ANL/DIS-14/2

Comparative Analysis for the Chicago Energy Retrofit Project: Project Report

Decision and Information Sciences Division

About Argonne National Laboratory
Argonne is a U.S. Department of Energy laboratory managed by UChicago Argonne, LLC under contract DE-AC02-06CH11357. The Laboratory's main facility is outside Chicago, at 9700 South Cass Avenue, Argonne, Illinois 60439. For information about Argonne and its pioneering science and technology programs, see www.anl.gov.

DOCUMENT AVAILABILITY

Online Access: U.S. Department of Energy (DOE) reports produced after 1991 and a growing number of pre-1991 documents are available free via DOE's SciTech Connect (http://www.osti.gov/scitech/)

Reports not in digital format may be purchased by the public from the National Technical Information Service (NTIS):
U.S. Department of Commerce National
Technical Information Service 5301
Shawnee Rd
Alexandra, VA 22312
www.ntis.gov
Phone: (800) 553-NTIS (6847) or (703) 605-6000
Fax: (703) 605-6900
Email: **orders@ntis.gov**

Reports not in digital format are available to DOE and DOE contractors from the Office of Scientific and Technical Information (OSTI):
U.S. Department of Energy
Office of Scientific and Technical Information
P.O. Box 62
Oak Ridge, TN 37831-0062
www.osti.gov
Phone: (865) 576-8401
Fax: (865) 576-5728
Email: **reports@osti.gov**

Disclaimer
This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor UChicago Argonne, LLC, nor any of their employees or officers, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of document authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof, Argonne National Laboratory, or UChicago Argonne, LLC.

ANL/DIS-14/2

Comparative Analysis for the Chicago Energy Retrofit Project: Project Report

prepared by
Leah B. Guzowski, Ralph T. Muehleisen, Yeonsook Heo, and Diane J. Graziano
Decision and Information Sciences Division, Argonne National Laboratory

January 2014

Contents

Notation vi
Summary vii
1 The Energy Analysis Tool: *EECalc* 1
2 Comparative Study Results 3
3 Comparison with EnergyPlus Predictions 5
3.1 Comparison with Data and Audits for Chicago Buildings 7
3.1.1 Savings from Reduced Data Collection Requirements 8
3.1.2 Characterization of the Risk of Underperformance 9
4 Conclusions and Recommendations 11
5 References 13
Appendix A: EnergyPlus Comparison Results 15
Appendix B: *EECalc* Calibrations and Predictions 19

Figures

1 Monthly EUI and Energy Savings Probability Distribution Outputs from *EECalc* 2
2 Sensitivity of Energy Consumption Predictions to the Building Energy Model 5
3 Comparison of the Initial LPD Probability Distribution and the Calibrated Posterior Distribution 8
4 Comparison of Uncalibrated and Calibrated *EECalc* Predictions of Monthly EUI for Building F 9
5 *EECalc* Predictions of Energy Savings Distributions and Audit Report Estimates for Building F Chiller Upgrade and Building G Window Upgrade 10
B.A-1 Energy Consumption Data for Building A Predicted by the Uncalibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data 20
B.A-2 Calibration Results for Building A 21
B.A-3 Energy Consumption Data for Building A Predicted by the Calibrated *EECalc* and the Calibrated eQuest in Comparison with Measured Data 22
B.A-4 Probability Distribution for Building A of Annual Energy Savings from Boiler Upgrade 22
B.B&C-1 Energy Consumption Data for Buildings B and C Predicted by the Uncalibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data 23
B.B&C-2 Calibration Results for Buildings B and C 24

Figures (Cont.)

B.B&C-3 Energy Consumption Data for Buildings B and C Predicted by the Calibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data, and Scatter Plot of Monthly Average Outside Temperatures and Electricity Consumption 25

B.B&C-4 Probability Distribution for Buildings B and C of Annual Energy Savings from Fan VFDs 25

B.D-1 Calibration Results for Building D Using Submetered Energy Consumption Data for Lighting and Appliances 27

B.D-2 Calibration Results of All Energy Use for Building D 28

B.D-3 Energy Consumption Data for Building D Predicted by the Calibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data 28

B.D-4 Probability Distributions for Building D of Annual Energy Savings from Lighting Upgrade and EMS Upgrade 29

B.E-1 Energy Consumption Data for Building E Predicted by the Uncalibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data 30

B.E-2 Calibration Results for Building E 31

B.E-3 Energy Consumption Data for Building E Predicted by the Calibrated *EECalc* and the Calibrated eQuest in Comparison with Measured Data 31

B.E-4 Probability Distributions for Building E of Annual Energy Savings from Chiller Upgrade and Interior Lighting Uupgrade 32

B.F-1 Energy Consumption Data for Building F Predicted by the Uncalibrated *EECalc* in Comparison with Measured Data 33

B.F-2 Calibration Results for Building F 34

B.F-3 Energy Consumption Data for Building F Predicted by the Calibrated *EECalc* in Comparison with Measured Data 34

B.F-4 Probability Distributions for Building F of Annual Energy Savings from Chiller Upgrade and Demand-Based Control 35

B.G-1 Energy Consumption Data for Building G Predicted by the Uncalibrated *EECalc* in Comparison with Measured Data 36

B.G-2 Calibration Results for Building G 36

B.G-3 Energy Consumption Data for Building G Predicted by the Calibrated *EECalc* in Comparison with Measured Data 37

B.G-4 Probability Distributions for Building G of Annual Energy Savings from Lighting Upgrade and Window Upgrade 37

B.H-1 Energy Consumption Data for Building H Predicted by the Uncalibrated *EECalc* in Comparison with Measured Data 38

B.H-2 Calibration Results for Building H 39

Figures (Cont.)

B.H-3 Energy Consumption Data for Building H Predicted by the Calibrated *EECalc* in Comparison with Measured Data 39

B.H-4 Probability Distributions for Building H of Annual Energy Savings from Chiller Upgrade and Lighting Control..... 40

B.I-1 Energy Consumption Data for Building I Predicted by the Uncalibrated *EECalc* in Comparison with Measured Data 41

B.I-2 Calibration Results for Building I 41

B.1-3 Energy Consumption Data for Building I Predicted by the Calibrated *EECalc* in Comparison with Measured Data 42

B.I-4 Probability Distributions of Annual Energy Savings for Building I from Chiller Upgrade and Lighting Upgrade and Control..... 42

B.J-1 Calibration Results for Building J 43

B.J-2 Energy Consumption Data for Building J Predicted by the Uncalibrated and Calibrated *EECalc* in Comparison with Measured Data 44

B.K-1 Calibration Results for Building K..... 45

B.K-2 Energy Consumption Data for Building K Predicted by the Uncalibrated and Calibrated *EECalc* in Comparison with Measured Data 45

B.L-1 Calibration Results for Building L 46

B.L-2 Energy Consumption Data for Building L Predicted by the Uncalibrated and Calibrated *EECalc* in Comparison with Measured Data 47

B.M-1 Calibration Results for Building M 48

B.M-2 Energy Consumption Data for Building M Predicted by the Uncalibrated and Calibrated *EECalc* in Comparison with Measured Data 48

Tables

1 Annual EUI Predicted by EnergyPlus and *EECalc* for DOE's Reference Buildings 6

2 Energy Savings Estimates from Energy Audits and *EECalc* 10

A-1 EnergyPlus Version 5 for Existing Buildings Constructed in or after 1980 15

Notation

ASHRAE	American Society for Heating, Refrigerating, and Air-Conditioning Engineers
BAS	building automation system
BTP	Building Technologies Program
CAV	constant air volume
CFL	compact fluorescent light
CEN	European Committee for Standardization
COP	coefficient of performance
DOE	U.S. Department of Energy
EEM	energy efficiency measure
EMS	energy management system
EUI	energy usage intensity
FDD	fault detection and diagnostics
HVAC	heating, ventilation, and air conditioning
IES-VE	Integrated Environmental Solutions Virtual Environment
ISO	International Organization for Standardization
LPD	lighting power density
MCMC	Markov chain Monte Carlo
MPLV	mean partial load value
TMY	typical meteorological year
SHGC	solar heat gain coefficient
VAV	variable air volume
VFD	variable frequency drive

Summary

For the Chicago Loop Energy Efficiency Retrofit project, Argonne is developing and piloting analytic methods that capture the energy performance of individual commercial buildings; can be scaled to communities; and appropriately evaluate retrofit options in real contexts. The decision tools under development span and integrate building energy performance calculations, uncertainty analysis, and financial risk assessment.

A key outcome from this project is an energy calculator, *EECalc*, developed in collaboration with the Georgia Institute of Technology. The energy modeling methodology used in *EECalc* was chosen specifically because it (1) is computationally efficient, (2) uses only observable building data that take a relatively low level of effort to compile, and (3) requires minimal modeling expertise and judgment from the user. These features expand the possibilities for *EECalc's* widespread, large-scale use in retrofit and uncertainty analysis.

In this comparative analysis study, we provide evidence confirming the utility of the *EECalc* tool. In particular, we note two important capabilities provided by *EECalc* that are supported by this analysis:

- Savings that result from the reduced number of data collection requirements and
- Ability to characterize the risk of underperformance.

In this report, we show that the uncertainty in important input parameters can be reduced through Bayesian calibration, allowing for accurate modeling of building energy use with less exhaustive and less expensive audits. We show that through the generation and analysis of expected savings distributions, the risk of underperformance of a given retrofit or combination of retrofits can be characterized. Finally, we show that for typical buildings in the Chicago Loop and for several common energy retrofits, *EECalc* can predict similar energy savings and whole building energy usage intensity (EUI) as well as professional auditors who use more extensive audit procedures and more complicated modeling tools.

This page intentionally left blank.

1 The Energy Analysis Tool: *EECalc*

The *EECalc* tool originates from the Energy Performance Standard Calculation Toolkit (Lee et al. 2011) developed by the Georgia Institute of Technology. This toolkit uses energy calculations developed by the European Committee for Standardization (CEN) and the International Organization for Standardization (ISO). Through the U.S. Department of Energy Building Technologies Program (DOE–BTP) project, we are further developing the toolkit to specifically apply it for energy efficiency retrofit analysis. The *EECalc* tool is currently available as an Excel spreadsheet.

Following the CEN–ISO standards, the *EECalc* tool calculates thermal energy demands for heating and cooling by using a monthly quasi-steady-state method. Thermal energy demand takes account of heat gains and losses by transmission and ventilation, heat gains from solar and internal sources, and the effect of thermal inertia driven by building mass. The total thermal energy demand benchmarks the energy efficiency of the architectural design. The toolkit also calculates energy consumption by end use. The calculation takes into account heating and cooling system efficiencies and distribution system losses to determine the energy requirements for each energy carrier. From the calculated delivered energy, the toolkit derives primary energy use and carbon dioxide (CO_2) emissions, considering the specific details of the generation and emission efficiency of the local mix of utilities.

Relative to standard building energy simulation approaches, the CEN–ISO approach requires significantly less effort for data collection, model construction, and computation. Its simplicity and unified modeling assumptions allow this approach to assess building energy performance in a standardized and transparent way (Hogeling and Dijk 2008). Currently, this energy modeling method is widely used to rate building energy performance throughout most of Europe and Qatar. The method has been validated for its applicability to rate designed buildings through a number of rigorous validation efforts (Jokisalo and Kurnitski 2007; Kokogiannakis et al. 2008). A recent validation study that compared CEN–ISO energy models with simulation models for 30 campus buildings helped validate the accuracy of the calculation method for predicting building energy performance (Lee 2012). A recent research project by Heo et al. (2012) showed the applicability of the energy calculation method to represent a building as operated and correctly evaluate candidate energy efficiency measures (EEMs) for retrofit projects when the model is adjusted by calibration (Heo et al. 2012).

As a basic tool, *EECalc* estimates the monthly energy usage for a building broken down by fuel type into the usage categories of heating, cooling, lighting, plug load, fans, pumps, and domestic hot water. When combined with Bayesian calibration and Monte Carlo wrappers, the *EECalc* tool generates probability distributions of energy use and energy savings rather than single deterministic estimates. Example results from an analysis with *EECalc* are shown in Figure 1. On the left is a graph of the monthly EUI predictions of *EECalc* with 95% confidence intervals denoted by error bars. On the right is a graph of the probability distribution of energy savings predicted for a proposed energy efficiency retrofit to that building. This graph provides the decision maker with valuable information about the energy savings proposal, particularly the probability of the energy savings being less than acceptable. The fractional area under the probability curve, to the left of the vertical line, represents the probability of underperformance.

Given the results shown in Figure 1, the decision maker could conclude that there was a 70% probability that the energy savings from the retrofit would be less than a target value of 5 kBtu/ft^2.

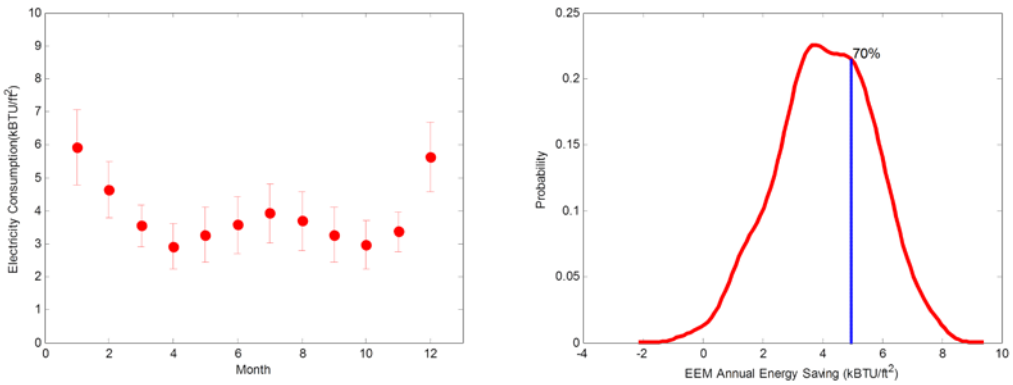


Figure 1: Monthly EUI and Energy Savings Probability Distribution Outputs from *EECalc*
(The annual EUI for the building is 45.0 kBtu/ft^2.)

2 Comparative Study Results

The comparative analysis of the *EECalc* tool was designed to explore the tool's:

- Applicability to diverse commercial building types across the nation,
- Consistency with regard to how well its results compare to those from other retrofit analysis approaches, and
- Value with regard to risk-conscious decision making.

The Chicago Loop buildings evaluated in this study are referenced here by generic names (Buildings A–M) to protect confidentiality without restricting distribution of the report. Information on the individual buildings can be provided separately. The buildings used in the study were typical of a high-rise office in the downtown Chicago Loop. On average, the buildings were 36 stories tall with a conditioned floor area of 1,400,000 ft^2. The buildings were constructed between 1926 and 1991. The older buildings use gas for space heating and domestic hot water, while the newer buildings use electricity. Most of the buildings had either glass or stone panel curtain walls.

This page intentionally left blank.

3 Comparison with EnergyPlus Predictions

To evaluate the capacity of the *EECalc* tool for retrofit analysis at a national scale, we compared *EECalc* predictions of energy consumption with those from EnergyPlus simulations. For this analysis, we generated energy consumption estimates by using *EECalc* for a subset of DOE's reference buildings:

- Large, medium, and small office buildings; a stand-alone retail building, a strip mall retail building, a quick-service restaurant, a warehouse, and a mid-rise apartment;
- Chicago, San Francisco, and Phoenix; and
- Post-1980 construction.

Our objective for this exercise was not to prove that the *EECalc* predictions precisely matched those from EnergyPlus simulations. EnergyPlus simulates heat transfer dynamically in buildings at much greater detail and in much smaller time steps than the quasi-steady-state, monthly calculations in *EECalc*. The translation of EnergyPlus input data into the significantly fewer input parameters used by *EECalc* was in itself a challenge and potential source of differing results. Other differences arose because the underlying models are not the same. As Figure 2 shows, there are differences, even between two versions of EnergyPlus, in the energy consumption predictions for the DOE large office reference building in Chicago.

For the study, we compared *EECalc* results for the subset of reference buildings with the EnergyPlus Version 5 results that are posted on the DOE reference building website. We set out to demonstrate that *EECalc* results matched reasonably well with EnergyPlus results and trended as would be expected from the physics of buildings. The results of the study are provided graphically in Appendix A. The calculated annual EUIs (in kBtu/ft^2) from both tools are shown in Table 1.

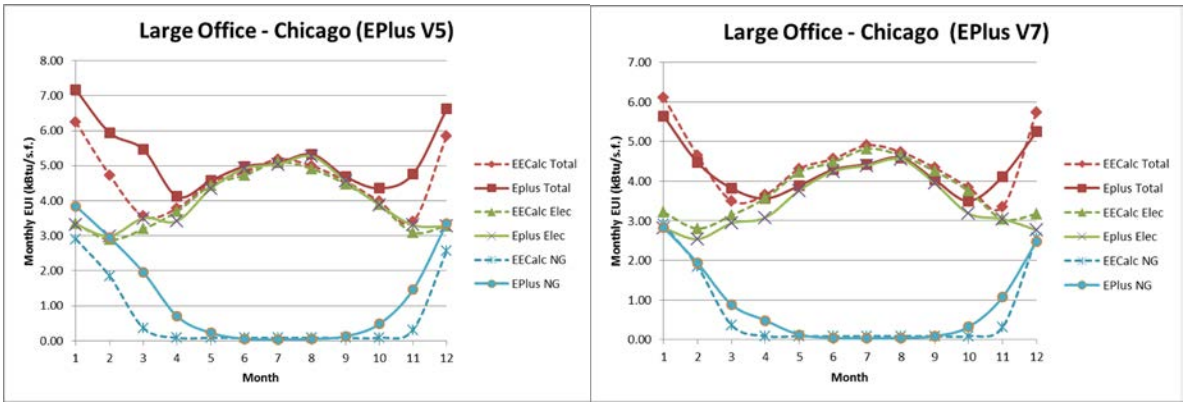


Figure 2: Sensitivity of Energy Consumption Predictions to the Building Energy Model (Note the differences in the EnergyPlus predictions between V5 and V7 versions of the software using the same input file.)

