ANALYSIS METHODOLOGY FOR LARGE ORGANIZATIONS' INVESTMENT IN ENERGY RETROFIT OF BUILDINGS

Yeonsook Heo
College of Architecture
Georgia Institute of Technology
Atlanta, GA, USA

Godfried Augenbroe
College of Architecture
Georgia Institute of Technology
Atlanta, GA, USA

Ruchi Choudhary
Engineering Department
University of Cambridge
Cambridge, UK

ABSTRACT

This paper presents a formal methodology that supports large organizations' investments in energy retrofit of buildings. The methodology is a scalable modeling approach based on normative models and Bayesian calibration. Normative models are a light-weight quasi-steady state energy models, which makes them scalable to large sets of buildings due to highly enhanced modeling efficiency. Then, Bayesian approach calibrates normative models such that calibrated models quantify uncertainty in the model while representing a building as operated. Calibrated models can further incorporate additional uncertainty from ECMs, and provide information about underperforming risks of ECMs. This paper illustrates the proposed retrofit analysis process through a case study, and demonstrates its feasibility to support large-scale retrofit decisions under uncertainty in the context of the ESCO industry.

INTRODUCTION

Large organizations (e.g., campuses, corporate owners, government entities) regard energy retrofits of their buildings as a profitable investment opportunity. Energy retrofits can be cost effective if they reduce the energy costs of large portfolio of buildings while increasing long term real estate value. Indeed, energy-efficiency services for large public-sector facilities yielded $2.8 billion in revenues for the Energy Service Companies (ESCOs) in 2008 alone (Satchwell, 2010). Also, the Department of Energy initiated the Federal Energy Management Program (FEMP) to assist in improving energy efficiency of federal government buildings through energy savings performance contracts with ESCOs (FEMP, 2011). The program has invested more than $2.4 billion in energy efficiency improvements of federal buildings.

Deciding on which specific set of technology or building improvements should be implemented requires analyzing the building portfolio and its existing status quo with regards to energy consumption. Indeed, it is standard to benchmark each individual building within the portfolio and identify those that are either most inefficient, consume significant amount of energy, and/or are in need of upgrades (due to end of service life of equipment). Once a set of buildings is selected for retrofits, candidate energy conservation measures (ECMs) are evaluated in terms of their energy saving potential and cost effectiveness. These two steps require auditing all buildings in the portfolio. ASHRAE provides guidelines for energy audits at three different levels of fidelity (ASHRAE handbook, 2007). ASHRAE audit level 1 recommends analyzing energy utility bills and a brief survey of the facility (e.g., walk-through and minimal interviews with a facility manager) to identify the most obvious choices of low-cost/no-cost ECMs. This audit level is sufficient only for revealing easily observable opportunities for energy savings in buildings. ASHRAE audit level 2 involves a more detailed survey of the buildings, supplemented with energy analyses. The purpose of the energy analysis is to evaluate candidate ECMs, not necessarily using engineering calculations, but according to an expert's estimate of their cost-effectiveness. Hence, this audit level tends to limit ECM recommendations to those with proven track records in yielding energy savings. ASHRAE audit level 3 is most detailed, requiring thorough audits of the buildings and engineering analysis of selected ECMs (using transient simulation model). Audit level 3 is most suitable when predicted energy savings have to be guaranteed with a high degree of confidence (for high-cost or high-risk ECMs).

Energy retrofit projects in the ESCO industry are increasingly recommended to follow International Performance Measurement and Verification Protocol to verify the effectiveness of energy retrofits (Hansen, 2004; IPMVP, 2010). The IPMVP provides three methods for evaluating the success of energy conservation measures (ECMs) in buildings: (a) whole building metering, (b) retrofit isolation, and (c) calibrated simulation. The first two methods use metered energy consumption of the buildings to calculate energy savings incurred from the pre-retrofit to the post-retrofit phase. They are thus not relevant at the decision-making stage. The third method (called 'calibrated simulation) is suitable for analyzing relative benefits of candidate ECM's before they are implemented.

ASHRAE Guideline 14 (ASHRAE, 2002) provides guidelines for how to subscribe to the IPMVP calibrated simulation approach. The guidelines require the use of transient energy simulation models to calculate the 'pre-retrofit' energy consumption of each building based on hourly weather data and detailed building information. The ASHRAE guidelines further require calibrating these simulation models by tuning or adjusting the model parameters so that the energy consumption computed by the model matches the actual consumption of the buildings. A simulation model is deemed 'calibrated' if the calculated monthly energy consumption of the building is close enough to its actual monthly consumption (Coefficient of Variation of Root Square Mean Error (*CVRMSE*) between the two sets of values should be within 15%). Once the energy model of each building is calibrated, they can be exercised for evaluating the effectiveness of a set of energy conservation measures

One of the main limitations of using this approach for a large portfolio of buildings is that transient simulation models can be extremely time-consuming; modeling each building at the detailed level is difficult, if not infeasible, in terms of required detailed level of audits and man-hours from simulation experts. Hence, longitudinal audits tend to be less detailed and rely on macro-scale rather than building-by-building analysis. However, in order to select the most optimum set of retrofits, investment decision-making should be supported by a methodology that enables full evaluation of ECMs in every building within the portfolio. Furthermore, in order to correctly reflect decision-makers' risk attitude, the decision-making should be supported by quantitative risk analysis that inspects the magnitude of risks associated with ECMs.

