SCALABLE METHODOLOGY FOR ENERGY EFFICIENCY RETROFIT DECISION ANALYSIS

Yeonsook Heo[1,2], Fei Zhao[1], Sang Hoon Lee[1], Yuming Sun[1], Jinsol Kim[1], Godfried Augenbroe[1],
Diane Graziano[2], Leah B. Guzowski[2], and Ralph T. Muehleisen[2]
[1]College of Architecture, Georgia Institute of Technology, Atlanta, GA
[2]Decision and Information Sciences Division, Argonne National Laboratory, Lemont, IL

ABSTRACT

This paper introduces a scalable methodology that supports energy retrofit decision-making at two levels. The methodology is based on normative energy models to provide objective and transparent benchmarking and assessment. The aggregate-level analysis evaluates the effectiveness of policy and business plans on energy savings by benchmarking the energy performance of a collection of buildings and projecting the effects of different retrofit scenarios over time. The individual-level analysis supports risk-conscious decision-making for building stakeholders by providing explicit information about the energy performance risks associated with specific retrofit alternatives. This paper describes model results for a small set of commercial buildings in the Chicago Loop and findings relevant to the method's application.

INTRODUCTION

Retrofitting existing buildings to achieve higher energy efficiency is one of the best ways to save energy and reduce CO_2 emissions. In 2008, the U.S. commercial building sector consumed 8.6 Quads of delivered energy, generating more than 5,800 million metric tons of CO_2 (DOE, 2010). This energy is predominantly consumed by existing buildings. According to the Commercial Buildings Energy Consumption Survey (EIA, 2003), the floor area of existing buildings totaled 71.6 billion square feet in comparison to the 1.6 billion square feet of newly constructed buildings in 2003.

In their seminal report, McKinsey & Company estimated an efficiency potential of 1.1 Quads in energy savings in retrofitting existing private and public commercial buildings, not considering plug loads (Granade et al., 2009). In a meta-analysis on retro-commissioning projects for 643 existing buildings, Lawrence Berkeley National Laboratory found that existing buildings contain energy inefficiency problems in heating and cooling plants, distribution systems, lighting systems, and building envelope that, when retrofitted, yielded a median energy savings of 16% (Mills, 2009). These studies

and energy data trends point to energy retrofits of existing buldings as essential to achieving reduction targets in energy consumption and CO_2 emissions from the commercial building sector.

In response to this need, federal, state, and city governments have established retrofit initiatives and programs to promote the reduction of energy consumption by the building sector. President Obama launched the "Better Buildings Initiative" with a target of reducing energy consumption by 20% in commercial buildings by 2020 through cost-effective retrofit interventions (White House, 2011). In response to the initiative, organizations so far have committed to enhancing the energy performance of 1.6 billion square feet of floor area (EERE, 2012). At the city scale, Chicago initiated a Chicago Climate Action Plan to achieve 30% energy reduction by 2020 through retrofitting 50% of existing commercial and residential buildings in Chicago (CCAP, 2011).

Reaching these targets will rely on the decisions made by public agencies in planning policy and incentives, utilities in executing energy efficiency programs, financiers in providing capital to the market, energy service companies in developing their business models, and building owners in investing in energy efficiency retrofits. These stakeholders face decisions that span individual buildings, portfolios of buildings, and large aggregates of buildings and are constrained by various degrees of available information about each building. Their decisions will be based on their evaluations of the cost, benefits, and risks associated with the implementation of energy efficiency technology. Currently, there are gaps in the analytic tools available to support these decisions.

The energy service company (ESCO) business model highlights one gap in decision support. For their retrofit projects, ESCOs typically perform an audit to evaluate the potential energy savings of feasible energy efficiency measures (EEMs). The audit involves collecting data about actual building physical and operational characteristics, establishing an energy baseline of the building, and evaluating the effects of EEMs. Moreover, ESCOs need to quantify risks

associated with EEMs because their service is based on performance contracting that guarantees certain savings and compensates the customer for what has not been realized according to the contract clauses. In practice, they often rely on their historical experience and expert judgment to estimate energy-saving potential of candidate EEMs and quantify their underperformance risks. The rule-of-thumb approach based on expertise tends to limit the set of EEMs to those with proven records while not properly evaluating all possible EEMs including advanced retrofit technologies. Properly supporting energy retrofit decisions can be realized by a formal method that can evaluate all feasible EEMs while accounting for all major sources of uncertainty.