Table 1: Annual EUI Predicted by EnergyPlus and *EECalc* for DOE's Reference Buildings

Annual EUI	EnergyPlus (kBtu/ft^2)	*EECalc* (kBtu/ft^2)	% Δ
Large Office			
Phoenix	61.99	64.01	−3.3
Chicago	63.08	55.64	11.8
San Francisco	51.26	49.32	3.8
Medium Office			
Phoenix	64.57	64.95	−0.6
Chicago	65.95	59.58	9.7
San Francisco	51.02	52.89	−3.7
Small Office			
Phoenix	68.78	79.37	−15.4
Chicago	72.24	76.40	−5.8
San Francisco	55.49	65.97	−18.9
Stand-Alone Retail			
Phoenix	90.64	84.51	6.8
Chicago	130.23	103.92	20.2
San Francisco	84.72	74.62	11.9
Strip Mall Retail			
Phoenix	99.85	96.43	3.4
Chicago	143.08	130.16	9.0
San Francisco	92.49	101.28	−9.5
Quick Service Restaurant			
Phoenix	554.92	646.96	−16.6
Chicago	682.70	714.20	-4.6
San Francisco	546.27	573.26	−4.9
Warehouse			
Phoenix	22.62	28.02	−23.9
Chicago	58.86	54.30	7.7
San Francisco	24.79	31.21	−25.9
Mid-rise Apartment			
Phoenix	52.12	58.89	−13.0
Chicago	79.29	87.61	−10.5
San Francisco	49.86	44.55	10.6

Although there were a couple of cases in which the differences in the estimated energy use predictions were greater than 20%, in general, the matches were reasonable. For the particular case of warehouses in Phoenix and San Francisco, the energy use was so low that the models were highly sensitive to slight variations in input parameters. We expect that with additional effort to better translate the EnergyPlus detailed building information into *EECalc* inputs, the differences would be further reduced. However, the point of the project is not to mirror EnergyPlus predictions but to provide a credible, reliable method for assessing retrofit options. For this purpose, the challenge is to overcome the recognized gap between model-predicted consumption and actual energy consumption. Here, model precision and complexity have not closed the gap. We have tackled the challenge by recognizing that uncertainty exists and then reducing it through a novel Bayesian calibration process described in Appendix B.

3.1 Comparison with Data and Audits for Chicago Buildings

In our outreach efforts to building owners and energy consulting firms, we received mostly positive feedback and enthusiasm about the concept and objectives of the project and *EECalc* tool. Organizations that subsequently agreed to collaborate by providing building data and energy audit reports for the comparative study included the City of Chicago, CleanUrbanEnergy, ComEd, Delta Institute, Merchandise Mart, Sieben Energy, Solomon Cordwell Buenz, Tishman-Speyer, and U.S. Equities. Some of these data were received too late to be analyzed for this report.

In the end, we evaluated audit reports that included eQuest model results from five buildings (Buildings A–E), an audit report using Integrated Environmental Solutions Virtual Environment (IES-VE) software from one building (Building F), EnergyPlus audit model results from three buildings (Buildings G, H, and I), and measured energy use data from four buildings (Buildings J, K, L, and M). For each building, we compiled and entered data on it into the *EECalc* tool to generate uncalibrated energy use predictions, then calibrated *EECalc* against measured energy consumption data using Bayesian methods, as described in Appendix B. For Buildings A–I, we also compared *EECalc* energy savings predictions with those reported in the energy audits. The full analysis and results for each of the buildings analyzed are provided in Appendix B.

A posit of the original *EECalc* research proposal was that the reduced number of input parameters for the calculation model and the ability to apply Bayesian calibration methods would reduce the amount of data that needed to be collected for each building, which, in turn, would reduce both the time and cost involved in producing a building energy efficiency audit, while providing decision makers with energy savings predictions comparable in accuracy to more traditional methods. This idea was confirmed by several examples that showed how the *EECalc* calibration was able to identify the proper values for input parameters, which would normally need to be obtained through very detailed (and expensive) surveys. Further, we confirmed that *EECalc* could accurately predict monthly utility usage with fairly low uncertainty on the basis of only a few known building input parameters.

3.1.1 Savings from Reduced Data Collection Requirements

As an example of how *EECalc* and Bayesian calibration can reduce data collection and audit needs, we highlight the case of Building D and the estimation of building lighting loads here. Although lighting loads are important when making energy assessments, they are notoriously difficult to estimate because of the variable use, controls, and upgrades associated with individual lighting units. For the Building D audit, an extensive survey was undertaken to count the number of lighting fixtures and measure their lighting power. From this survey, the lighting power density (LPD) was determined to be 6.7 W/m^2. In our calibration of *EECalc* plug and lighting loads using measured submetered electricity consumption, we derived a mean value for the LPD of 7.8 W/m^2, as shown in Figure 3. This comparable value was obtained without conducting an expensive lighting survey and without using submetered data for individual lighting circuits. In addition, the result quantified the expected uncertainty in lighting load (due to variable use and operation) that is implicit in the measured data.

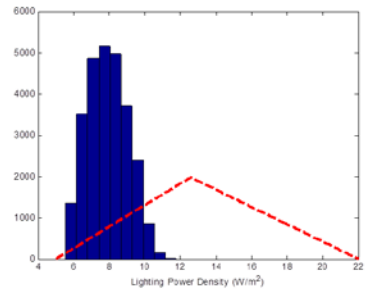


Figure 3: Comparison of the Initial LPD Probability Distribution (red dashes) and the Calibrated Posterior Distribution (solid blue histogram) (The red dashed line shows our initial estimate of the LPD between 5 W/m^2 and 22 W/m^2, with 13 W/m^2 as the most probable value.)

We also confirmed in this study that through calibration and use of informed default parameter values, *EECalc* can provide good predictions for monthly and overall energy use on the basis of very limited building data. Buildings E and F had energy audits that were highly redacted to ensure the exact buildings could not be identified. The only information provided to us was the building age; building height; general type of heating, ventilation, and air-conditioning (HVAC) unit; approximate extent of conditioned space; and a minimal description of the building envelope. In short, the information we used in the analysis was no more than that required to obtain an Energy Star rating for the building plus a general description of the building envelope.

Figure 4 shows results from the analysis of Building F. Monthly energy consumption predictions from the uncalibrated and calibrated *EECalc* tool are compared to measured data. Even with the very limited amount of building-specific input data, the uncalibrated *EECalc* predictions matched well with measured energy consumption data. The *EECalc* calibration further improved the fit of the predictions to measured data as well as reducing the uncertainty associated with the predictions (as shown by the narrower confidence intervals).

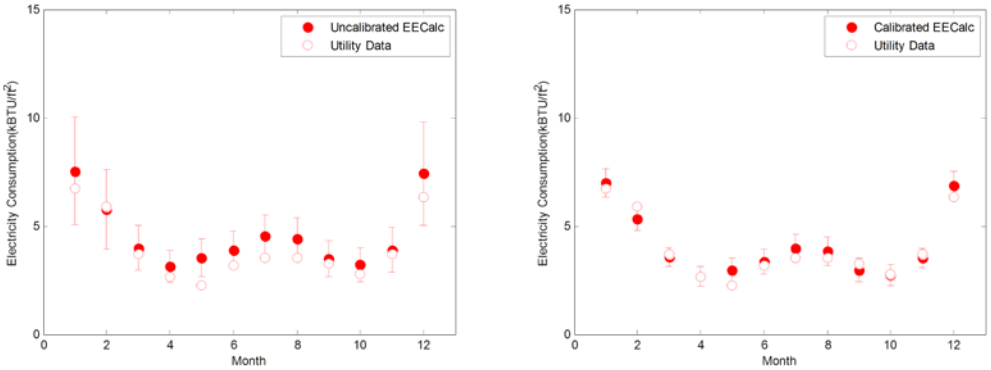


Figure 4: Comparison of Uncalibrated (left) and Calibrated (right) *EECalc* Predictions of Monthly EUI for Building F (There was very limited information for this building.)

3.1.2 Characterization of the Risk of Underperformance

Although most of the audit reports we studied were full of details, they all reported single value estimates for energy savings associated with the proposed EEMs. When given these estimates, the decision maker may still be uncertain about whether to invest in the retrofit. *What is the likelihood that the estimated energy savings will be realized? What is the probability that energy cost savings will not cover the costs of the retrofit?* Results from *EECalc* can help answer these questions, as illustrated in Figure 5. Shown are energy savings for a chiller retrofit for Building E (left) and a window retrofit for Building G (right) as predicted by *EECalc* and compared to estimates reported in the audit. The red curves are energy savings distributions predicted by *EECalc*; the dashed vertical lines represent the energy savings estimates from the audits. For the chiller retrofit for Building E, *EECalc* predicts a 70% chance that the actual energy savings will be less than determined by the audit. In the window retrofit for Building G, *EECalc* predicts a 28% chance that the actual energy savings will be lower than estimated or, alternatively, a 72% chance that the energy savings will be greater than estimated.

The *EECalc* results quantify the uncertainty in achievable energy savings, and hence the investment risk of the retrofit, for the decision maker. Through *EECalc* analysis, uncertainty about energy savings estimates can be replaced with the confidence that a minimum energy savings goal can be met.

Table 2 summarizes the data from all the audit comparisons. Although the energy savings reported in the audits were mostly within the 95% confidence limits of *EECalc* predictions, they were not necessarily near the *EECalc*-predicted means. As a “post-mortem” exercise, several uncertainties could be at the root of the differences. For one, we do not know if the energy savings reported in the audit were those computed by using eQuest or came from expert judgment informed by eQuest results. In addition, some assumptions regarding the input parameters for *EECalc* had to be made in order to fill in gaps in the building data available from the audit reports. In the future, *EECalc* would be better tested if it were tested as part of active audits rather than after the audits were completed.

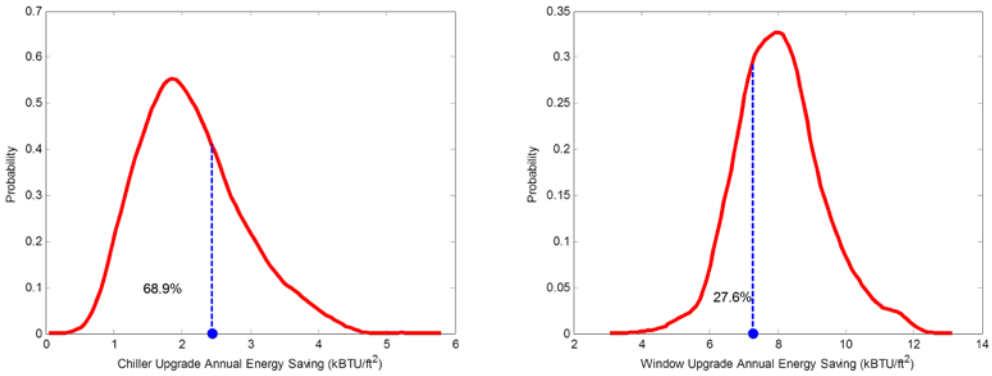


Figure 5: *EECalc* Predictions of Energy Savings Distributions (red curve) and Audit Report Estimates (blue point) for Building F Chiller Upgrade (left) and Building G Window Upgrade (right)

Table 2: Energy Savings Estimates from Energy Audits and *EECalc*

Building	Retrofit EEM	Annual EUI *EECalc* (kBtu/ft^2/yr)	Energy Savings Audit Estimate (kBtu/ft^2/yr)	Energy Savings *EECalc* Estimate (kBtu/ft^2/yr)
A	Boiler efficiency upgrade	56.8	10.3	11.7 +/− 2.6
B and C	Supply & return fan variable frequency drive (VFD)	60.7	1.6	2.1 +/− 0.7
D	Lighting upgrade	117.7	2.4	5.7 +/− 3.9
	Energy management system (EMS) upgrade		0.3	1.6 +/− 1.3
E	Chiller efficiency upgrade	75.7	6.0	3.3 +/− 2.1
	Interior lighting upgrade		3.5	6.0 +/− 1.6
F	Chiller efficiency upgrade	48.8	2.4	2.1 +/− 1.5
	Demand based control		1.6	0.6 +/− 0.8
G	Lighting upgrade	46.4	4.2	4.1 +/− 3.2
	Window upgrade		7.3	8.1 +/− 2.5
H	Chiller upgrade	42.1	3.3	2.5 +/− 1.2
	Lighting control		1.7	2.5 +/− 0.7
I	Chiller upgrade	73.3	2.2	2.0 +/− 1.4
	Lighting control		7.8	8.4 +/− 3.4

4 Conclusions and Recommendations

This comparative study showed the general performance of the *EECalc* tool in predicting monthly and annual building EUI by comparing predictions to measured EUI as well as its performance in predicting the energy savings of various EEMs. The study validated *EECalc's* ability to make fairly accurate energy predictions with little information about the building, as well as its ability to use Bayesian calibration to improve the estimates of important input parameters, reducing the need for expensive and time-consuming audits. Finally, the study showed *EECalc's* ability to compute probabilities of EUI and energy savings for selected EEMs, allowing the characterization of the risk of underperformance of the selected retrofit.

The study results further validate the utility of the *EECalc* tool as a scalable, transparent, and affordable platform for:

- Benchmarking building energy performance;
- Evaluating energy savings potential of energy efficiency technologies; and
- Analyzing national, regional, and market impacts of energy efficiency initiatives, strategies, codes, and standards.

Moving ahead, we note that the *EECalc* tool is now available as an Excel spreadsheet for energy performance evaluation. Minor modifications are required to the tool to facilitate its use for energy retrofit analysis. After these modifications are made, we propose to partner with architecture and engineering (A&E) firms and energy consultants who have agreed to pilot the *EECalc* tool in parallel with their existing tools for their energy retrofit projects. These "live" pilots will provide invaluable feedback to fine-tune the *EECalc* tool in preparation for a broader deployment within the building energy services community.

We also propose to continue the development of retrofit analysis tools through three efforts:

1. Create the software code to automate the Bayesian calibration of the *EECalc* energy results to individual building's measured energy use data.
2. Pursue the development of the web-based energy efficiency investment decision tool, *EEInvest*, which couples *EECalc* energy calculations with stochastic finance calculations previously developed for the DBPD financial risk management tool.
3. Create *EECalc* tool versions specifically designed as decision tools to support DOE's deployment goals for specific DOE building technologies.

This page intentionally left blank.

5 References

Gelman, A., J.B. Carlin, H.S. Stern, and D.B. Rubin, 2004, *Bayesian Data Analysis*, Chapman & Hall/CRC.

Heo, Y., R. Choudhary, and G. Augenbroe, 2012, "Calibration of Building Energy Models for Retrofit Analysis under Uncertainty," *Energy and Buildings* 47:550–560.

Hogeling, J., and D.V. Dijk, 2008, *P60: More Information on the Set of CENS Standards for the EPBD.*

Jokisalo, J., and J. Kurnitski, 2007, "Performance of EN ISO 13790 Utilisation Factor Heat Demand Calculation Method in a Cold Climate," *Energy and Buildings* 39:236–247.

Kennedy, M.C., and A. O'Hagan, 2001, "Bayesian Calibration of Computer Models," *Journal of the Royal Statistical Society*, Series B, 63(3):425–464.

Kokogiannakis, G., P. Strachan, and J. Clarke, 2008, "Comparison of the Simplified Methods of the ISO 13790 Standard and Detailed Modelling Programs in a Regulatory Context," *Journal of Building Performance Simulation* 1(4):209–219.

Lee, S.H., 2012, *Management of Building Energy Consumption and Energy Supply Network on Campus Scale*, Ph.D. thesis, Georgia Institute of Technology.

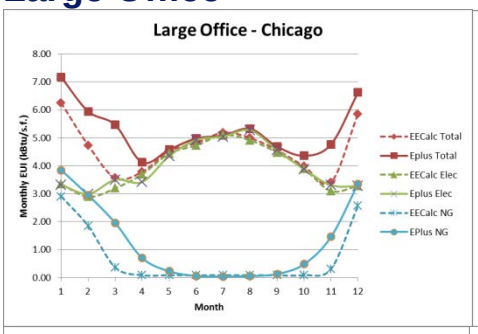
Lee, S.H., F. Zhao, and G. Augenbroe, 2011, "The Use of Normative Energy Calculation beyond Building Performance Rating Systems," in *Proceedings of the 12th International Building Performance Simulation Association Conference*, Sydney, Australia.

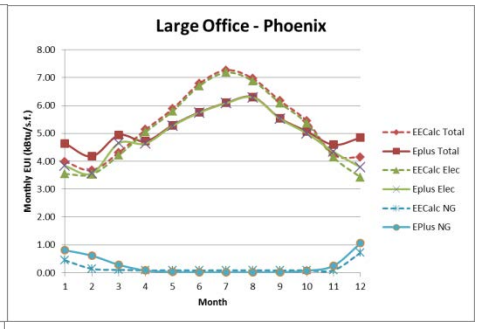
This page intentionally left blank.