This paper proposes a scalable modeling methodology that supports large organizations' investments in energy retrofit of buildings. The methodology is based on Bayesian calibration of normative energy models. A normative energy model is a light-weight quasi-steady state model that allows energy flows in a building to be represented with a substantially fewer set of macro-parameters. Because the normative model uses lumped parameters to describe building systems as a whole (as against specifications of each component), their values are highly uncertain compared to the detail simulation model. By using a Bayesian approach for model calibration, we can reduce uncertainty in these parameters, and obtain probability distributions of plausible model parameter values. The calibrated model is used with probabilistic risk analysis for evaluating energy conservation measures. Therefore, additional uncertainties associated with candidate ECMs are also incorporated in the analysis. As an outcome, we are able to quantify energy savings as probability distributions. These probabilistic outputs can be straightforwardly translated to quantify risks of underperformance associated with retrofit options. Tailoring the analysis to quantify the decision-makers' objectives and risk attitude leads to more informed decision-making.

This paper outlines the proposed methodology through an illustrative study.

PROPOSED METHOD

Normative Model

We propose a normative energy model as an alternative modeling method that enables modeling a large portfolio of buildings while greatly alleviating burdens in data collection, model construction, and computation. The normative method defines energy flows in a building with normatively defined parameters that capture all the major characteristics of a building and its components. A widely used normative model is defined in CEN-ISO standards (ISO 13790, 2007; CEN prEN 15203/15315, 2006). The normative model used in this study is the Energy Performance Standard Calculation Toolkit (EPSCT) developed by Georgia Institute of Technology based on the CEN-ISO standards (Lee, 2011).

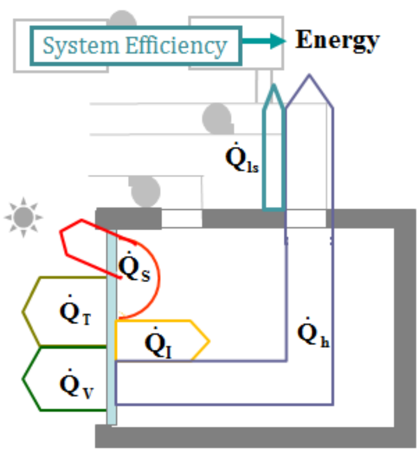


Figure 1. Schematic of the Normative Model

Figure 1 illustrates approximations of energy flows in the normative model for the energy performance calculation. The calculations of heat gains and losses by transmittance, ventilation, solar radiation, and internal gains are aggregated at the boundaries of the building envelope. From these aggregated heat gains and losses, the normative model calculates heating and cooling needs ($Q_{H,nd}$

and $Q_{C,nd}$ respectively) with the use of utilization factors that approximate thermal inertia effects due to the buildings' thermal capacity following equations 1 and 2:

Heating need: $Q_{H,nd} = Q_{ht} - \eta_H Q_{gn}$ (1)

Cooling need: $Q_{C,nd} = Q_{gn} - \eta_C Q_{ht}$

(2)

Where Q_{ht} refers to the total heat losses due to transmission and ventilation, Q_{gn} refers to the total heat gains due to solar and internal gains, and η_H and η_C refer to a utilization factor for heating and cooling respectively. Following the calculation of various energy demands of a building in a similar manner, the model utilizes overall efficiency of the energy generation and the distribution system to calculate the net energy consumption by end use. The aggregate-level representation of systems in a building enormously enhances modeling efficiencies by lightening burdens in the modeling process.

The normative model is similar to other simplified calculation models such as Radiant Time Series method and Heat Balance method (ASHRAE, 2009). These models are essentially grounded on first-order principles of building physics and simplified calculation methods that approximate the dynamic behavior of heat transfer phenomena in a building. However, unlike other simplified methods, normative models provide a set of modeling rules that result in a standard energy performance measure for a building regardless of modelers. Indeed, normative models were initially developed to benchmark buildings in a standardized manner, and thus the modeling process does not involve any modeler's bias.

