieve this goal, the team will focus on the following tasks:

1. Conduct additional comparative analysis case studies. Although the normative model has been extensively used in building energy performance benchmarking, it has not been widely used and/or studied for assessing retrofit options when deployed.
2. Examine approaches for aggregate-level analysis to better achieve scale. Because the normative model requires fewer data than many traditional models, it has the potential to be further developed for portfolios, communities, cities, clusters of buildings, etc.
3. Enhance the functionality of the normative model by developing a user-friendly interface and adding financial analysis ability, including energy retrofit cost assessments as the basis for the financial analysis. The financial analysis component represents an opportunity to tie energy assessments directly into business case development.

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