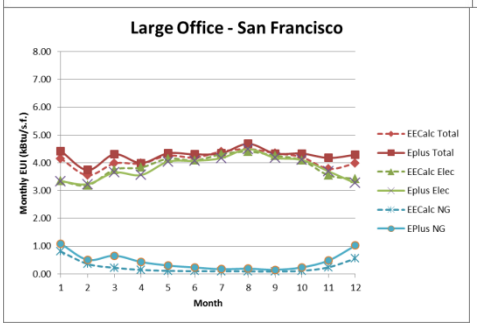
Appendix A: EnergyPlus Comparison Results

Table A-1: EnergyPlus Version 5 for Existing Buildings Constructed in or after 1980 (Results are from the following web site: http://www1.eere.energy.gov/buildings/commercial_initiative/after_1980.html.)

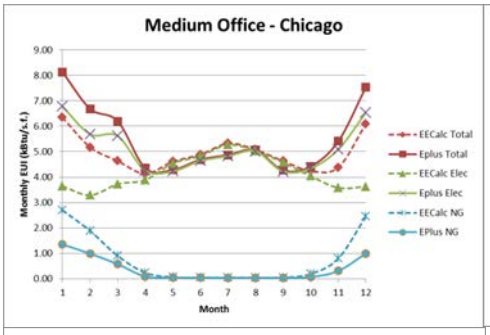
Large Office

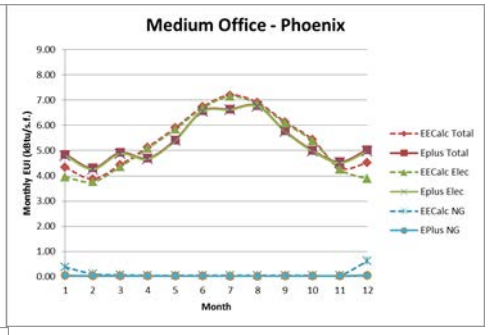


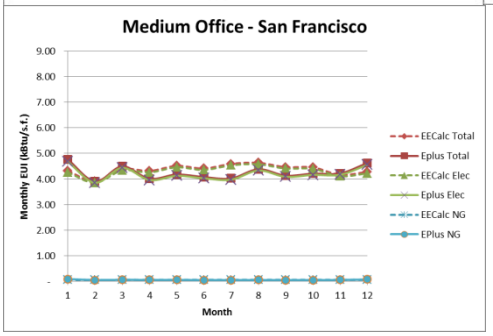




Medium Office[a]

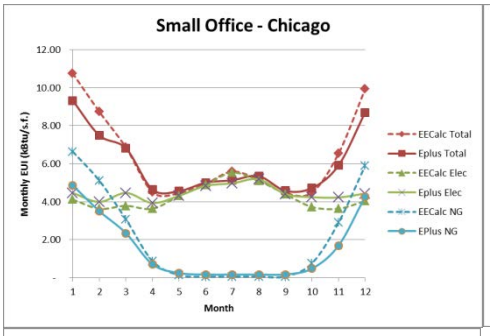


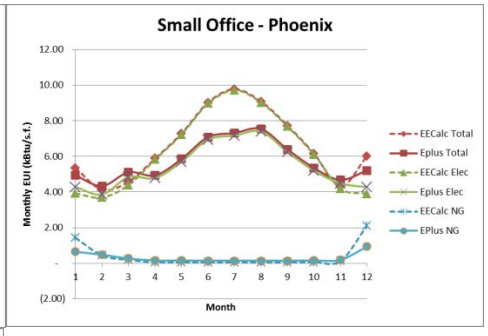


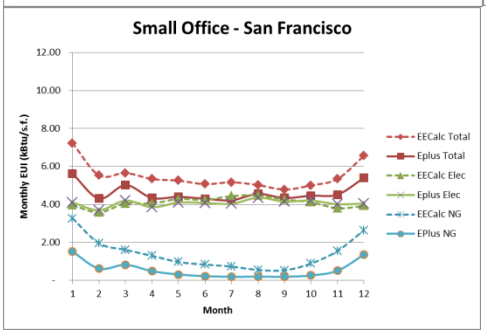


[a] The medium office had both electric reheat and gas heat. This version of *EECalc* allows for only once source of heating fuel, and so it predicted higher natural gas consumption and lower electricity consumption than did EnergyPlus in the heating season.

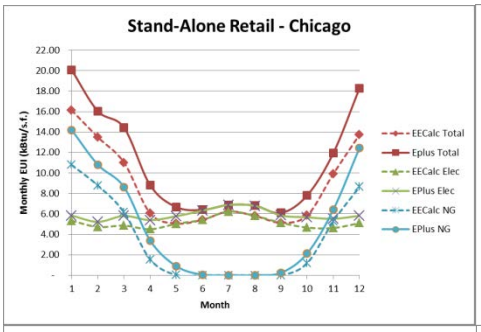
Small Office

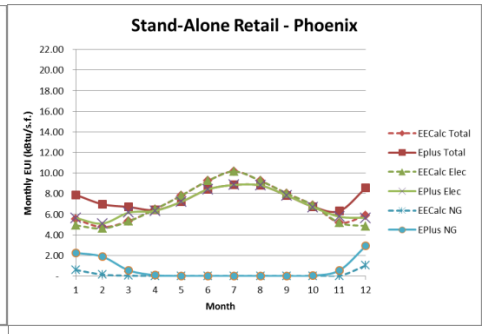


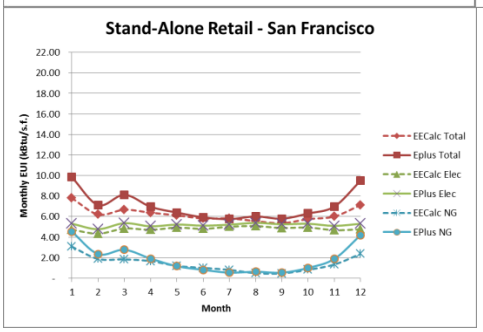




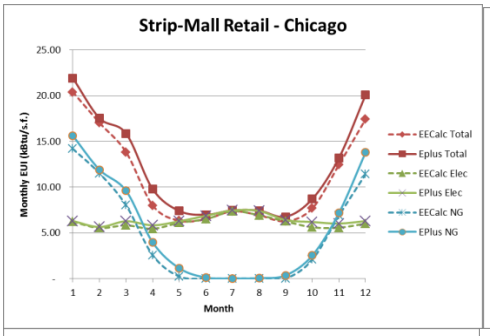
Stand-alone Retail

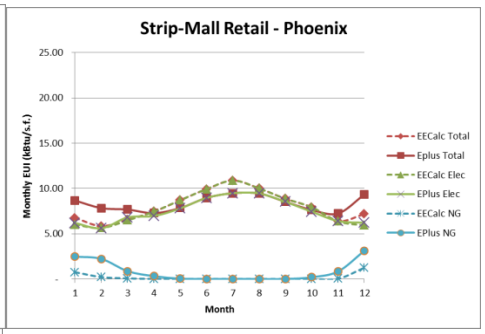


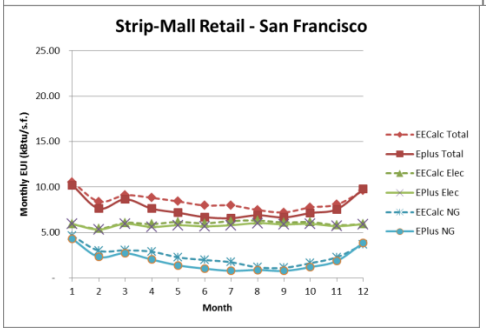




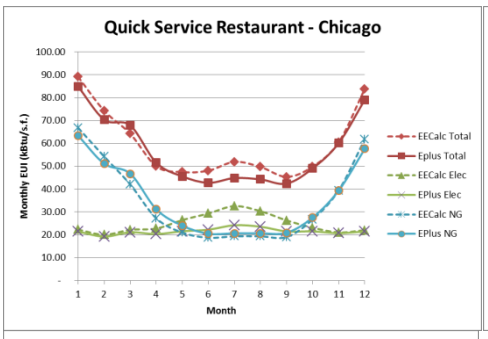
Strip Mall Retail

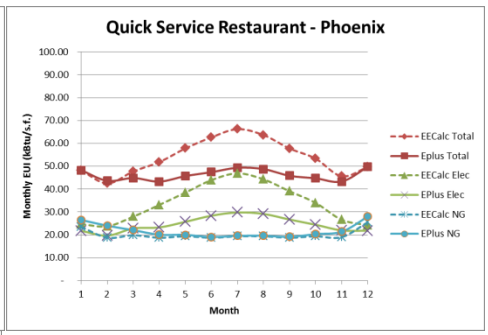


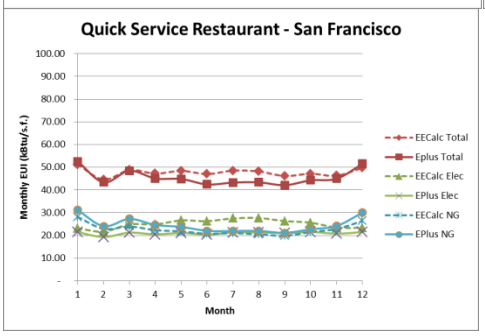




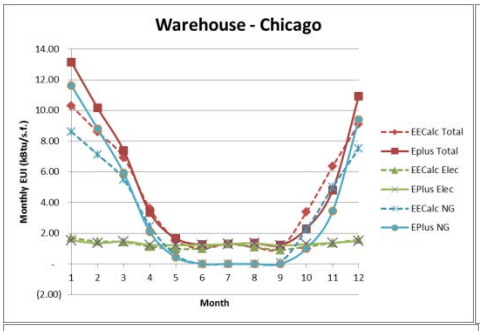
Quick-service Restaurant

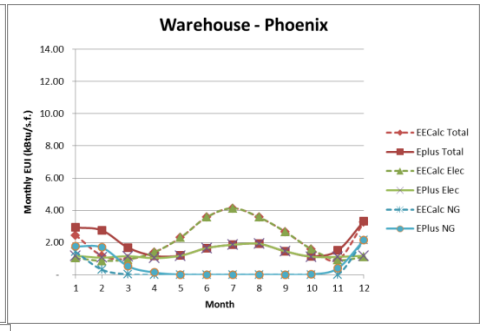


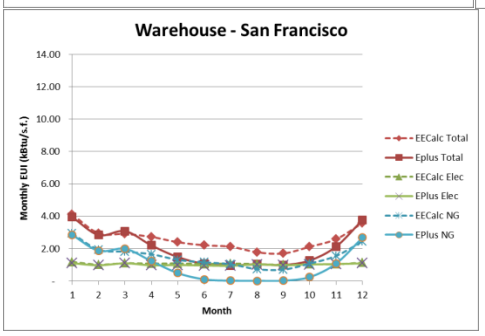




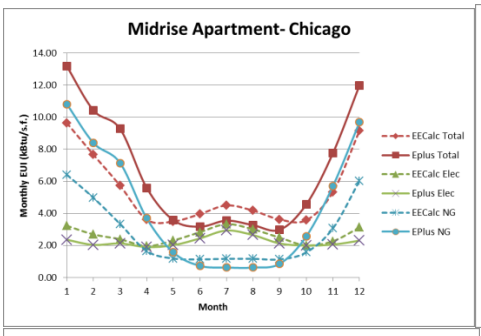
Warehouse

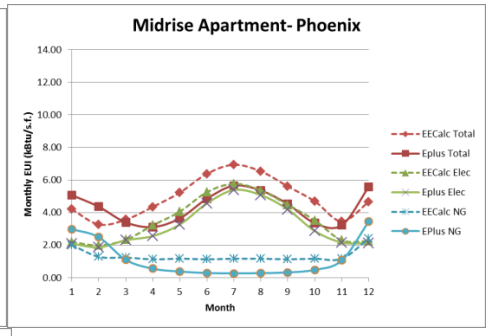


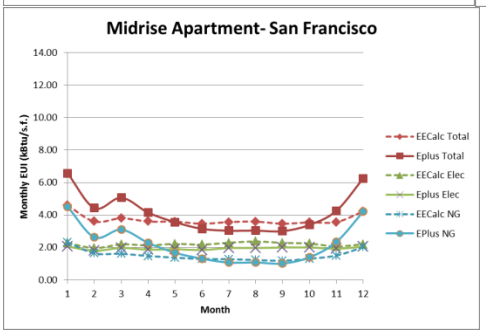




Mid-rise Apartment







Appendix B: EECalc Calibrations and Predictions

We apply Bayesian inference as a new approach for calibrating and factoring uncertainty into building energy models, including the *EECalc* tool. Bayesian calibration is an alternative to traditional, expert-intensive approaches that require "tweaking" of energy model input parameters to match measured data. Bayesian statistical methods instead derive the most likely distributions (posterior distributions) of input parameters from their predefined probability density functions (i.e., prior distributions) to explain the measured energy use data. The resulting posterior distributions are then used in Monte Carlo samplings of the energy model to yield probabilistic outcomes of predicted energy savings.

The Bayesian paradigm treats a probability as a numerical estimate of the degree of belief in a hypothesis. Under this paradigm, our prior belief in the true values of calibration parameters is quantified as prior density functions $p(\theta)$. The prior distributions are updated (given measured data on building performance) through the likelihood function $p(y|\theta)$. The likelihood function compares how closely model outcomes with testing parameter values match the measured data. As the result of Bayesian calibration, we obtain posterior distributions of calibration parameters $p(\theta|y)$:

$$p(\theta|y) \propto p(\theta) \times p(y|\theta)$$

where the symbol $\propto$ denotes proportionality. After the Bayesian process is completed, the resulting likelihood function is scaled so that the function is a true probability density function.

The Bayesian calibration module requires three major steps: (1) specification of prior probability distributions for uncertain parameters, (2) formulation of the likelihood function, and (3) application of the Markov chain Monte Carlo (MCMC) method for posterior simulation. We quantify prior distributions on the basis of expert knowledge developed through reviewing technical papers and industry reports. We formulate the likelihood function as the Gaussian process model, following the Bayesian framework of Kennedy and O'Hagan (2001). To approximate posterior distributions from one joint multivariate distribution $p(\theta) \times p(y|\theta)$, we apply one of the MCMC methods: the Metropolic-Hastings method. The method explores the parameter space in an iterative manner and accepts those steps that satisfy an acceptance criterion (Gelman et al. 2004). As a result, the Bayesian calibration module provides a set of accepted parameter values as posterior distributions. The calibration process is described in more detail in Heo et al. (2012).

Building A

Building A is a 28-story, high-rise tower with concrete panel cladding that was completed in 1971. It has a conditioned floor space of 392,000 ft^2 (36,431 m^2). It uses gas boiler and domestic hot water heating and electric centrifugal chillers for cooling. The windows are first-generation, insulated, glazing units with a fairly dark tint. The roofing was recently replaced, and insulation was added to bring the roof to R20. The lighting is a mixture of T12, T8, T5, and compact fluorescent light (CFL) with an estimated LPD of 0.9 W/ft^2 (10 W/m^2). Billing data were

provided for the 2008 calendar year. One important note is that tenant electric loads (lighting and equipment plug loads) were billed directly to the tenant, and so the measured billing data do not include the tenant loads. The auditors estimated that 90% of the total building electrical lighting and plug loads were billed to the tenants but contributed to the heating and cooling load of the building HVAC system. To calibrate the eQuest energy model, the auditors had to add the unbilled electric loads back into the heating and cooling loads of the building. For the sake of consistency and comparison, we opted to model tenant electricity usage in the same manner, although a variation of the fraction with season is probably more appropriate. Using the total estimated building electric consumption, the overall building EUI was estimated to be 57 kBtu/ft^2 (178 kWh/m^2).

The building audit we received was not a formal ASHRAE (American Society for Heating, Refrigerating, and Air-Conditioning Engineers) level 2 audit. In addition, it focused on small retrofits with only one major retrofit – a boiler upgrade to replace the aging original boilers. The auditors created and calibrated an eQuest model for the building and used it for estimating the energy savings from upgrading the boiler to a high-performance condensing gas boiler. The existing boilers were estimated to have an efficiency of about 60%. The predicted energy savings from the boiler upgrade was 40,665 therms/yr, which converts to a savings of 10.4 kBtu/ft^2 (30.4 kWh/m^2).

Figure BA-1 compares energy consumption data calculated by the uncalibrated *EECalc* model against measured data from the utility bills and results from the eQuest modeling conducted by the energy auditor. Without calibration, the tool estimates monthly gas consumption data that closely match measured data. However, the tool estimates electricity consumption data differently than the measured data: It overpredicts electricity consumption during the summer and underpredicts electricity consumption during the winter when compared with the measured data. The difference can arise from incorrect parameter values estimated on the basis of drawings and specifications. Calibration can enhance the reliability of the model by tuning highly uncertain parameters (due to lack of information) with of utility bill data.