Owing to the scalability and the transparency of the modeling process, the normative model is a good candidate for large-scale retrofit analysis. Recent work by the author has shown that, when supported with Bayesian calibration, normative models can adequately support retrofit decisions without compromising the accuracy of model outcomes (Heo, 2011).

Bayesian Calibration

We propose a Bayesian approach for calibration since it can quantify uncertainty in model parameters and result in probabilistic analysis of energy retrofits. We follow the mathematical formulation of Bayesian calibration developed by Kennedy and O'Hagan (2001). The statistical formula captures three types of uncertainties: (a) parameter uncertainty in the energy simulation model, (b) discrepancy between the model and the true behavior of the building, and (c) observation errors. We quantify these uncertainties with respect to known conditions *x* under which the observations are taken. The relationship between observations and model outputs follows:

$$y(x) = \eta(x,\theta) + \delta(x) + \varepsilon(x) \quad (3)$$

Observations are denoted by $y(x)$; $\eta(x,\theta)$ denotes energy simulation model outputs computed at known conditions x (e.g. external temperature, known occupancy, etc.) and calibration parameters θ. The energy simulation model may not capture the actual consumption of the building even with the best possible values of the calibration parameters. Indeed, simulation models are based on approximations of the heat transfer processes occurring in a building. This discrepancy between the model and the true physical behavior of the building is represented by $\delta(x,\theta)$. This term prevents over-estimation of calibration values and describes how the energy simulation falls short. Any errors in recording observations (energy consumption in this case) are denoted by $\varepsilon(x)$.

In the Bayesian paradigm uncertain parameters are assigned prior distributions $p(\theta)$ based on some expert judgment, which could be derived from a pool of sources (experiments, surveys, expert knowledge, industry standards, etc). Prior distributions are updated using observations through a formal set up in which the likelihood of obtaining observations from the energy simulation model drives the updating process. As a result, we collect plausible distributions of calibration parameters, also known as posterior distributions.

BAYESIAN CALIBRATION OF NORMATIVE MODEL

We apply the proposed method to evaluate energy retrofits for a four-storey office building located in London, UK. The three floors above the ground consist of open offices and meeting rooms while the basement floor includes open offices and a copy room with heavily loaded printers. The building has two condensing boilers that provide hot water to radiators for space heating. All floors except the basement are naturally ventilated without any auxiliary cooling. Due to high equipment density, the basement floor is air-conditioned. Electric lighting is provided by T-8 high frequency fluorescents, and domestic hot water is supplied by decentralized electric heaters. The following sections describe the full process of calibrating the normative model of this building with monthly gas and electricity utility bills.

Step 1: Prior Uncertainty Quantification

As the first step, we quantify uncertainties in model parameters based on values published in the literature (e.g., technical reports, industry reports, standards) and onsite surveys. Table 1 lists the uncertain parameters in the normative model and their uncertainty ranges. Chapter 3 in (Heo, 2011) provides detailed information on sources of these parameters.

Table 1. Uncertain Parameters and Their Ranges

Model Parameters	Base	Min	Max
Thermal Properties			
roof U value (W/m²·K)	0.51	0.46	0.56
roof solar absorptance	0.40	0.34	0.46
roof Emissivity	0.90	0.86	0.94
wall U value (W/m²·K)	0.52	0.47	0.57
wall solar absorptance	0.40	0.34	0.46
wall emissivity	0.90	0.86	0.94
window U value (W/m²·K)	3.16	2.84	3.47
window solar transmittance	0.84	0.76	0.92
window emissivity	0.84	0.82	0.85
envelope heat capacity(kJ/m²·K)	260	160	275
Internal Loads			
appliance power multiplier	1	0.8	1.5
lighting power density (W/m²)	15	11	19
occupant metabolic rate (W)	80	70	130
Control			
indoor heating temperature	22	20	24
indoor cooling temperature	24	22	26
Ventilation			
infiltration rate (1/h)	0.50	0.10	1.25
discharge coefficient	0.68	0.60	0.75
intercept c[1]	-2.92	-3.80	-2.09
Heating System			
generation efficiency	0.86	0.84	0.88
distribution loss factor	0.08	0.06	0.15
Cooling System			
mean partial load factor	0.84	0.83	0.96
distribution loss factor	0.06	0.02	0.15
DHW System			
generation efficiency	0.91	0.88	0.95

Step 2: Parameter Screening

We use the Morris method (Morris, 1991) to rank uncertain parameters with respect to their effects on the total energy consumption of the building. The Morris method first discretizes the parameter space: it divides each parameter interval into a chosen number of levels that correspond to a pre-selected number of quantiles of the corresponding parameter. This forms a grid of values in the parameter space. After starting from an initial fixed point in that grid, the move to the next step is done by changing one parameter value at a time while the other parameter values stay the same; there is no diagonal move, only moves along axes. Eventually, this allows moves in all directions. At the end of each step, we obtain a number: the elementary effect equal to the change in the model outcome as the result of the change in one input value. At the end of the entire procedure, we obtain distributions of elementary effects for all parameters. The mean value of each distribution represents the overall importance of an individual parameter. Table 3 ranks the uncertain parameters by their relative importance. The parameter Intercept c for windows open is the most dominant parameter, followed by indoor heating temperature, infiltration rate, appliance power density multiplier, and discharge coefficient. We selected the five top ranked parameters for the calibration.