Improving the energy efficiency of a large set of buildings requires a new generation of scalable and adaptable modeling methodologies. The new retrofit analysis framework is based on normative energy models that greatly enhance the cost-effectivenss of the analysis process in terms of data collection, modeling, and computation. The speed and ease of normative modeling enables analysis in the aggregate using consistent, proven calculations for energy performance of the individual buildings and retrofit technologies.

METHODOLOGY

This study proposes a scalable methodology as the core of a retrofit decision-making environment to support two distinct levels of analysis:

- Aggregated Level: This level targets the support of commercial and policy-makers' decision-making by evaluating the effectiveness of business plans or policy in reducing energy consumption. This analysis inspects buildings in the large portfolio and projects the effects of different energy improvement scenarios over time. At this level, one can decide which level of intervention in certain categories of buildings is necessary to reach certain overall energy improvement targets.

- Individual Level: This level targets the support of individual building stakeholders' decision-making by selecting the right mix of EEMs while adequately recognizing risks associated with them. This analysis can indicate whether certain interventions satisfy the mandate or incentive to obtain a certain energy savings. In addition, this analysis can support establishing performance contracts by providing explicit information about risks in failing to realize the expected performance from EEMs.

At both levels, all decisions are supported by building energy models based on actual information about the buildings in the portfolio. The main driver of the methodology is the choice of normative energy models, which are particularly suited for scalable, transparent, and state-of-the-art energy benchmarking and assessment over time. In addition, the individual level calibrates normative energy models such that resulting models can reliably project actual savings while quantifying risks associated with testing EEMs. The section below summarizes the major features of the normative model and Bayesian calibration, and elaborates how the two analysis levels take different approaches to supporting their distinct decision-making contexts.

Normative Model

We propose a normative energy-modeling approach for assessing energy use in groups of buildings. Relative to standard building energy simulation approaches, this approach requires significantly less effort in data collection, model construction, and computation. The European Committee for Standardization (CEN) defines the recipe according to a set of normative statements about functional building category, building usage scenario, system efficiency, etc., for calculating and rating the energy performance of new and existing buildings. Its simplicity and unified modeling assumptions allow this approach to assess building energy performance in a standardized and transparent way (Hogeling and Dijk, 2008). The normative calculation method does not intend to "predict" the actual use of the building but rather provides an objective measure to compare the energy performance of buildings.

The use of the normative calculation method offers two major strengths. First, the method greatly enhances the cost-effectiveness of the modeling process, since it requires a much smaller set of parameter data to capture major characteristics of a building and systems. Second, the method does not involve modelers' bias, since it uses all normative assumptions and usage scenarios. Hence, the normative model promises to be a good candidate for a scalable approach for large-scale benchmarking and retrofit studies.

Currently, the normative calculation method is widely used to rate building energy performance in many European countries 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 normative models with simulation models for 30 campus buildings helped validate the accuracy of the normative calculation for predicting building energy performance (Lee, 2012). Beyond rating, a recent research project by Heo et al. (2012) showed the applicability of the normative calculation method to represent a building as operated and correctly evaluate

candidate EEMs for retrofit projects when the model is adjusted by calibration.

Following the CEN-ISO standards, Georgia Institute of Technology developed an Energy Performance Standard Calculation Toolkit (Lee et al., 2011). The toolkit calculates thermal energy demands for heating and cooling on the basis of the monthly quasi-steady-state method. Thermal energy demand takes account of heat 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 can assess the energy efficiency of the architectural design. The toolkit also calculates energy consumption by the end uses: heating, cooling, ventilation, lighting, pumps, and domestic hot water (DHW) systems. The calculation takes into account heating and cooling losses through the distribution and heating and cooling system efficiency to determine the energy for each energy carrier. From the calculated delivered energy, the toolkit derives primary energy and CO_2 emissions, considering the specific details of the energy supply utilities and network and tracking the generation and emission efficiency of the local mix of utilities.

Bayesian Calibration

We apply the Bayesian approach as a new calibration method for the normative energy model to quantify uncertainty in calibration parameters in the form of probability distributions. Bayesian calibration can enhance the reliability of predictions by using calibration outcomes as a set of plausible baseline scenarios in which candidate EEMs are evaluated and by yielding 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 true values of calibration parameters is quantified as prior density functions $p(\theta)$. The prior distributions are updated, given monitored 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 monitored data. As the result of Bayesian calibration, we obtain posterior distributions of calibration parameters $p(\theta|y)$:

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

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 collected by 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 aceptance 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 detail elsewhere (Heo et al., 2012).