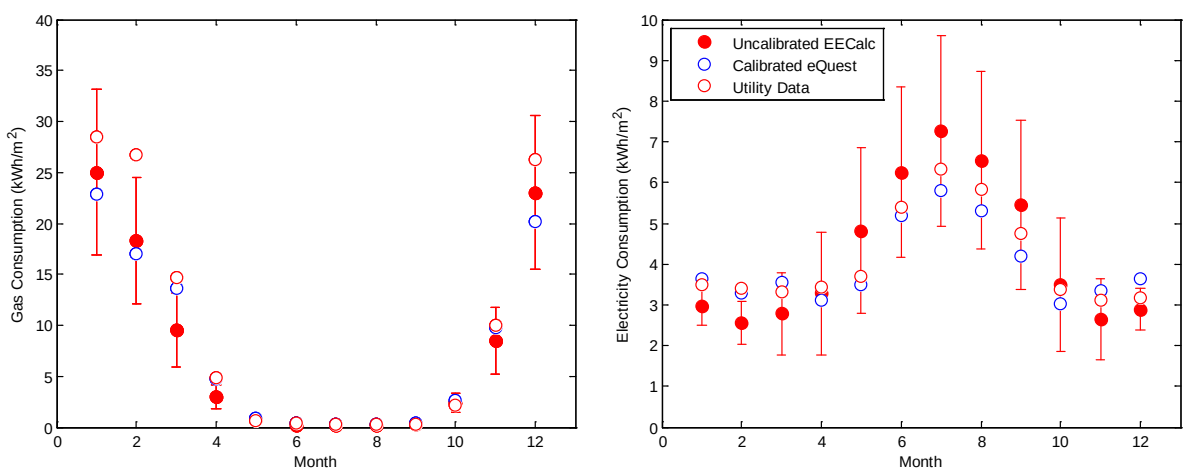


Figure B.A-1: Energy Consumption Data for Building A Predicted by the Uncalibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data

Before calibration, we applied the Morris method to identify the dominant uncertain parameters with respect to their effect on gas and electricity consumption. Since we used both gas and electricity bills for calibration, we ranked uncertainty parameters separately with respect to item consumed and selected the top two parameters in each ranking list. The selected parameters for calibration were (1) plugload–occupied, (2) cooling system mean partial load value (MPLV), (3) infiltration rate, and (4) heating system efficiency.

Figure BA-2 shows calibration results in the form of probability distributions. The red dashed line indicates prior beliefs about true parameter values, and the blue histogram indicates a probability of true values updated through the calibration process. For plugload–occupied, the expected value does not change from our prior estimate, but the magnitude of uncertainty is greatly reduced. For the cooling system MPLV, the expected value changes from 0.7 to 0.9. For infiltration rate, the results suggest that the building envelope is most likely leakier than expected. For the heating system efficiency, the posterior distribution does not change much from the prior distribution.

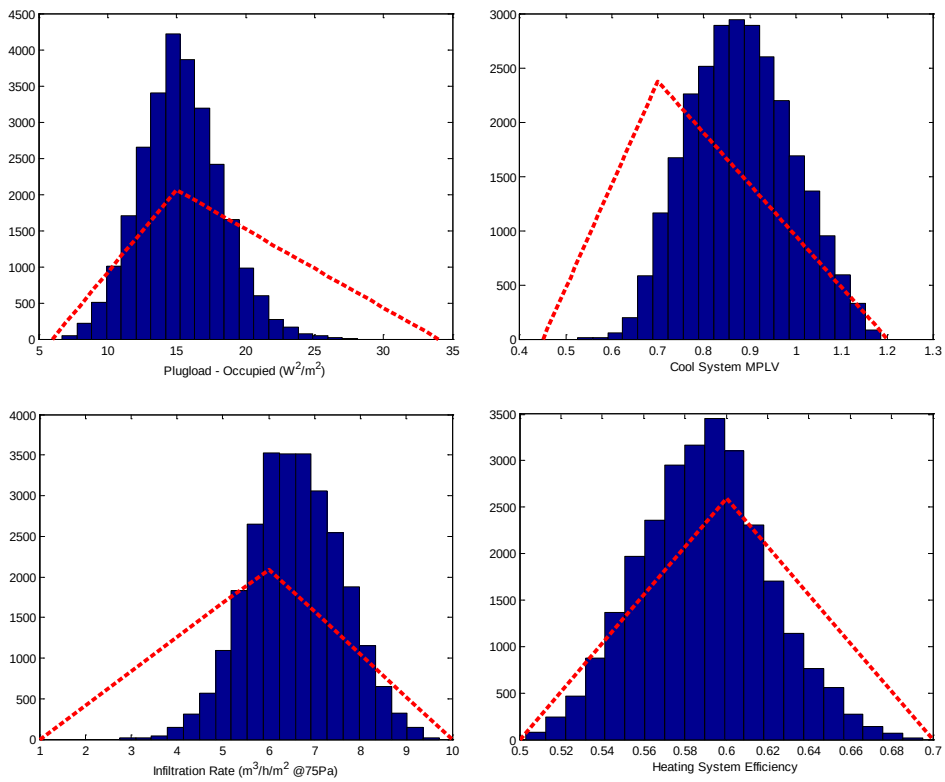


Figure B.A-2: Calibration Results for Building A (red dashed line = prior, blue histogram = posterior distribution)

Figure BA-3 displays the baseline energy consumption data predicted by the calibrated *EECalc* model compared with eQuest results and measured data. The calibrated model results in much narrower confidence intervals for predictions than does the uncalibrated model. This comparison demonstrates that Bayesian calibration enhances the reliability of the baseline model by

improving its fit to measured data and reducing its uncertainty. Although the calibrated 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 at least partially attributed to the inability of the monthly *EECalc* model to capture cooling loads that occur during peak hours during the winter and the intermittent season.

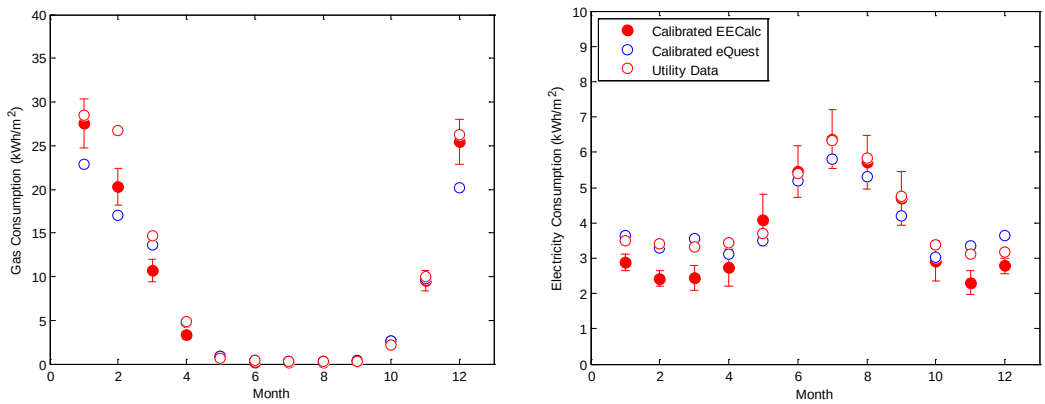


Figure B.A-3: Energy Consumption Data for Building A Predicted by the Calibrated *EECalc* and the Calibrated eQuest in Comparison with Measured Data

The audit project evaluated upgrading a boiler from an efficiency of 0.60 to 0.95, using an eQuest model under typical meteorological year (TMY) weather conditions. In our analysis process, we propagated uncertainty in the model quantified by the Bayesian approach and additional uncertainty from the retrofit option (ranging between 0.90 and 0.97). By subtracting post-retrofit energy consumption data from baseline energy consumption data, we obtained probabilistic outcomes of annual energy savings. Figure BA-4 shows a plausible range of annual energy savings and their likelihoods calculated by the proposed method in comparison with the deterministic value predicted by the typical audit project with the eQuest model. The single value obtained by using the eQuest model slightly underpredicts the effect of the retrofit intervention in comparison with the expected value by the *EECalc* model.

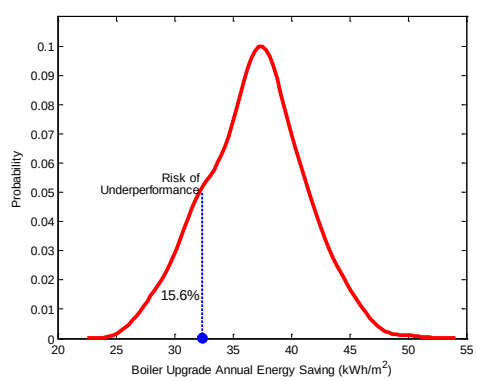


Figure B.A-4: Probability Distribution for Building A of Annual Energy Savings from Boiler Upgrade. Red line is the *EECalc* savings prediction and the blue dashed line is the eQuest saving prediction. These results can be compared to the overall annual use of the building, which was estimated by eQuest to be 144 kWh/m^2.

Buildings B and C

Buildings B and C are two buildings that share parts of the HVAC system, have some common utility billing, and are conjoined by a 15-story common space. Because of the systems and billing overlaps, we analyzed the complex as a single large building. The buildings are stone panel curtain wall high-rises with a combined conditioned area of 2,880,000 ft^2 (268,000 m^2). The taller building is 60 stories tall, and the shorter building is 35 stories tall. The buildings were completed in 1989 and 1992, respectively. Glazing is standard double-insulated glazing from about 1990 with a fairly dark tint. The building is heated by electric boilers and is cooled by centrifugal electric chillers, both of which are original to the building. The building has a building automation system (BAS) that is used for monitoring building operation and central control of the building HVAC setpoints, but automatic controls and fault detection and diagnostics (FDD) are not implemented. In 2011, the building had an EUI of 75 kBtu/ft^2 (237 kWh/m^2).

An ASHRAE level 2 audit was performed on the building, which included development of an eQuest model that was used for EEM savings estimation. Most of the EEMs suggested in the audits were small upgrades to individual lighting elements (exit lighting, occupancy sensors on bathroom only). An upgrade of the supply and return fans to variable frequency drive (VFD) was one of the larger upgrades suggested. That EEM was chosen for comparison.

Figure BBC-1 compares electricity consumption data calculated by the uncalibrated *EECalc* tool with measured data from utility bills in 2010 and results from the eQuest model (from the audit project). Without calibration, the tool underpredicted electricity consumption for most of the months except the winter season.

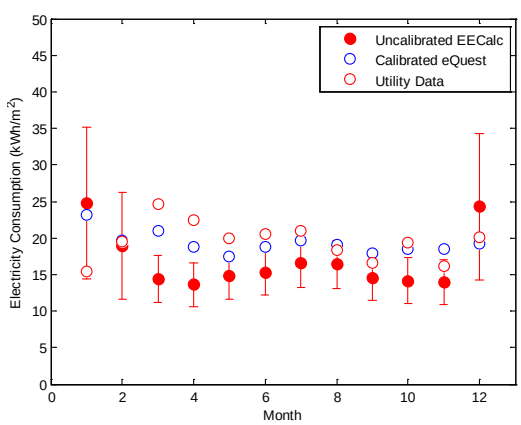


Figure B.B&C-1: Energy Consumption Data for Buildings B and C Predicted by the Uncalibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data

Based on the ranking of model parameters from the Morris method, we selected the top four for calibration: (1) infiltration rate, (2) plugload–occupied, (3) LPD, and (4) heating temperature setpoint. Figure B.B&C-2 exhibits posterior distributions of the calibration parameters updated from prior distributions. Overall, uncertainty in the plausible range of parameter values was not

reduced much, but the distribution shape changed noticeably. The calibration results suggest that the infiltration

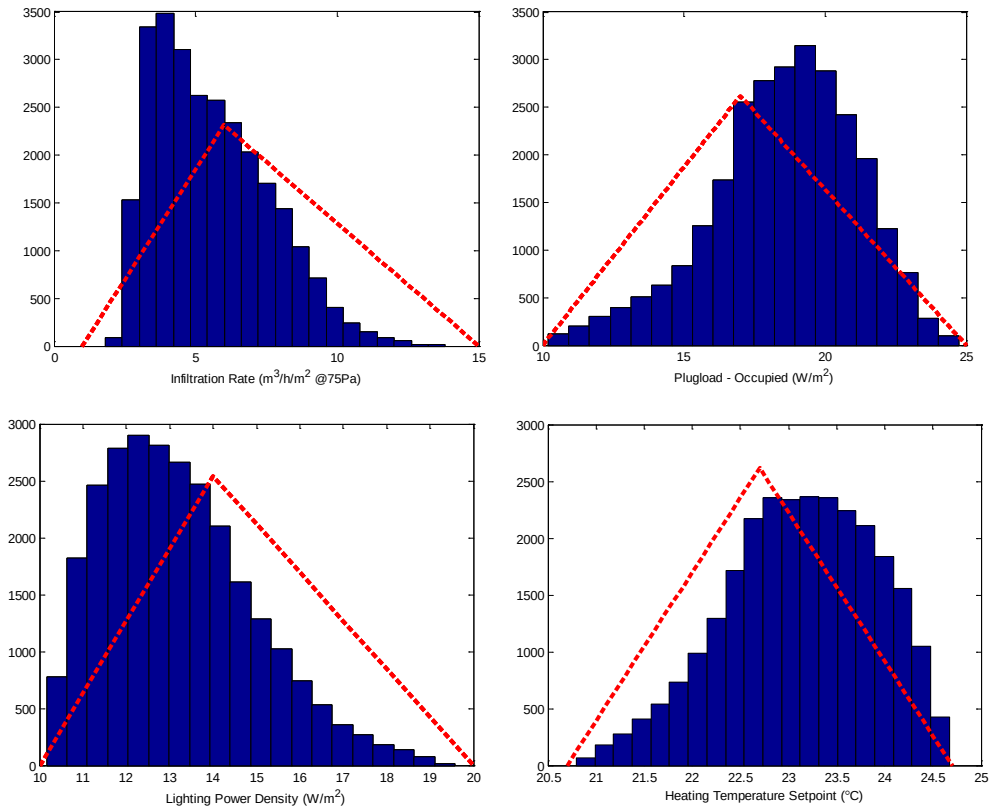


Figure B.B&C-2: Calibration Results for Buildings B and C (red dashed line = prior, blue histogram = posterior distribution)

rate was most likely lower than initial estimates. For plugload–occupied, the expected value changed from 17 to 18.5 W/m^2, while the expected value of the LPD changed from 15 to 13 W/m^2. For the heating temperature setpoint, the expected value did not change much from the prior distribution.

Figure B.B&C-3 (left side of graph) shows the baseline electricity consumption data predicted by the calibrated *EECalc* tool compared with eQuest results (from the audit project) and measured data from the utility bills. The electricity consumption data predicted by the calibrated *EECalc* model did not perfectly match measured consumption data. One explanation for the discrepancy is that the characteristics of building usage are stochastic in reality, whereas the model regards the average building usage schedules throughout the year (common assumption for calibration). Figure B.B&C-3 (right side of graph) shows poor correlations between the outside temperature and electricity consumption, which suggests that building usage schedules vary quite a bit over time and greatly impact electricity consumption data. The current calibration module regards calibration parameters as constant over the simulation period. Hence, further study is required to incorporate time-varying parameters in the calibration process.

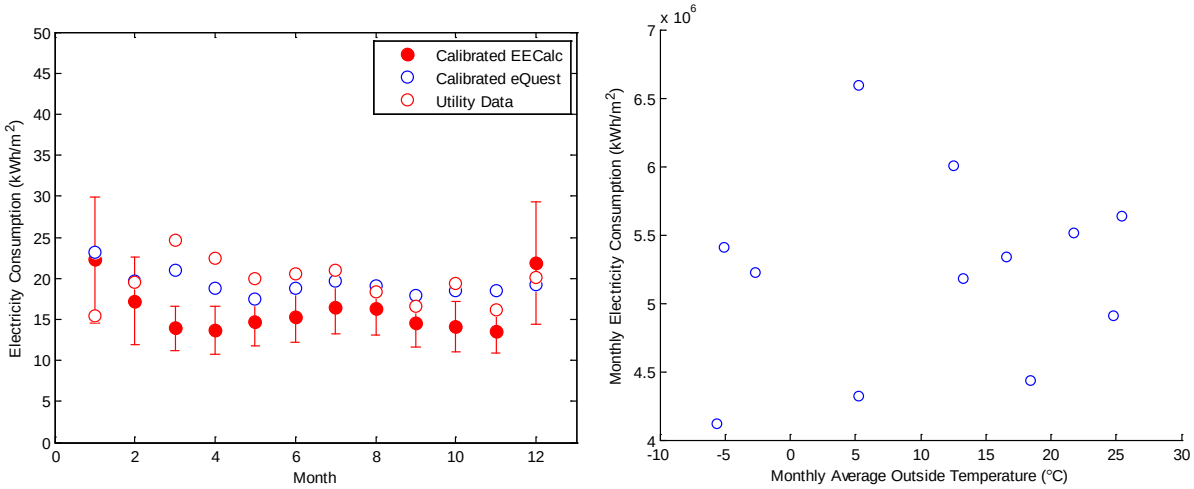


Figure B.B&C-3: Energy Consumption Data for Buildings B and C Predicted by the Calibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data (left), and Scatter Plot of Monthly Average Outside Temperatures and Electricity Consumption (right)

The audit project evaluated the installation of VFDs on supply and return fans, using an eQuest model under TMY weather conditions. Figure B.B&C-4 shows a probability distribution of annual energy savings predicted by the calibrated *EECalc* model in comparison with the single value of annual energy savings documented in the audit report. *EECalc* results suggest that the expected energy savings are likely to be higher than the audit estimate.

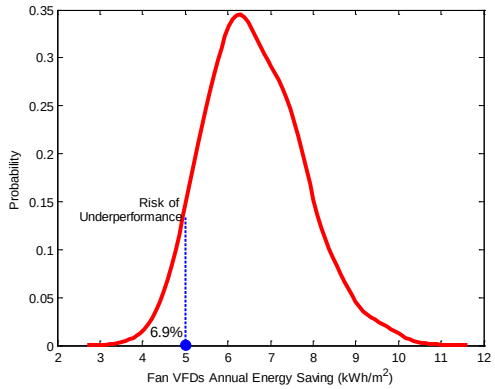


Figure B.B&C-4: Probability Distribution for Buildings B and C of Annual Energy Savings from Fan VFDs. Red line is the *EECalc* savings prediction and the blue dashed line is the eQuest saving prediction. These results can be compared to the overall annual use of the building which was estimated by eQuest to be 190 kWh/m^2.