Table 2. Ranking of Uncertain Parameters

Rank	Model Parameter
1	Intercept c for windows open
2	Indoor heating temperature
3	Infiltration rate
4	Appliance power density multiplier
5	Discharge coefficient
6	Envelope heat capacity
7	Heating distribution loss factor
8	Lighting power density
9	Heating generation efficiency
10	Window U-value

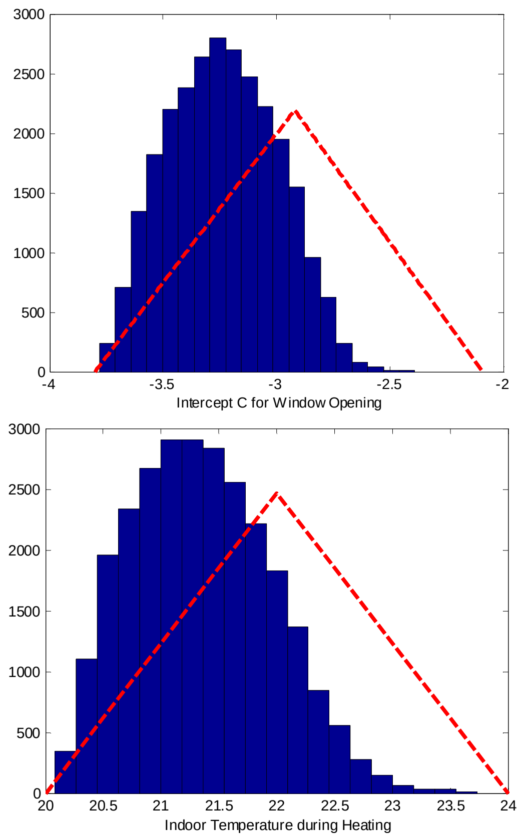
Step 3: Model Calibration

The calibration requires three types of inputs: (1) prior density functions of calibration parameters, (2) energy model outcomes exploring the calibration parameter space, and (3) monthly utility bills. We assigned the prior density functions with a triangular distribution based on the quantified values in Table 1. For the parameter-space exploration, we used the Latin Hypercube Sampling (Wyss, 1998) since it can efficiently explore the parameter space with a much smaller sample size. For the observation data, we utilized monthly gas and electricity bills of the building covering five years.

Figure 2 shows the posterior distributions of the five calibration parameters compared with their prior distributions. For the intercept c, the posterior distribution shifts toward the lower bound. This change suggests that the proportion of open windows

[1] 'intercept c' is a term from a statistical ((logit) model that calculates the percentage of windows open as a function of outdoor temperature (Rijal, 2007). Lower values in the given range indicate a smaller proportion of open windows.

in this case is smaller than the average in UK buildings. For the indoor temperature during heating, the posterior distribution shifts to the lower bound by around 1°C. This update indicates that spatially-averaged indoor temperatures during heating in reality is most likely to be lower than the set-point temperature (22°C) due to vertical and horizontal stratifications in spaces. For the infiltration rate, the posterior distribution tells that the building is leakier than average UK buildings. For the appliance power density multiplier the posterior distribution is refined the most from the prior distribution. The expected appliance power density in reality is most likely 20% higher than our prior estimates, and the spread of uncertainty is significantly reduced. On the contrary, the posterior distribution of the discharge coefficient does not change much from the prior distribution.