EEM Database

We have used a database for common retrofit technologies in the market and grouped them following the hierarchy of Category, EEM, and Retrofit Technology. The database includes 30 retrofit technologies for envelope, HVAC, lighting, DHW, appliance, and building energy management systems. The database further defines the input parameters adjustments that are required to represent the retrofits in the energy model. The details have been summarized by Zhao et al. (2011).

Retrofit Decision-Making Environment

Figure 1 shows the components and interfaces of the overall system in the Retrofit Decision-Making Environment. The two level analyses are based on normative energy models, but have different approaches in treating normative models and translating decision-making contexts.

The aggregate-level layer strictly follows the normative scenarios and assumptions in the CEN-ISO standards to benchmark buildings and relatively evaluate the effectiveness of retrofit scenarios. This layer uses the normative model without calibration to support the deterministic analysis. This approach arises from our hypothesis that the normative model without calibration is still adequate for the comparative study.

On the other hand, the individual-level layer tackles the questions of what energy savings are achievable from EEMs and at what level of confidence. Hence, we apply two additional steps in this layer: (1) operational adjustment based on site visits and measurements, and (2) parameter estimation based on the Bayesian approach, such that the resulting baseline model can accurately reflect a building as operated and reliably predict potential energy savings from candidate packages of EEMs. This layer no longer follows normative scenarios for building usage and operation, but makes operational adjustments to the model parameters such that the model is in alignment with actual building operation. Furthermore, this layer calibrates the model on the basis of the Bayesian

approach to enhance the reliability of the baseline model and quantify uncertainty in the energy use predictions. Then, we incorporate uncertainties associated with the EEMs to provide probabilistic predictions of retrofit scenarios.
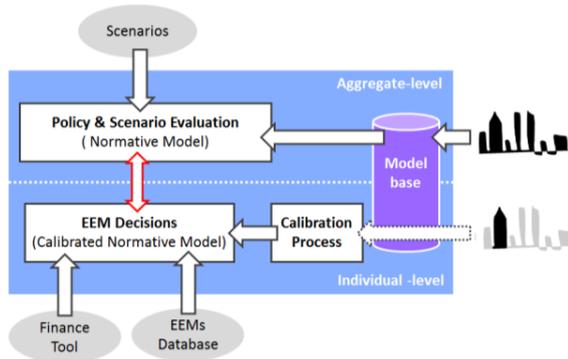

Figure 1 Scheme of the analysis environment

AGGREGATE-LEVEL ANALYSIS

This section illustrates the proposed aggregate-level analysis process using a pilot pool of seven office buldings in the Chicago Loop. We illustrate the use of normative energy modeling for (1) benchmarking building energy performance; and (2) evaluating alternative retrofit scenarios.

The aggregate analysis capability will be useful to stakeholders with interests in large numbers of buildings, as examples: policy analysts with access to building data collected through city mandates; owners and managers of building portfolios; utilities in designing energy efficiency programs; and energy service companies for market development. Compared to less rigorous energy savings evaluation methods, the normative energy model allows the unique characteristics of the individual buildings and the interactions of systems within a building to be reliably factored into the assessments of portfolio investments.

Benchmark Buildings

With a normative energy model, one is able to rate buildings without performing deep dynamic simulation. We use a standardized expression of performance, referred to as the energy performance coefficient (EPC), to benchmark individual buildings by their performance with respect to thermal need (denoted as EPC_{need}), delivered energy (EPC_{del}), and primary energy (EPC_{pri}).

EPCs are an objective measure of energy performance to rate buildings in a standardized manner and identify those with the greatest opportunity for energy efficiency improvement. Equation 1 defines the calculations of EPCs:

$$EPC = \frac{Energy\ Calculated}{Energy\ Referenced} \qquad (1)$$

Energy Calculated is the whole-building annual energy use calculated by the normative model, and *Energy Referenced* is a reference value representing the annual energy use for a functionally equivalent building of the same type. There are various ways of defining such a reference value. For our pilot example, we select the building with the best energy performance (Building 1) from our seven building sample to serve as a reference for the EPCs. In practice, the reference values would be derived from a statistical analysis of all buildings in the portfolio or from national-level databases and ratings, such as Energy Star ratings, CBECS data, or those under development by the DOE (Asset Rating and Buildings Performance Database programs) (DOE, 2012a; DOE, 2012b).