Building D

Building D is a 28-story, steel and glass high rise completed in 1963. It has a conditioned space of 1,540,000 ft^2 (143,287 m^2). The building was designed to be used primarily as a courthouse and civic center and has an extremely high floor-to-floor span of 19.7 ft (6 m). Because of the many civic center functions that occur in the open space outside the building, some electricity and hot water use patterns are very abnormal. The building HVAC system also provides hot and cold water for another nearby building. Finally the building houses a small data center (approximately 460 kW) for which electricity is billed separately, but which contributes to the cooling load of the building. Because of the potentially high occupancy of the building, the HVAC system is designed to provide extremely high ventilation rates: five times higher than the standard ventilation rate used for offices. As a result, the fan power loss factors are quite uncertain, offering a good opportunity to show the power of Bayesian calibration to reduce uncertainty. In addition, the ventilation system is a combination of constant air volume (CAV) and variable air volume (VAV) as part of the air handling system has been upgraded during the buildings lifetime. The heating and hot water are provided by gas boilers and cooling is provided by centrifugal chillers.

The building audit was extremely thorough and well conducted. Submetering of lighting and plugloads was installed. A full (and expensive) lighting audit was conducted to determine the true connected lighting load. A comparison of *EECalc* results to these audit data offered the opportunity to see how the Bayesian calibration methods of *EECalc* can accurately estimate the same lighting load with far less effort. Of the audit recommendations, two were appropriate to be modeled with *EECalc*: lighting upgrades and upgrades/optimization of the Energy Management System (EMS). The lighting upgrades included the addition of occupancy sensors, daylighting controls, and the reduction of the lighting load. The EMS upgrade included development of an optimized fan/chiller startup sequence, additional set point control, and online diagnostics to detect abnormal building operation. We will compare *EECalc* energy savings predictions to these two EEM.

This building has submetered electricity consumption for appliances and lighting in addition to total electricity and gas utility bills. In order to fully exploit measured data available in the calibration process, we conducted a two-step calibration process: (1) calibrating part of the *EECalc* model relevant to the submetered data and (2) calibrating the whole *EECalc* model using the total utility bills.

As the first step, we calibrated a subset of model parameters for plugload and lighting against the submetered data: (1) plugload–occupied, (2) LPD, and (3) fraction of lighting on while occupied. Figure B.D-1 shows the posterior distributions of the three parameters refined from the prior distributions. For plugload and LPD, the results indicate that actual power densities were most likely to be much lower than the prior estimates, and uncertainty was greatly reduced. The audit project conducted an extensive survey to count the number of lighting fixtures and to instantly measure their lighting powers. From this survey, it was determined that the LPD was 6.7 W/m^2, a value close to the expected value (7.9) from the calibration. By calibrating the submodel of plugload and lighting with submeter data but without completing an extremely expensive survey, we can adequately derive the lighting baseline that matches the survey result well. For the

fraction of lighting–unoccupied, the result shows that any value from the prior range of parameter values is equally likely.

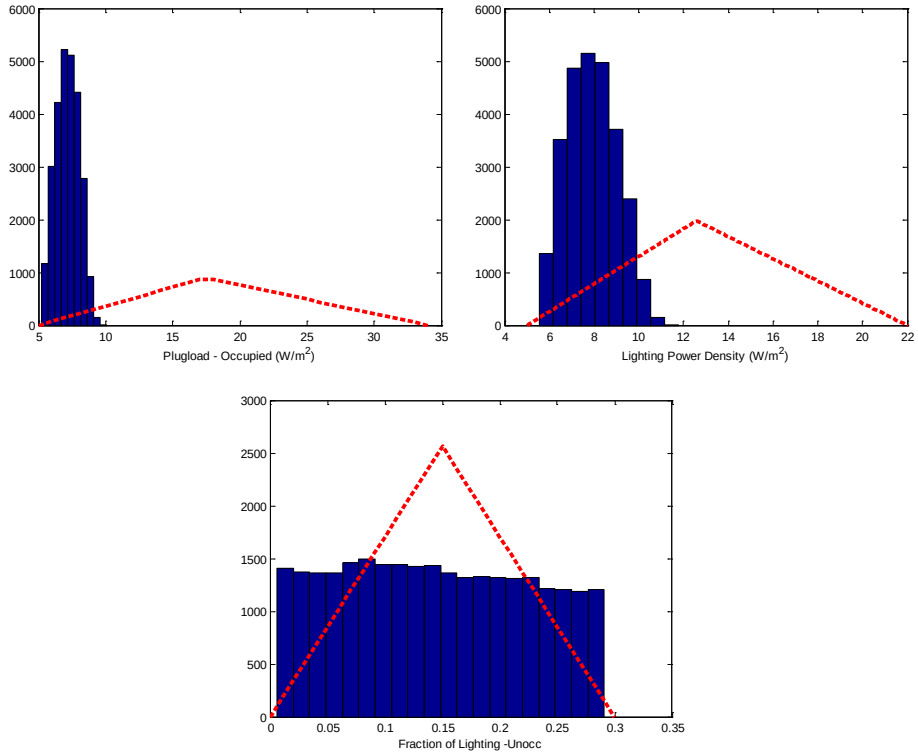


Figure B.D-1: Calibration Results for Building D Using Submetered Energy Consumption Data for Lighting and Appliances (red dashed line = prior, blue histogram = posterior distribution)

Using the refined uncertainty information for the three parameters, we applied the Morris method to rank model parameters with respect to their effect on the total energy consumption data. As a result, we selected the top four parameters for calibration: (1) fan power, (2) mechanical ventilation rate, (3) cooling system MPLV, and (4) cooling system coefficient of performance (COP). Figure B.D-2 shows the posterior distributions of the four calibration parameters. For the fan power, the posterior distribution is toward the upper bound, which suggests that the fan power of the building is very likely to be far less efficient than expected. In addition, the posterior distribution of mechanical ventilation rate suggests that the building is most likely to be highly overventilated, which unavoidably causes energy to be wasted in cooling and fan energy consumption. The posterior distributions of the cooling system MPLV and COP reveal that the seasonal cooling system efficiency is likely to be less than or initial estimates.

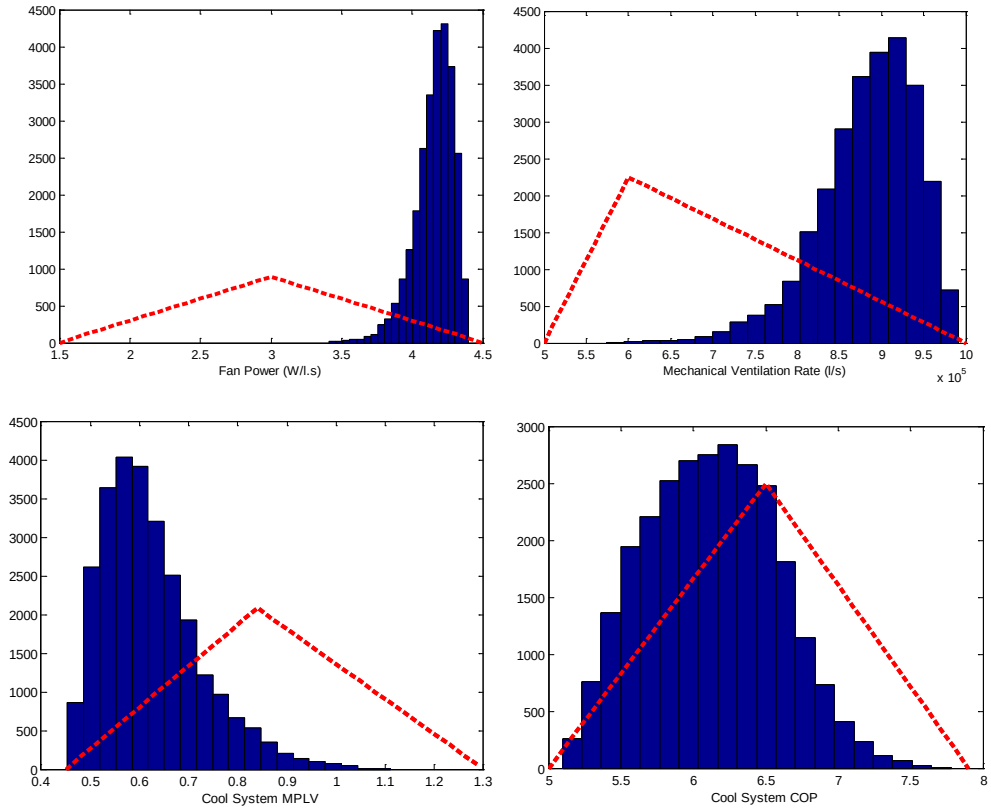


Figure B.D-2: Calibration Results of All Energy Use for Building D (red dashed line = prior, blue histogram = posterior distribution)

Figure B.D-3 exhibits the baseline gas and electricity consumption data predicted by the calibrated *EECalc* model in comparison with the energy audit's eQuest results and measured data from the utility bills. Overall, both gas consumption and electricity consumption predicted by the calibrated *EECalc* model are in good alignment with measured values.

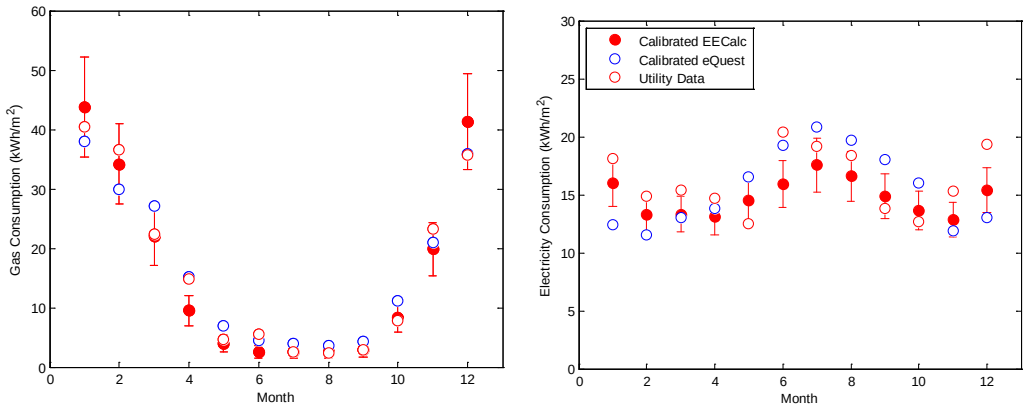


Figure B.D-3: Energy Consumption Data for Building D Predicted by the Calibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data

The audit project evaluated (1) upgrading lighting to high-efficiency T8 lighting systems and (2) upgrading the EMS to optimize control schedules. Figure B.D-4 displays a probability distribution of annual energy savings per EEM against a single value of energy savings from the audit report. The comparison indicates that energy savings are likely to be much higher than the estimated values documented in the audit report.

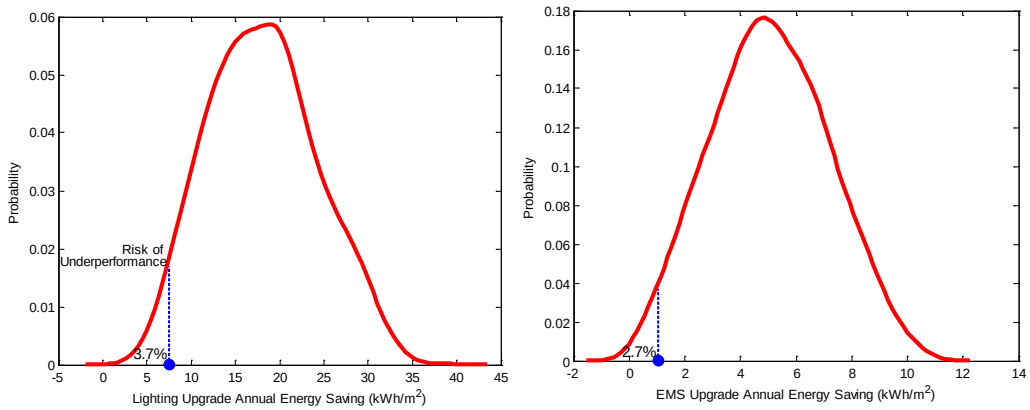


Figure B.D-4: Probability Distributions for Building D of Annual Energy Savings from Lighting Upgrade (left) and EMS Upgrade (right). Red line is *EECalc* savings prediction, blue dashed line is eQuest saving prediction. These results can be compared to the overall annual use of the building which was estimated by eQuest to be 371 kWh/m^2

Building E

This building is one of three buildings for which the building audits were highly redacted for confidentiality reasons. The three buildings offer the opportunity to evaluate the overall energy use and EEM savings predictions from *EECalc* when only very limited building information was available. Building E is over 40 stories tall, with a floor area in excess of 1,000,000 ft^2 (100,000 m^2). It was built before 1975. The building has original HVAC chillers, electric boilers, and first-generation insulated glazing units and a 130-kW exterior lighting load.

For this building, we assumed a 2:1 aspect ratio for the building depth-to-width ratio. From this ratio, the building height and building envelope size (wall size and roof size) were estimated. Assuming a 40% vision glazing fraction (as was common for a 1970s-era, glass, high-rise office), window and opaque wall areas were estimated. Based on common construction techniques from the year that the building was built, the U value for the walls and the U and solar heat gain coefficient (SHGC) values for the window were estimated. The roof was assumed to have been replaced sometime between 1990 and 2000, and it was assumed additional insulation was used to bring the roof to R15. Since the chillers and boilers were original to the building, equipment efficiencies were estimated. Standard office operating schedules and heating/cooling efficiencies were assumed. Because the chillers and boilers were original, it was assumed that there was no BAS, or, if there was one, it was not being used for highly automated control.

The audit was an ASHRAE level 2 audit. A building energy model was created in eQuest that was used to evaluate the larger EEM suggestions. We will compare the *EECalc* results to the interior lighting upgrades and chiller replacement/upgrades suggested in the audit.

Figure B.E-1 compares energy consumption data calculated by the uncalibrated *EECalc* tool against measured data from the utility bills and results from the eQuest modeling from the audit report. Without calibration, the tool overestimates total electricity consumption data, especially during the winter, when compared with the measured consumption data. This overestimation can be simply due to overestimated parameter values in the base *EECalc* model, which will be corrected through the calibration process.

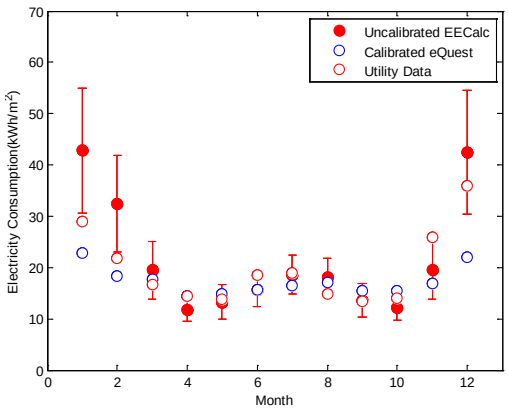


Figure B.E-1: Energy Consumption Data for Building E Predicted by the Uncalibrated *EECalc* and Calibrated eQuest in Comparison with Measured Data

Based on the ranking of model parameters from the Morris method, we selected the top four parameters: (1) wall U value, (2) infiltration rate, (3) heating temperature setpoint, and (4) LPD. Figure B.E-2 shows probability distributions of the four parameters as the result of the Bayesian calibration process. The actual wall U value is very likely to be lower than our initial estimate, which suggests that the building envelope is more insulated than our initial estimate. For the infiltration rate, the expected value changes from 3.5 to 2 $m^3/h/m^2$ at 75 Pa, which suggests the building envelope is more air-tight than we initially estimated. For the heating temperature setpoint, the expected value did not change much from the prior estimate. For the LPD, the expected value shifted from 10 to 12 W/m^2, which reveals that the lighting consumes more energy than our initial estimate showed.