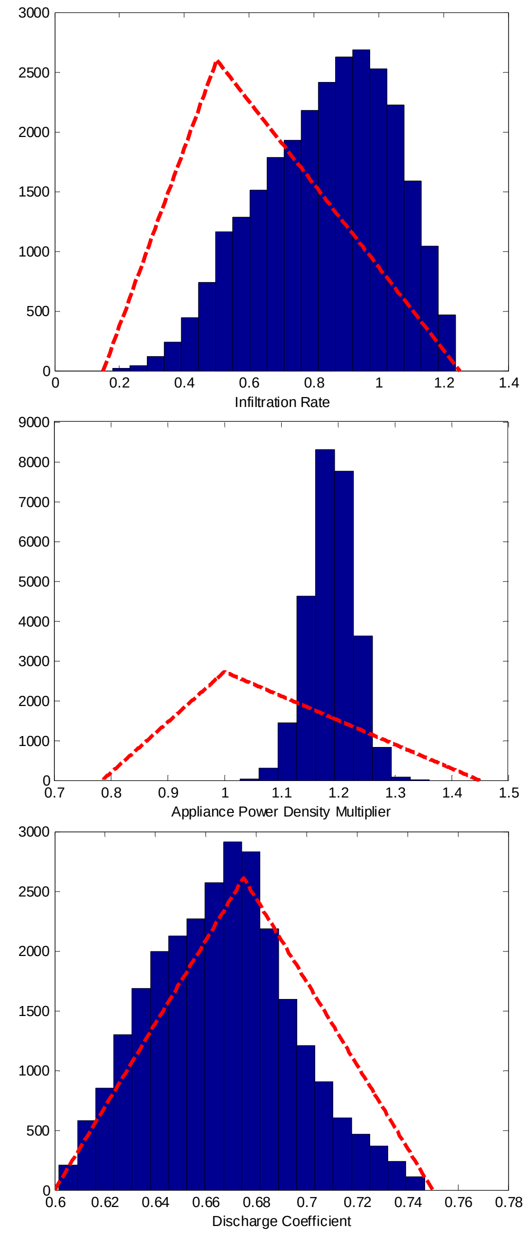


Figure 2. Posterior Distributions of the Five Calibration Parameters (Blue - Posterior, Red - Prior)

<u>Step 4: Model Validation</u>

We evaluate the validity of the calibrated model in terms of agreements between predicted and monitored energy uses. ASHRAE Guideline 14 (2002) defines a validation criterion in terms of the coefficient of variation of the root mean square error (*CVRMSE*); it stipulates that *CVRMSE* should range within 15% when monthly energy consumption data is used for calibration. Table 3 shows *CVRMSE* values of the uncalibrated and the Bayesian calibrated model. The comparison tells that Bayesian calibration improves the accuracy of the baseline model by reducing the *CVRMSE* values by about 65 percent for both gas and electricity consumption. The remaining inaccuracies in the calibrated model are quantified as uncertainties in the posterior distributions of the model parameters.

Table 3. Validation Measures for Uncalibrated and Bayesian Calibrated Model

	CVRMSE	
	Gas	Electricity
Uncalibrated model	0.95	0.38
Calibrated model	0.34	0.14

RETROFIT DECISION-MAKING

We exercised the calibrated normative model to evaluate six ECMs: (1) insulation upgrade, (2) window replacement, (3) air-tightening of the building envelope, (4) boiler upgrade, (5) air-conditioning upgrade, and (6) lighting upgrade. Table 4 summarizes model parameters associated with each ECM and their uncertainty ranges: refer to (Heo, 2011) for the detail description about the uncertainty estimates. Table 5 shows the cost of these upgrades, including labor and equipment costs (cost estimates are taken from BCIS, 2010). We set the gas price at 2.4 pence/kWh and the electricity price at 8.6 pence/kWh (DECC, 2010).

Table 4. Uncertain Parameters for the Six ECMs

Parameters	Base	Min	Max
ECM 1:			
U-value (W/m²·K)	0.30	0.27	0.33
ECM 2:			
U-value (W/m²·K)	1.53	1.38	1.68
Solar transmittance	0.77	0.75	0.79
Emissivity	0.05	0.04	0.06
ECM 3:			
Infiltration reduction (%)	11	1	31
ECM 4:			
Boiler efficiency	0.97	0.95	0.98
ECM 5:			
Mean partial load factor	0.84	0.83	0.96
ECM 6:			
Lighting power density (W/m²)	13.2	11.6	14.8

Table 5. Investment Cost Estimates of the Six ECMs (in 1000£)

ECMs	Base	Min	Max
ECM 1	11	10.5	12
ECM 2	55	52	58
ECM 3	7.2	6.8	7.5
ECM 4	3.4	3.2	3.6
ECM 5	3.2	3.0	3.3
ECM 6	5.7	5.4	6.0

The cost effectiveness of ECMs is typically evaluated using measures such as cost-benefit ratios and simple payback time (Goldman, 2002). We selected Simple Payback Time (SPT), which is defined as investment costs divided by annual energy cost savings. For each ECM, we use the calibrated model to calculate the probability distribution of its SPT using the uncertainty ranges in ECMs (shown in Tables 8 & 9).

Table 6 provides the statistical summary of the SPT distributions for the six ECMs. The mean of the distributions denote the average value of SPT whereas the standard deviation quantifies the magnitude of uncertainty (risk) associated with the mean SPT. In terms of the mean values, air-conditioning upgrade (ECM 5) will be most effective in terms of payback, followed by boiler (ECM 4) and lighting upgrade (ECM 6). In general, in the case of this building, envelope-related ECMs will not yield sufficient energy savings to justify the investment. In terms of magnitude of uncertainty, air-conditioning upgrade (ECM 5) is still the safest choice whereas the payback period for air-tightening (ECM 3) is more uncertain. The high risk associated with air-tightening is expected since its performance depends on a diverse set of highly uncertain factors such as workmanship, outdoor weather conditions, and building operation conditions.

Table 6. Statistical Summary of the SPT distributions for the six ECMs

ECMs	Mean	Standard Deviation
ECM 1	26.8	2.3
ECM 2	86.9	8.7
ECM 3	88.6	89.8
ECM 4	6.1	0.8
ECM 5	4.4	0.5
ECM 6	9.0	5.6

These distributions can be further translated into a single value that captures a decision-makers' risk attitude. In the ESCO industry, energy-efficiency projects are usually delivered through energy performance contracts that guarantee savings. The guarantee can be quantified to 95-quantile of the distribution of SPT. Table 7 lists the ranking of the six ECMs. The most preferred ECM is air-conditioning upgrade, followed by boiler upgrade and lighting upgrade.

Table 7. Ranking of the Six ECMs

	Ranking

ECM 1: insulation upgrade	4
ECM 2: window replacement	5
ECM 3: infiltration air-tightening	6
ECM 4: boiler upgrade	2
ECM 5: air-conditioning upgrade	1
ECM 6: lighting upgrade	3

DISCUSSIONS

Weather Data for Calibration

Generally it is better to use actual weather data for calibrating simulation models (ASHRAE, 2002). No doubt, actual weather data covering the same period as the metered energy consumption data provides the most reliable scenario for calibration. However, actual weather data is not always accessible. Hence, we investigate if the TMY data is good enough for the calibration.

Figure 3 plots observed monthly outdoor monthly temperatures over a three-year period against TMY temperatures. The plot demonstrates that the TMY temperatures well coincide with the average of the three-year observations. This implies that TMY data is good enough for the calibration when the calibration is based on monthly utility data.

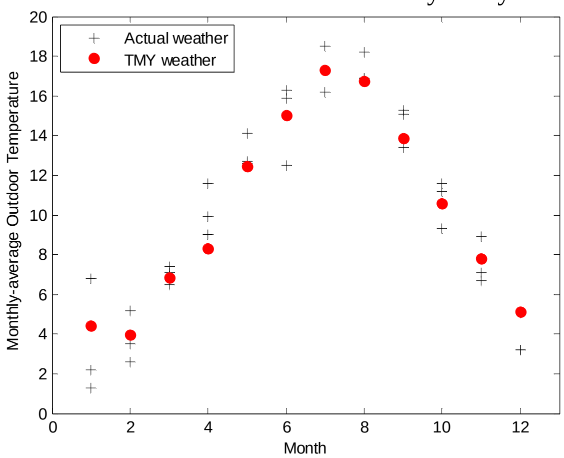


Figure 3. Three-year Actual Temperatures against TMY Temperatures

Effects of Prior Estimates on Calibration Results

Bayesian calibration updates prior estimates of calibration parameters given observed data on building performance. Ideally, a large number of observations at various levels (e.g., utility data, sub-metered data) can result in similar posterior distributions even without good prior estimates. However, in reality, metered energy consumption data (observations) is often only available for a limited period. Hence, it is expected that calibration results can be considerably influenced by the prior estimates. In order to investigate the effects of prior estimates on calibration results, we calibrate the model with two different prior distributions:

1. Prior 1: increase the upper and lower limits of the original prior distributions by 50% while maintaining the distribution shape
2. Prior 2: use uniform distributions within the limits specified for the original prior distributions.

Figure 4 overlays posterior distributions from Prior 1 (red color) against those derived using the original prior estimates (black color). Increasing the range of prior estimates results in wider ranges of the posterior distributions because the observations are insufficient to curtail wider uncertainty assigned in the prior distributions. However, except the spread, the two posterior distributions have similar distribution characteristics: both the distribution shapes and the expected values are similar. Figure 5 shows posterior distributions from Prior 2 (blue color) in comparison to the posterior distributions derived from the original prior estimates (black color). Change in the distribution shape significantly impacts the posterior distributions. With the uniformly distributed priors, the resulting posterior distributions are strongly weighted toward one bound. But, both the posteriors shift toward the same bound due to the same likelihood function given the monitored data. Particularly for the appliance power density, the three posteriors (Original, Prior 1, and Prior 2) are quite similar despite the different priors since the monitored data contains enough information to derive the posterior estimate.