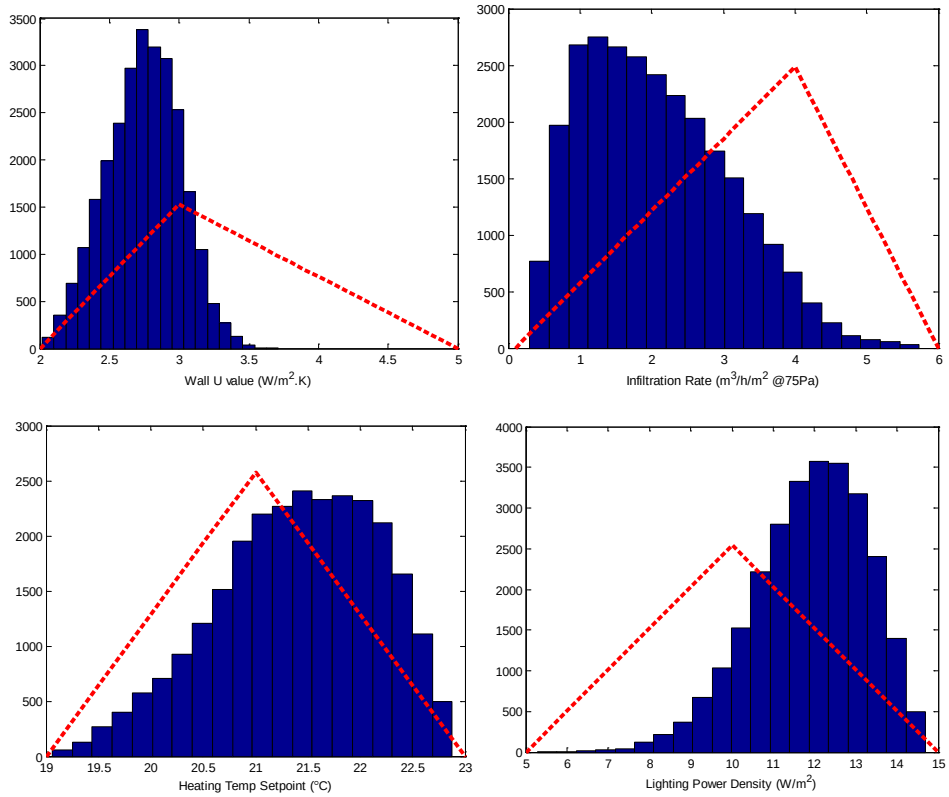


Figure B.E-2: Calibration Results for Building E (red dashed line = prior, blue histogram = posterior distribution)

Figure B.E-3 displays the baseline energy consumption data predicted by the calibrated *EECalc* model compared with eQuest results and the measured consumption data. After the calibration, the *EECalc* model predictions were in good alignment with the measured consumption data, with greatly reduced confidence intervals. The calibrated eQuest model underpredicted electricity consumption during the winter.

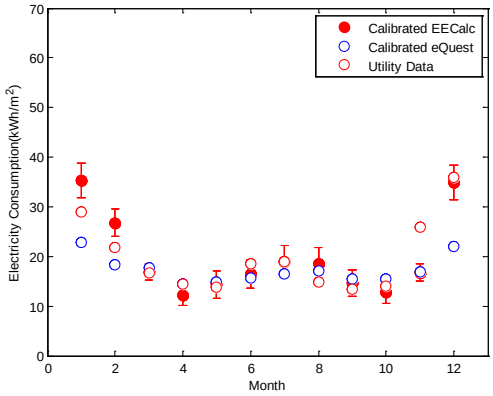


Figure B.E-3: Energy Consumption Data for Building E Predicted by the Calibrated *EECalc* and the Calibrated eQuest in Comparison with Measured Data

We evaluated two EEMs from the audit report: (1) upgrading a chiller's efficiency from 4.0 to 7.0 and (2) upgrading interior lighting. Figure B.E-4 shows probability distributions of annual energy savings per EEM. Relative to *EECalc* predictions, energy savings estimated in the audit were likely to be less for the chiller upgrade and more for the lighting upgrade.

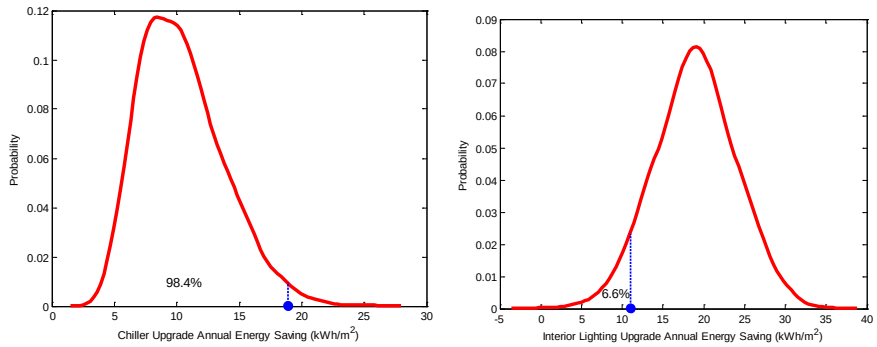


Figure B.E-4: Probability Distributions for Building E of Annual Energy Savings from Chiller Upgrade (left) and Interior Lighting Uupgrade (right). Red line is the *EECalc* savings prediction and the blue dashed line is the eQuest saving prediction. These results can be compared to the overall annual use of the building which was estimated by eQuest to be 239 kWh/m^2.

Building F

This is another of the buildings with the highly redacted audits. Building F is over 30 stories tall of mixed retail and office space with over 400,000 ft^2 (40,000 m^2) of conditioned floor space and was built before 1975. The building is a concrete panel curtain wall construction with first generation insulated glazing original to the building. HVAC is electric chillers with electric boilers and electric baseboard heating, all original to the building. All HVAC equipment is constant speed and air delivery is via a CAV system. For this building, a 1.5:1 side ratio with 40% glazing ratio was assumed. This information was used to estimate opaque wall and window sizes. From knowledge of the year of build, the U value for the walls and the U and SHGC values for the windows were estimated. The roof was assumed to have been replaced sometime between 1990 and 2000 and additional insulation to bring the roof to R15 was assumed. Since the chillers and boilers were original to the building, equipment efficiencies were estimated. Standard office operating schedules and heating/cooling efficiencies were assumed. Because the chillers and boilers were original, it was assumed that there was no BAS, or, if there was one, it was not being used for highly automated control.

The audit was an ASHRAE level 2. An Integrated Environmental Solutions Virtual Environment (IES-VE) model and custom software of the auditors was used for estimating EEM savings, but a monthly estimate of energy use was not presented. Of the suggested EEMs, we modeled two: a chiller replacement/upgrade and the conversion of the CAV system to a demand-control ventilation system.

Figure B.F-1 compares energy consumption data calculated by the uncalibrated *EECalc* tool against measured data from the utility bills. Without calibration, the tool still calculated the total electricity consumption data close to measured data, although it slightly overpredicted the consumption data throughout the year. The magnitude of uncertainty in predictions was quite large, especially for the winter season.

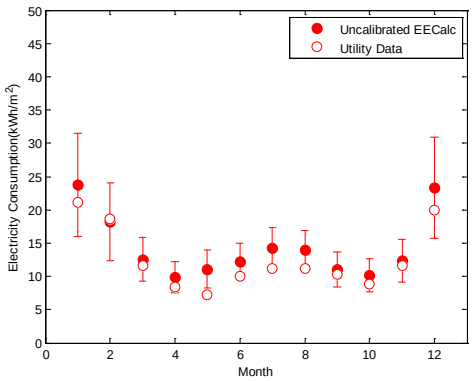


Figure B.F-1: Energy Consumption Data for Building F Predicted by the Uncalibrated *EECalc* in Comparison with Measured Data

Through the Morris method, we ranked model parameters in terms of their effect on energy consumption data, and selected the top four parameters: (1) wall U value, (2) LPD, (3) window U value, and (4) infiltration rate. Figure B.F-2 shows posterior distributions of the four parameters updated from prior distributions. For the wall U value, the expected value did not change much, but the magnitude of uncertainty was noticeably reduced. For the LPD, the posterior distribution shifted toward the lower bound, which suggests that actual LPD is very likely to be much lower than originally estimated. For the window U value, the posterior distribution did not change much from the prior distribution. For the infiltration, the magnitude of uncertainty was not reduced, but the expected value changed by 0.5 $m^3/h/m^2$ at 75 Pa.

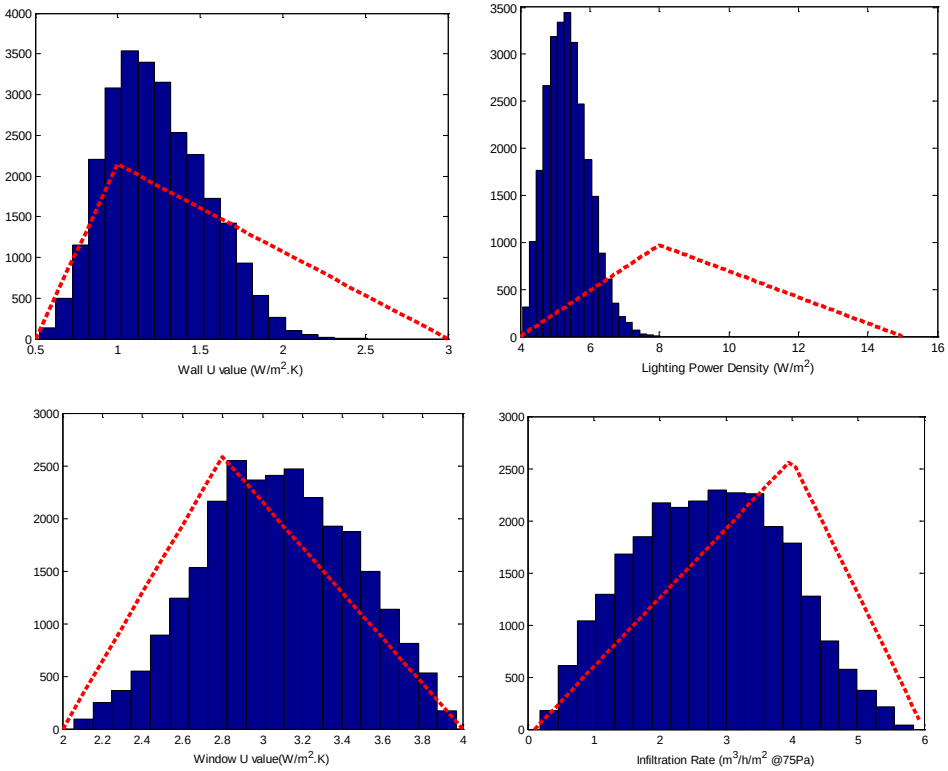


Figure B.F-2: Calibration Results for Building F (red dashed line = prior, blue histogram = posterior distribution)

Figure B.F-3 displays the baseline energy consumption data predicted by the calibrated *EECalc* model in comparison with the measured data from the utility bills. After the calibration, the *EECalc* model predicted electricity consumption data that perfectly matched measured data, with much narrower confidence intervals than those from the uncalibrated *EECalc*.

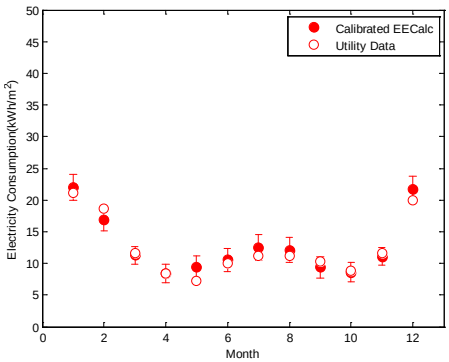


Figure B.F-3: Energy Consumption Data for Building F Predicted by the Calibrated *EECalc* in Comparison with Measured Data

We evaluated two EEMs reported in the audit: (1) upgrading a chiller's efficiency from 4.0 to 7.0 COP, and (2) implementing demand-based control. Figure B.F-4 shows a probability distribution of annual energy savings per EEM. In comparison with the *EECalc* results, the energy savings reported in the audit for the chiller upgrade are well within the 95% confidence limits. The *EECalc* results suggest that the reported energy savings for demand-based control are likely to be too high.

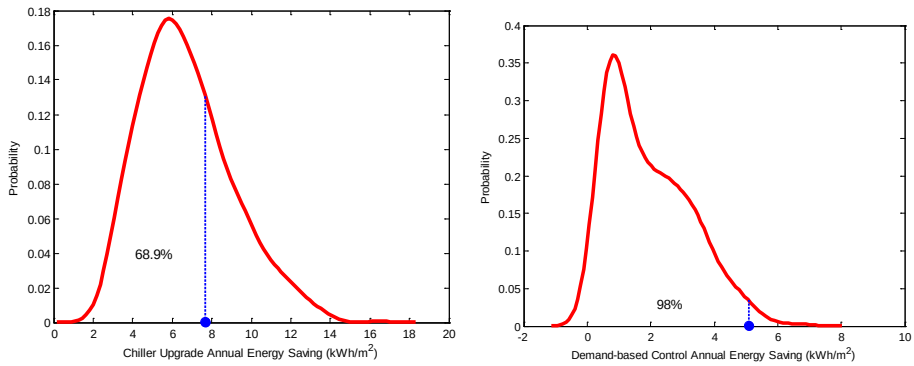


Figure B.F-4: Probability Distributions for Building F of Annual Energy Savings from Chiller Upgrade (left) and Demand-Based Control (right). Red line is the *EECalc* savings prediction and the blue dashed line is the IES-VE saving prediction. These results can be compared to the overall annual use of the building which was estimated byIES-VE to be 154 kWh/m^2.

Building G

This building is one of three buildings for which full audit documentation was not provided to us. Instead, our collaborator shared the results of EnergyPlus models of the existing building, with and without specific recommended upgrades. Building G is a 32-story glass curtain wall, built in the 1980s, with a conditioned floor space of 835,000 ft^2 (76,660 m^2) and a high fraction of vision glass. HVAC equipment is original to the building, with an electric boiler used for heating and an electric chiller use for cooling. The building underwent some recent lighting upgrades, so the LPD is actually quite low, but there are still opportunities for lighting energy savings through daylighting and occupancy controls. The EEMs presented by the auditors were a lighting system upgrade, including occupancy and daylighting controls, and the upgrade of the façade to utilize very-high-performance, translucent glazing in place of standard vision glass.

Figure B.G-1 compares energy consumption data calculated by the uncalibrated *EECalc* tool with measured data. Without calibration, the tool fairly predicted the total electricity consumption data, although it overpredicted the consumption data during the winter. We further updated the model by calibrating it using the Bayesian approach.

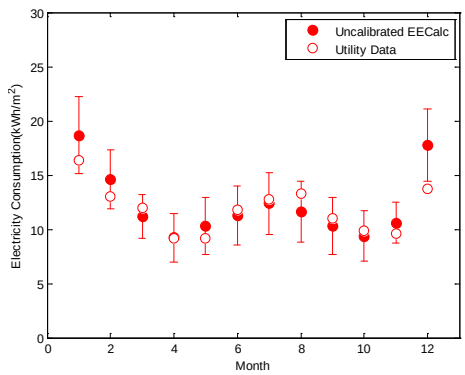


Figure B.G-1: Energy Consumption Data of Building G Predicted by the Uncalibrated *EECalc* in Comparison with Measured Data

Through the Morris method, we ranked model parameters and selected the top four for calibration: (1) LPD, (2) plugload–occupied, (3) infiltration rate, and (4) heating temperature setpoint. Figure B.G-2 shows probability distributions of the four parameters refined from the prior distributions. For the LPD, the expected value is likely to be slightly higher than the prior estimate. For plugload–occupied, the posterior distribution did not change much from the prior distribution. For the infiltration rate, the posterior distribution shifted toward the lower bound, and uncertainty was greatly reduced. For the heating temperature setpoint, the expected value did not change much.

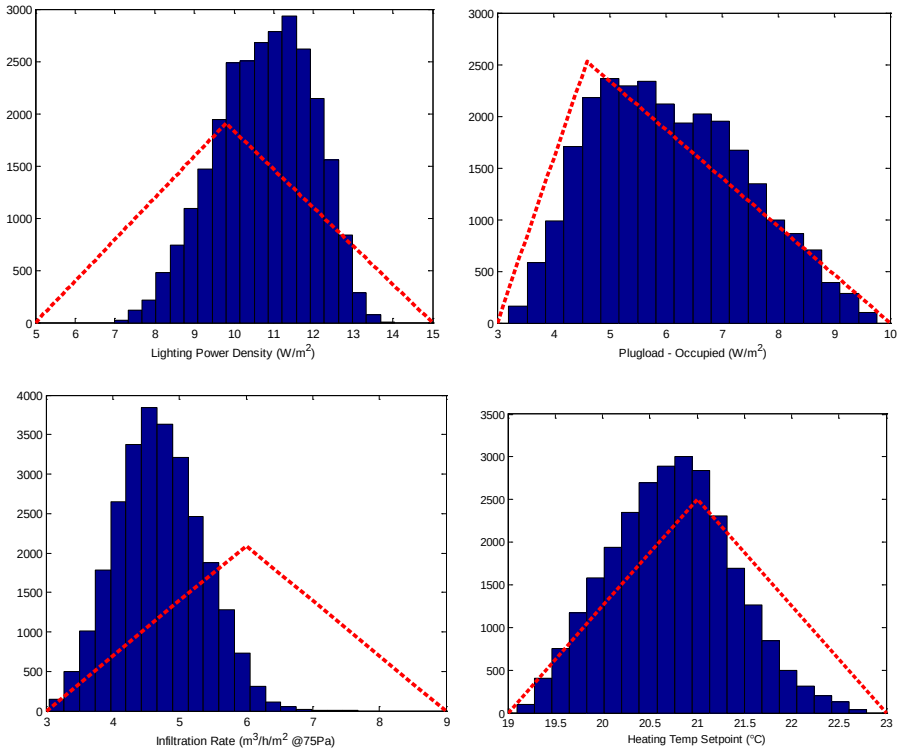


Figure B.G-2: Calibration Results for Building G (red dashed line = prior, blue histogram = posterior distributions)

Figure B.G-3 displays the baseline energy consumption data predicted by the calibrated *EECalc* model in comparison with the measured consumption data. The calibrated *EECalc* model predicted total electricity consumption data closely matching measured data and also yielded quite narrow 95% confidence intervals associated with their predictions.