In conclusion, Bayesian calibration can correct (update) our prior beliefs about true parameter values, but its results still significantly depend on the prior estimates. This relationship implies that prior estimation is important. One point to be emphasized is that prior estimates are set up based on collective expert knowledge and change only when there is additional expert knowledge in the process of prior uncertainty quantification. Given prior estimates are further refined through Bayesian calibration.

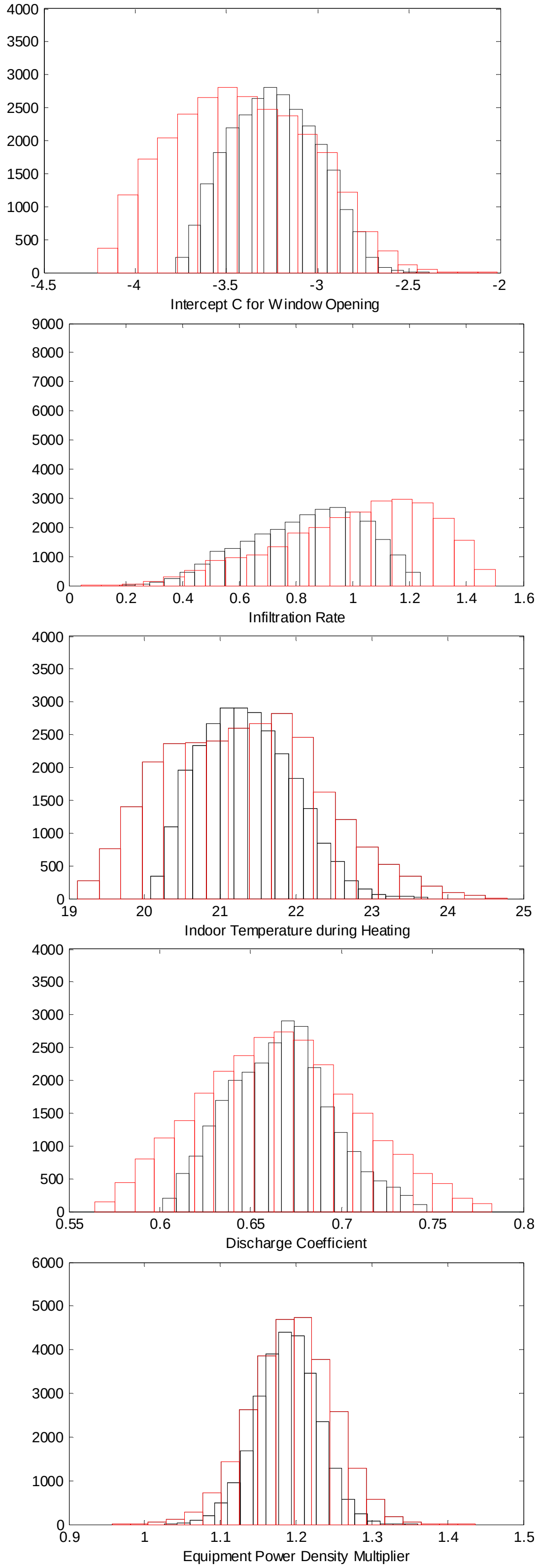


Figure 4. Posterior Distributions of Calibration Parameters (black - from original prior estimates, red - from wider ranges of prior estimates)

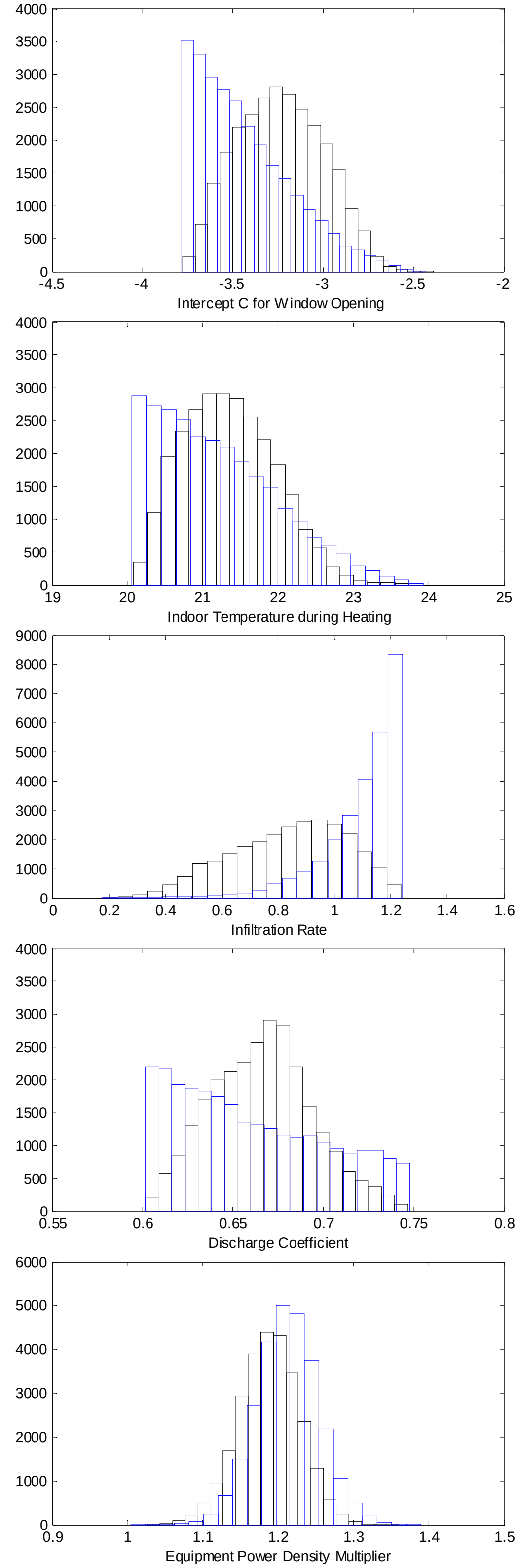


Figure 5. Posterior Distributions of Calibration Parameters (black - from original prior estimates, blue - from uniformly distributed prior estimates)

CONCLUSIONS

The paper proposes a scalable methodology that is suitable for large-scale retrofit analysis. The methodology is based on Bayesian calibration of normative models. The normative model can efficiently evaluate a large set of buildings to identify those that need energy-efficiency improvements and extensively assess feasible ECMs for identified buildings. In addition, Bayesian calibration results in quantification of risks associated with ECMs while taking into account uncertainties in the modeling process.

ACHKNOWLEDGEMENT

This study was partly funded by the Energy Efficient Cities Initiatives (EECi) at University of Cambridge and the NSF-EFRI SEED grant for the project, "Risk-conscious Design and Retrofit of Buildings for Low Energy", awarded to Georgia Institute of Technology.

REFERENCES

ASHRAE 2002. *ASHRAE Guideline 14-2002: measurement of energy and demand savings*. Atlanta: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.

ASHRAE 2007. *ASHRAE Handbook - HVAC applications*. Atlanta: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.

ASHRAE 2009. *ASHRAE Handbook – Fundamentals*. Atlanta American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.

BCIS 2010. *BCIS Wessex alterations & refurbishment price book*. Building Cost Information Service of Royal Institute of Chartered Surveyors.

CEN, prEN 15203/15315. 2006. Energy performance of buildings – overall energy use, CO2 emissions and definition of energy ratings.

DECC 2010. Electricity market assessment. *Technical Report*, Department of Energy and Climate Change.

FEMP. 2011. Federal Energy Management Program. http://www1.eere.energy.gov/femp/financing/espcs.html

Goldman, C. A., Osborn, J. C., Hopper, N. C., and Singer, T. E. 2002. Market trends in the U.S. ESCO industry: results from the NAESCO database project. *Technical Report*, Lawrence Berkeley National Laboratory.

Hansen, S. J., and Brown, J. W. 2004. *Investment Grade Energy Audit: making smart energy choices*. Fairmont Press, Inc, Lilburn, GA.

Heo, Y. 2011. Bayesian calibration of building energy models for energy retrofit decision-making under uncertainty. *Ph.D. Thesis*, Georgia Institute of Technology.

IPMVP 2010. International Performance Measurement and Verification Protocol: concepts and options for determining energy and water savings volume 1. Efficiency Valuation Organization.

ISO 13790. 2008. Energy performance of buildings - calculation of energy use for heating and cooling.

Kennedy, M. C., and O'Hagan, A. 2001. Bayesian calibration of computer models. *Journal of the Royal Statistical Society, Series B*, 63(3):425-464.

Lee, S. H., Zhao, F., and Augenbroe, G. 2011. The use of normative energy calculation beyond building performance rating systems. *Proceedings of the 12th International Building Performance Simulation Association Conference*, Sydney Australia

Morris, M. D. 1991. Factorial sampling plans for preliminary computational experiments. *Technometrics*, 33(2):161-174.

Rijal, H. B., Tuohy, P., Humphreys, M. A., Nicol, J. F., Samuel, A., and Clarke, J. (2007). Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. *Energy and Buildings*, 39:823-836.

Satchwell, A., Goldman, C., Larsen, P., Gilligan, D., and Singer, T. (2010). A survey of the U.S. ESCO industry: market growth and development from 2008 to 2011. *Technical Report*, Lawrence Berkeley National Laboratory.

Wyss, G., and Jorgensen, K. 1998. *A user's guide to LHS: Sandia's Latin Hypercube Sampling Software*. Sandia National Laboratories, Albuquerque, NM.