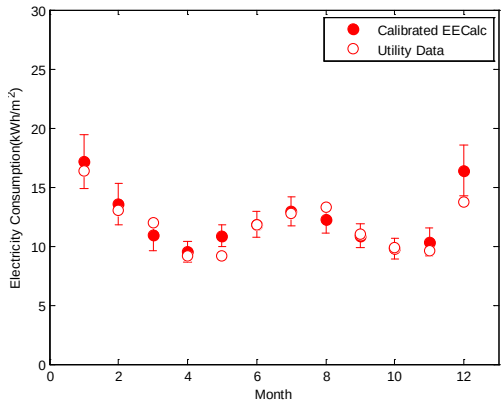


Figure B.G-3: Energy Consumption Data for Building G Predicted by the Calibrated *EECalc* in Comparison with Measured Data

We evaluated two EEMs: (1) upgrading lighting and (2) upgrading windows. Figure B.G-4 shows the probability distributions of annual energy savings per EEM. The deterministic audit results from the Energy Plus model fairly matched the expected value of savings for the lighting upgrade but underestimated the expected value of savings relative to the *EECalc* results.

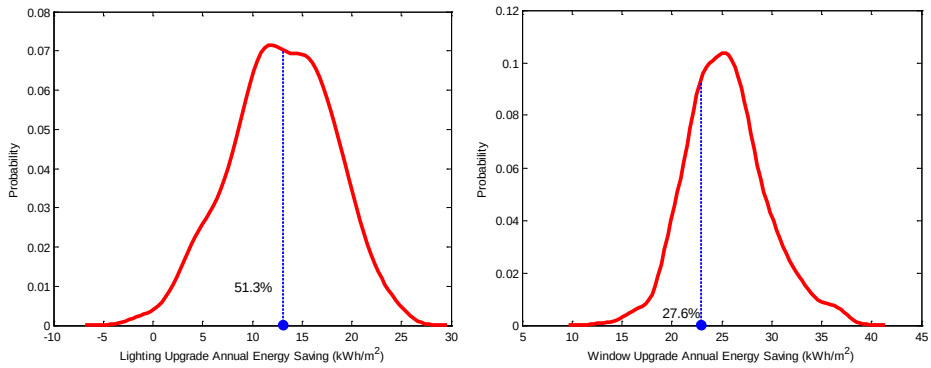


Figure B.G-4: Probability Distributions for Building G of Annual Energy Savings from Lighting Upgrade (left) and Window Upgrade (right). Red line is the *EECalc* savings prediction and the blue dashed line is the EnergyPlus saving prediction. These results can be compared to the overall annual use of the building which was estimated by EnergyPlus to be 147 kWh/m^2.

Building H

This is the second of the three buildings for which full audit documentation was not provided to us. Instead, our collaborator shared the results of EnergyPlus models of the existing building, with and without specific recommended upgrades. Building H is a 44-story, 1,030,000 ft^2 (95,052 m^2) glass curtain wall high-rise built in the 1960s. The building uses electric boilers for heating and hot water and an electric centrifugal chiller for cooling. Additional insulation was added to the spandrel glass to increase energy efficiency in a previous retrofit, and a recent lighting upgrade reduced the LPD significantly.

The auditors suggested adding daylighting and occupancy controls and replacing the existing chiller (COP = 4.3, MPLV = 0.7) with a very-high-efficiency centrifugal chiller (COP = 7.5, MPLV = 1.17).

Figure B.H-1 shows total electricity consumption data predicted by the uncalibrated *EECalc* tool in comparison with measured electricity consumption data. Without calibration, the tool fairly predicted the consumption data during the summer, while it overestimated the consumption data during the winter, with higher uncertainty associated with predictions. This implies that certain parameters in the base *EECalc* model played a more significant role in heating loads during the winter than in cooling loads during the summer. We further investigated the sensitivity of model parameters and updated the most important parameters through the calibration process.

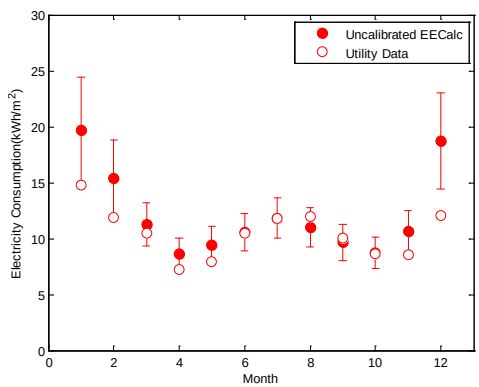


Figure B.H-1: Energy Consumption Data for Building H Predicted by the Uncalibrated *EECalc* in Comparison with Measured Data

We applied the Morris method to rank model parameters with respect to their effect on the total energy consumption data. Based on the ranking, we selected the top four parameters for calibration: (1) LPD, (2) plugload–occupied, (3) infiltration rate, and (4) heating temperature setpoint. Figure B.H-2 exhibits calibration results of the four parameters in the form of probability distributions. For the infiltration rate, the calibration results suggest that the Building H is very likely to be far more air-tight than originally estimated, with high confidence. For the LPD and plugload–occupied, the expected values did not change much from the prior estimates. For the heating temperature setpoint, the actual temperature was most likely to be 1°C lower than the setpoint temperature originally assumed.

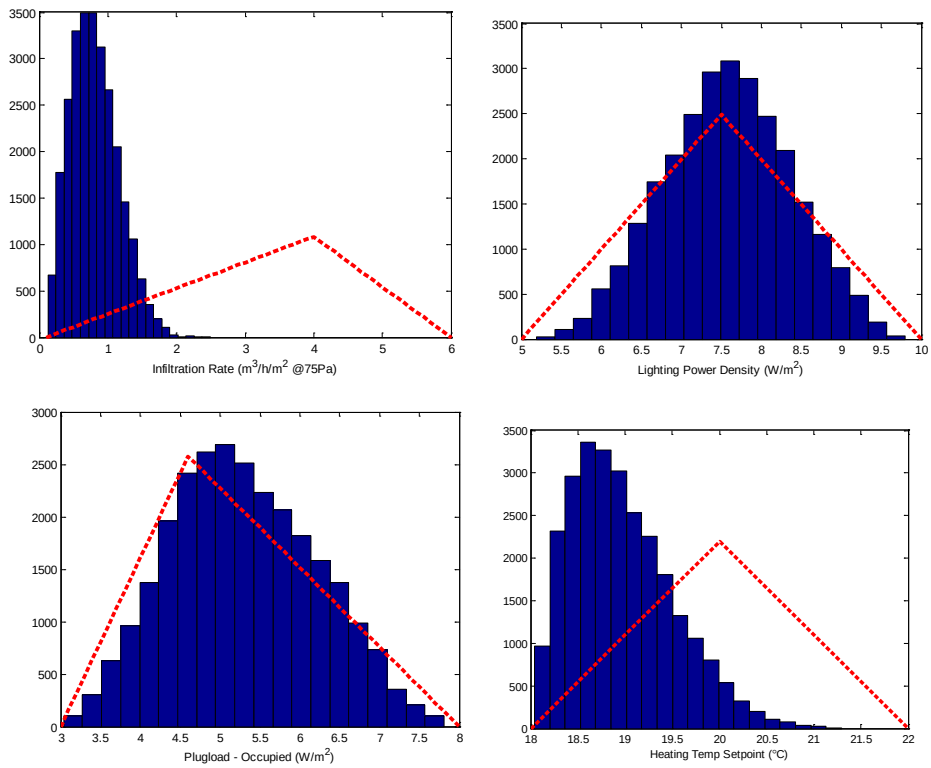


Figure B.H-2: Calibration Results for Building H (red dashed line = prior, blue histogram = posterior distributions)

Figure B.H-3 compares the baseline electricity consumption data calculated by the calibrated *EECalc* model with measured consumption data. The calibrated model improved the prediction of electricity consumption data throughout the year and also enhanced the confidence level associated with its predictions.

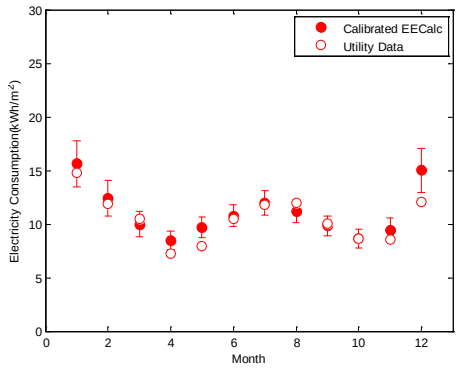


Figure B.H-3: Energy Consumption Data for Building H Predicted by the Calibrated *EECalc* in Comparison with Measured Data

We evaluated two EEMs: (1) upgrading a chiller's efficiency from 4.3 to 7.5 and (2) implementing lighting control (occupancy sensor and daylighting sensor). Figure B.H-4 shows probability distributions of annual energy savings for each EEM. Compared with the *EECalc* results, the audit project predicted higher annual energy savings for the chiller upgrade and lower annual energy savings for the lighting upgrade.

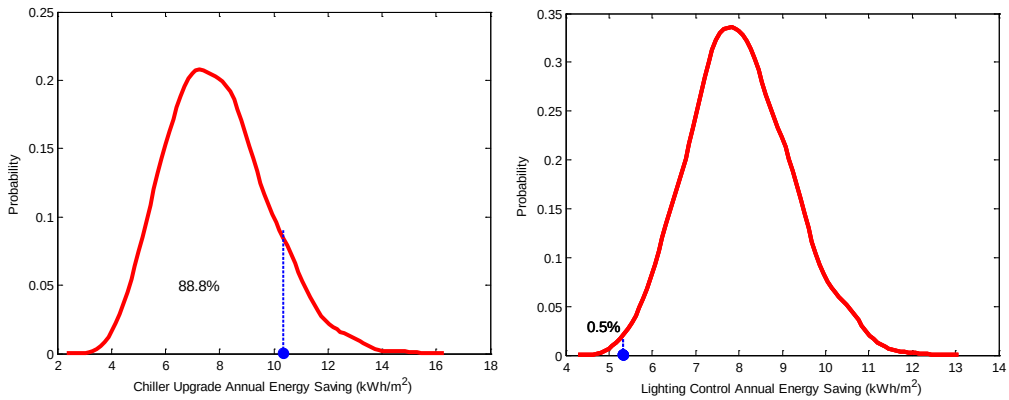


Figure B.H-4: Probability Distributions for Building H of Annual Energy Savings from Chiller Upgrade (left) and Lighting Control (right). Red line is the *EECalc* savings prediction and the blue dashed line is the EnergyPlus saving prediction. These results can be compared to the overall annual use of the building which was estimated by EnergyPlus to be 133 kWh/m^2.

Building I

This building is the last of three buildings for which full audit documentation was not provided to us. Instead, our collaborator shared the results of EnergyPlus models of the existing building, with and without specific recommended upgrades. Building I is an 18-story glass curtain wall with 2,070,000 ft^2 (192,000 m^2) of conditioned space. It was built in the 1990s and is home to a large data center. The data center is a ~3 MW electrical load, which includes the electrical use of the computer room air conditioning units. This electrical load does not contribute to the building heating and cooling load but does contribute to the overall electrical usage of the building. Heating and hot water are provided by electric boilers, and cooling is provided by a centrifugal chiller. The audit evaluated a chiller upgrade and lighting upgrade with occupancy sensors and daylighting controls.

Figure B.I-1 compares energy consumption data calculated by the uncalibrated *EECalc* tool with measured data. The uncalibrated tool overestimated total electricity consumption data during the winter, while it fairly estimated consumption data during the summer. The discrepancy between the predicted and measured consumption will be reduced through calibration.

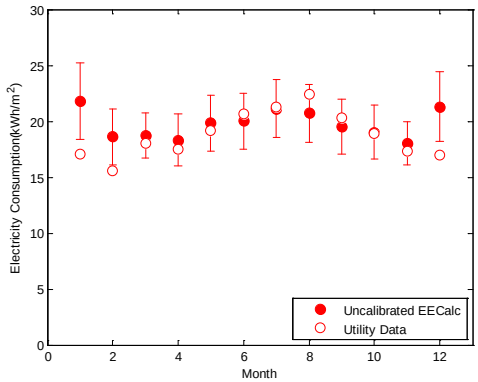


Figure B.I-1: Energy Consumption Data for Building I Predicted by the Uncalibrated *EECalc* in Comparison with Measured Data

Based on the ranking of uncertain parameters, we selected the top four parameters for calibration: (1) LPD, (2) plugload–occupied, (3) infiltration rate, and (4) window U value. Figure B.I-2 shows probability distributions of the four parameters. For the LPD, the expected value did not change much, while the magnitude of uncertainty was substantially reduced. For plugload–occupied, the posterior distribution did not change noticeably from the prior distribution. For the infiltration rate and window U value, the posterior distribution shifted toward the lower bound, while uncertainty in the parameter value was greatly reduced.

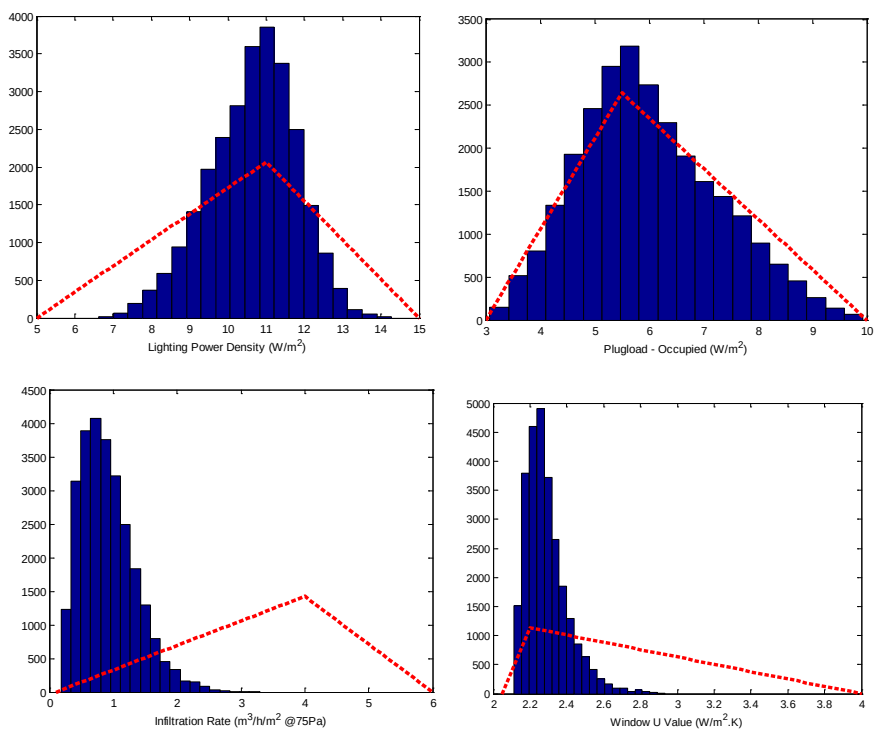


Figure B.I-2: Calibration Results for Building I (red dashed line = prior, blue histogram = posterior distributions)

Figure B.I-3 compares the baseline energy consumption data predicted by the calibrated *EECalc* model with the measured consumption data. Although a discrepancy between predictions and measurements still existed, especially during the winter season, the calibration did enhance the *EECalc* model so it more accurately predicted electricity consumption data in comparison with the uncalibrated *EECalc* model.

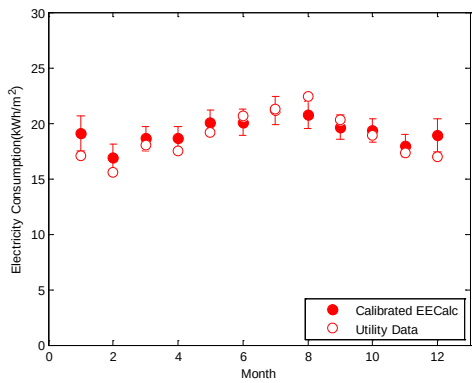


Figure B.I-3: Energy Consumption Data for Building I Predicted by the Calibrated *EECalc* in Comparison with Measured Data

We evaluated the two EEMs: (1) upgrading a chiller's efficiency from 4.8 to 7.5 and (2) implementing lighting control (occupancy sensor and daylighting control). Figure B.I-4 shows probability distributions of annual energy savings against a single estimate from the audit report per EEM. The single estimates were close to the expected values of the probabilistic outcomes.

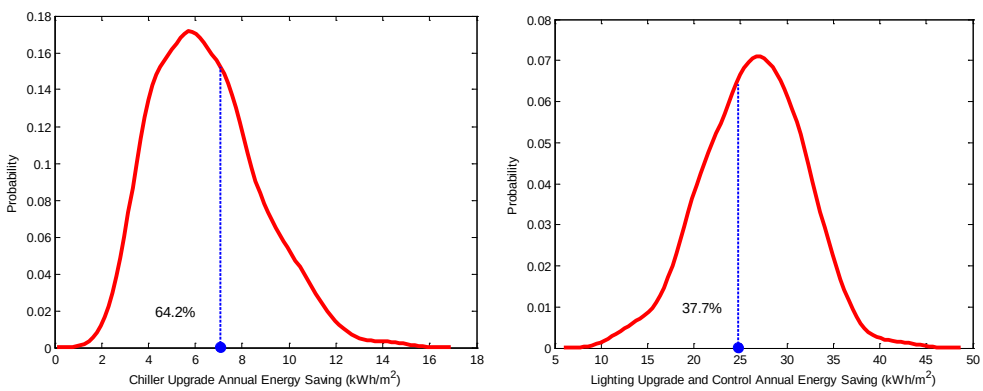


Figure B.I-4: Probability Distributions of Annual Energy Savings for Building I from Chiller Upgrade (left) and Lighting Upgrade and Control (right). Red line is the *EECalc* savings prediction and the blue dashed line is the EnergyPlus saving prediction. These results can be compared to the overall annual use of the building, which was estimated by EnergyPlus to be 231 kWh/m^2.

Building J

Through the Morris method, we selected the top four important parameters with respect to their effect on energy consumption data: (1) LPD, (2) plugload–occupied, (3) wall U value and (4) infiltration rate. Figure B.J-1 shows probability distributions of the four parameters updated through the calibration process. The actual LPD is very likely to be lower than our initial estimate, and uncertainty in the LPD was greatly reduced after the calibration. For the wall U value, the expected value shifted toward the low bound by roughly 1W/m^2/K. For plugload–occupied and infiltration rate, the posterior distribution did not change much from the prior distribution.

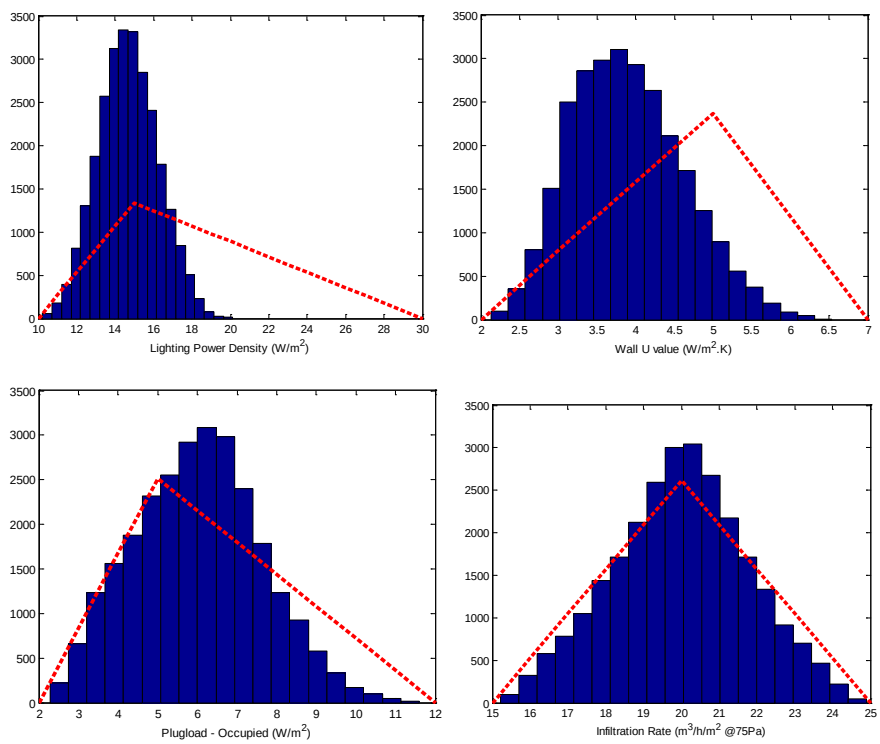


Figure B.J-1: Calibration Results for Building J (red dashed line = prior, blue histogram = posterior distributions)

Figure B.J-2 displays the probabilistic outcomes of gas and electricity consumption data predicted by the calibrated *EECalc* model in comparison with measured data and the outcomes predicted by the uncalibrated model. After the calibration, uncertainty in predicted energy consumption data was greatly reduced, especially for electricity consumption predictions. The calibrated *EECalc* model predicted electricity consumption more accurately than the uncalibrated model, but the calibration did not noticeably reduce the discrepancy between predicted and measured gas consumption data.

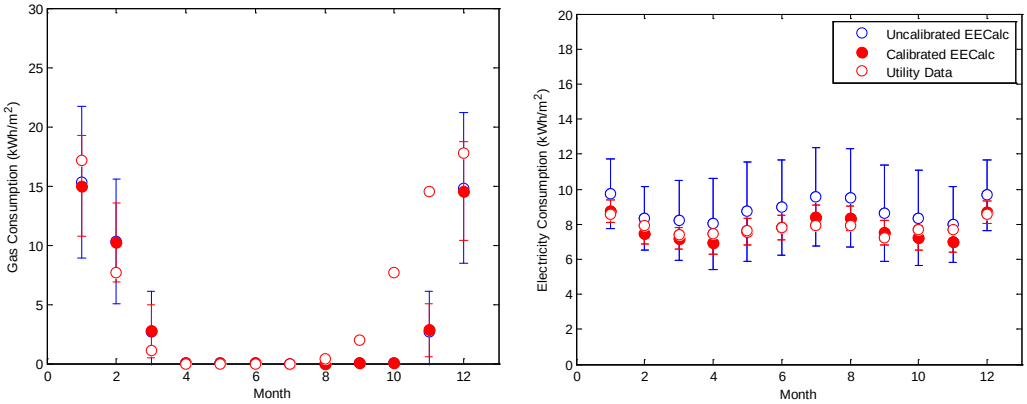


Figure B.J-2: Energy Consumption Data for Building J Predicted by the Uncalibrated and Calibrated *EECalc* in Comparison with Measured Data

Building K

Based on the ranking of model parameters by the Morris method, we selected the top four parameters for calibration: (1) plugload–occupied, (2) infiltration rate, (3) LPD, and (4) heating temperature setpoint. Figure B.K-1 shows probability distributions of the calibration parameters updated through the calibration process. For plugload-occupied, the calibration results reveal that Building K most likely has a much higher plugload than the average plugload of office buildings. The posterior distribution of the infiltration rate suggests that the building is likely to be much leakier than the average building, and the magnitude of uncertainty is substantially reduced. For the LPD, the posterior distribution did not change much from the prior distribution. For the heating temperature setpoint, the expected value shifted from 22°C to 23°C.

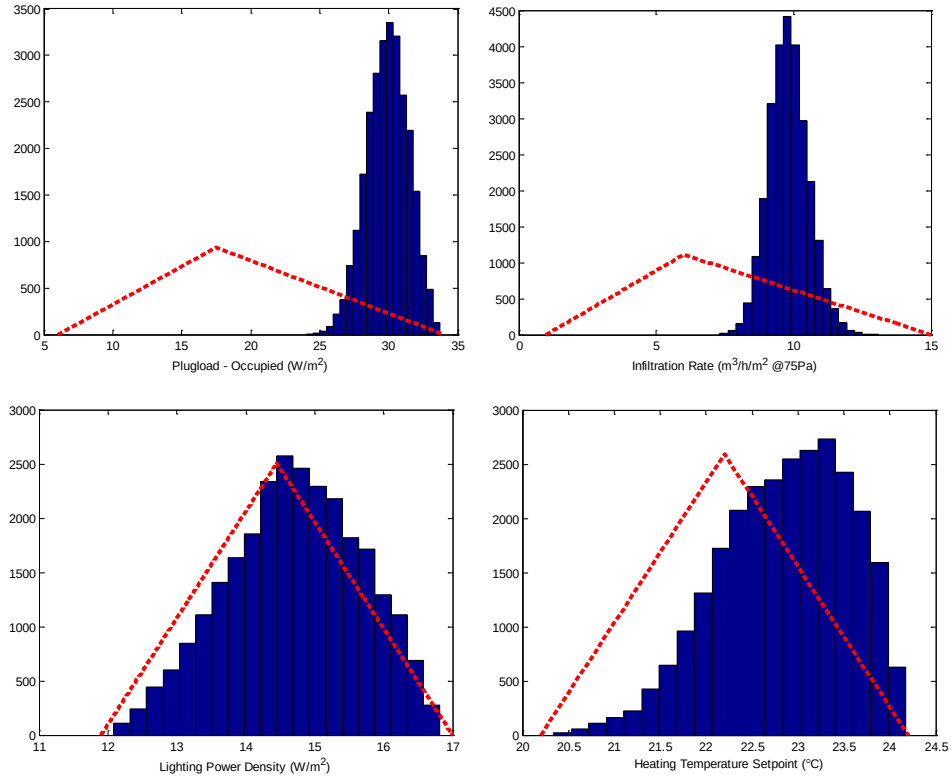


Figure B.K-1: Calibration Results for Building K (red dashed line = prior, blue histogram = posterior)

Figure B.K-2 compares the baseline electricity consumption data predicted by the calibrated model against measured data from the utility bills. After the calibration, the *EECalc* model predicted electricity consumption data that closely matched actual consumption data. The comparison between the uncalibrated and calibrated model proves that calibration did not only enhance the model to accurately predict energy consumption data but also greatly reduced the uncertainty in predictions.

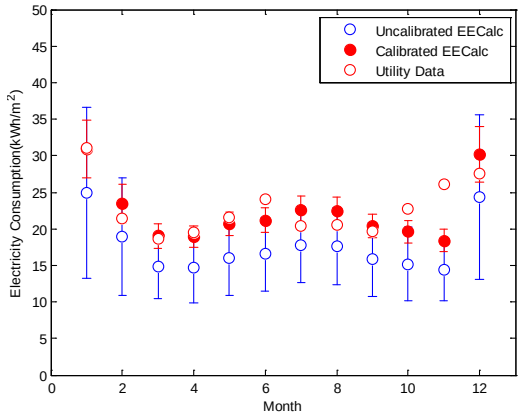


Figure B.K-2: Energy Consumption Data for Building K Predicted by the Uncalibrated and Calibrated *EECalc* in Comparison with Measured Data

Building L

We applied the Morris method to identify the dominant parameters in terms of their effect on energy consumption data. As a result, we selected the top four parameters for calibration: (1) plugload–occupied, (2) LPD, (3) cooling system MPLV, and (4) infiltration rate. Figure B.L-1 shows calibration results in the form of probability distributions. For plug load–occupied, the expected value is very likely to be much higher than the initial estimate, and the magnitude of uncertainty was greatly reduced. For the LPD and cooling system MPLV, the expected value did not change much from the prior estimates. For infiltration rate, the posterior distribution was toward the bound, which suggests that the building envelope is very likely much leakier than expected.

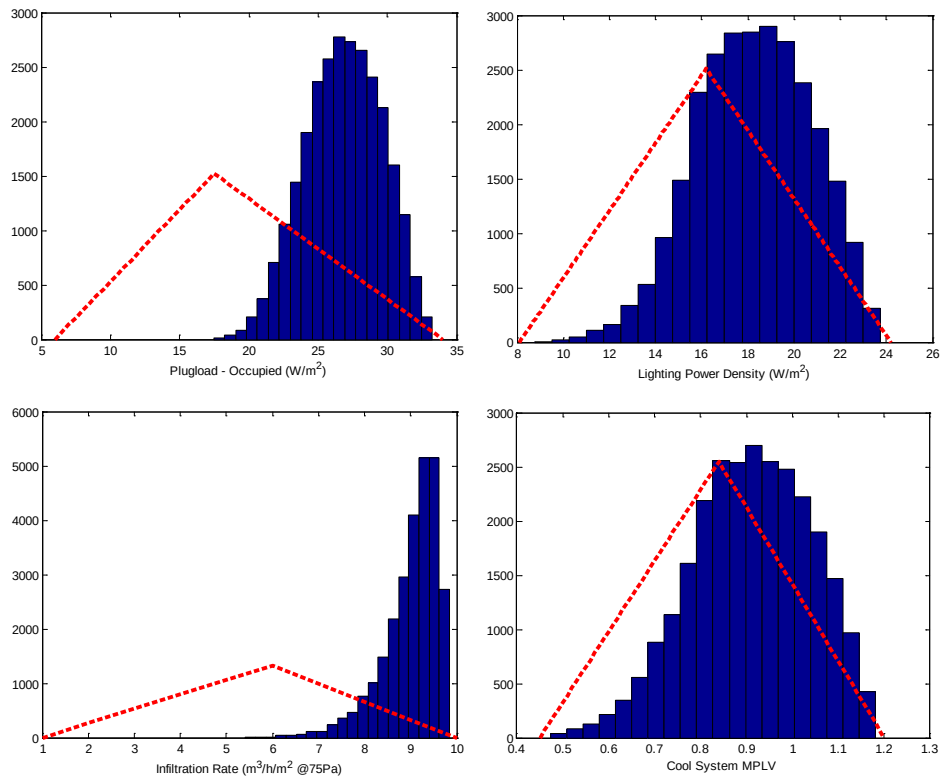


Figure B.L-1: Calibration Results for Building L (red dashed line = prior, blue histogram = posterior distribution)

Figure B.L-2 displays the probabilistic outcomes of energy consumption data predicted by the calibrated *EECalc* model, the outcomes predicted by the uncalibrated model, and measured energy consumption data. Bayesian calibration enhanced the model to represent building energy performance and significantly reduced uncertainty in baseline predictions. However, there is still a discrepancy between predictions by the calibrated model and measurement data; the model underpredicted total energy consumption data during the winter. This could possibly be due to unexpected changes in building operation use during the winter that were not reflected in the model.

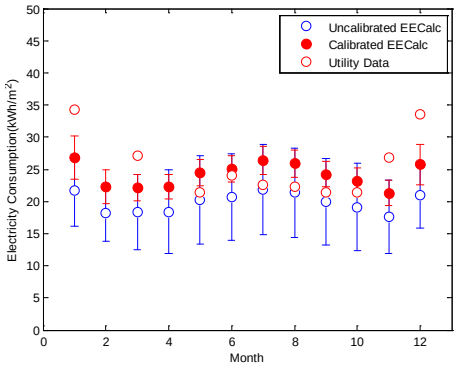


Figure B.L-2: Energy Consumption Data for Building L Predicted by the Uncalibrated and Calibrated *EECalc* in Comparison with Measured Data

Building M

After applying the Morris method, we identified the top four dominant parameters for calibration: (1) plugload–occupied, (2) LPD, (3) cooling system MPLV, and (4) infiltration rate.
Figure B.M-1 shows probability distributions of the calibration parameters. For plugload–occupied, the results suggest that actual plug load was very likely higher than the initial estimate. For the LPD and cooling system MPLV, the expected values did not change much from the prior estimates. For infiltration rate, the posterior distribution was toward the upper bound, which suggests that the building envelope was most likely much leakier than expected.

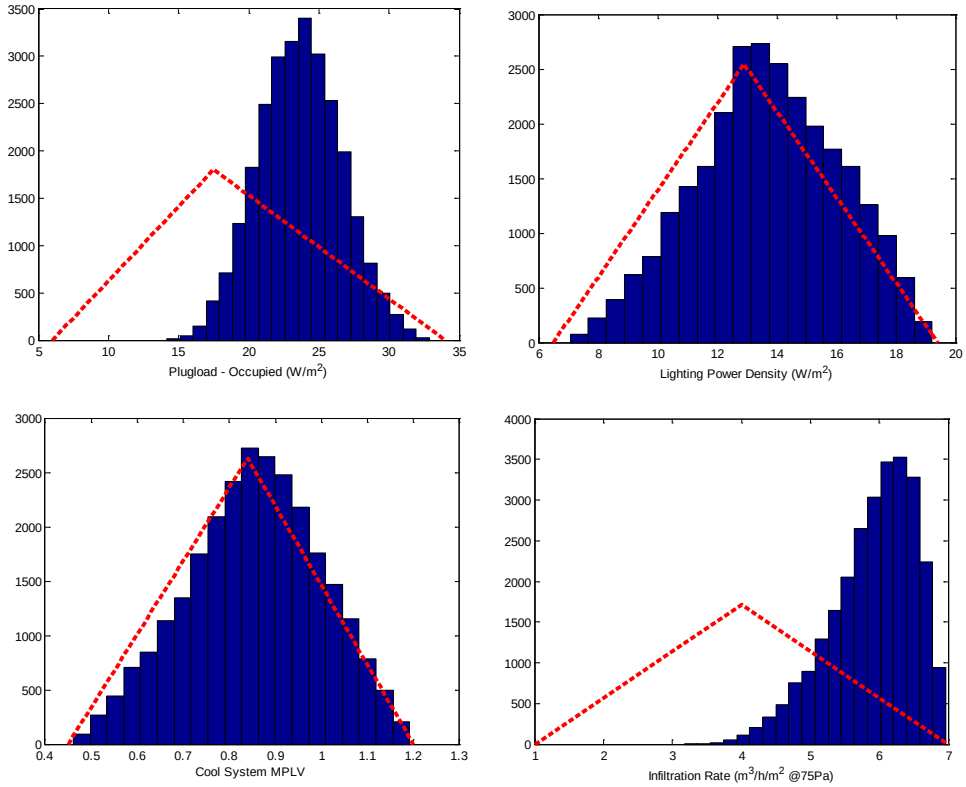


Figure B.M-1: Calibration Results for Building M (red dashed line = prior, blue histogram = posterior distribution)

Figure B.M-2 displays the probabilistic outcomes of energy consumption data predicted by the calibrated *EECalc* model in comparison with measured energy consumption data and the outcomes predicted by the uncalibrated model. After the calibration, the *EECalc* accurately predicted actual electricity consumption data, with greatly reduced confidence intervals.

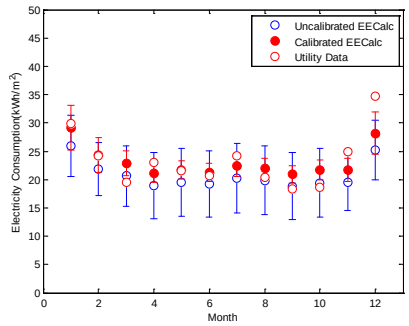


Figure B.M-2: Energy Consumption Data for Building M Predicted by the Uncalibrated and Calibrated *EECalc* in Comparison with Measured Data

Decision and Information Sciences Division
Argonne National Laboratory
9700 South Cass Avenue, Bldg. 221
Argonne, IL 60439-4844

www.anl.gov

Argonne National Laboratory is a U.S. Department of Energy
laboratory managed by UChicago Argonne, LLC