Table 1 shows EPCs calculated for each the seven case buildings. These data show a significant range of energy performance amongst the seven buildings and highlight those buildings with the greatest thermal loads and least efficient energy systems. The EPC_{need} and EPC_{del} benchmark data reveal that possible improvements could be achieved by upgrading both the building envelopes and the mechanical and lighting systems in the buildings.

The value of benchmarking with the normative energy model is the capability to evaluate the performance of buildings independent of differences in how they are occupied or operated. Comparison of normative energy model benchmark rankings against those based on measured energy consumption (for example Energy Star Portfolio Manager) will provide a deeper understanding of energy use in the buildings and the focus areas for energy improvements.

Table 1 EPCs of seven case buildings

BUILDING	EPC_{need}	EPC_{del}	EPC_{pri}
Building 1	1.0	1.0	1.0
Building 2	1.8	1.6	1.9
Building 3	1.5	1.8	1.8
Building 4	1.5	1.8	1.4
Building 5	1.3	1.4	1.3
Building 6	1.5	1.5	1.4
Building 7	1.3	1.3	1.1

Retrofit Scenario Analysis

In addition to benchmarking, the normative energy modeling methodology can be used to study retrofit scenarios, testing the effects of a mix of retrofit technologies on certain groups of buildings for energy savings. First, we design a set of retrofit palettes by selecting specific retrofit technologies. Then, we associate different palettes with different sets of buildings to create retrofit scenarios. For demonstration purposes, we selected all seven buildings for energy efficiency improvements and applied two retrofit

SimBuild
2012

palettes (shown in Table 2), which consist of both envelope-related and system-related EEMs, to all. Hence, we have two retrofit scenarios: (1) retrofit palette 1 on the seven buildings and (2) retrofit palette 2 on the seven buildings.

Table 2 Specification of the two retrofit palettes

PALETTE	ENERGY EFFICIENCY MEASURE
1	High-efficiency Chiller / Energy Recovery Occupancy Sensor / Infiltration Reduction /
2	High-efficiency Chiller / Energy Recovery Occupancy Sensor / Infiltration Reduction / Triple Glazing, Low-e

Using the normative energy model, we evaluated the two retrofit scenarios in relation to the Chicago Climate Action Plan target of 30% energy use reduction. Figure 2 shows that scenarios 1 and 2 reduce the total delivered energy expressed as Energy Use Intensity (EUI) by 10% and 20%, respectively, in comparison to the baseline. The results suggest the need for more aggressive retrofit strategies to achieve the Chicago Climate Action Plan (green bars).
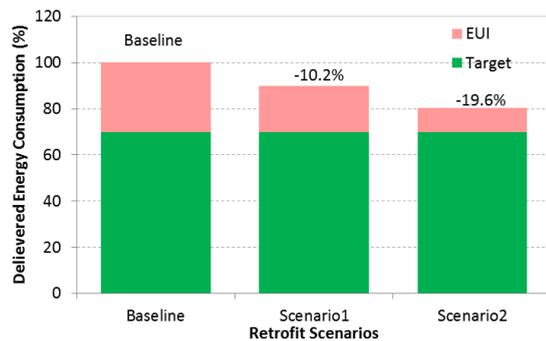

Figure 2 Effects of retrofit scenarios on energy consumption at aggregate level

INDIVIDUAL-LEVEL ANALYSIS

This section illustrates the proposed individual-level analysis process through a case study. In the individual-level analysis, one can closely inspect the energy savings potentials of EEMs and their associated performance risks. As a result, decision-makers can rationally select EEMs according to their objectives and risk attitude.

Quantify Uncertainties in Model

We quantified uncertainties in model parameters of the normative model. Uncertainty information is used to objectively identify dominant parameters and derive calibration results. Table 3 summarizes the base, the minimum, and the maximum value for uncertain model input parameters on the basis of industry reports, standards, and technical reports.

Table 3 Range of uncertainty in model parameters

PARAMETER	BASE	MIN	MAX
Roof U value (Btu/h·ft²·°F)	0.09	0.08	0.10
Roof Solar Absorptance	0.63	0.43	0.83
Roof Emissivity	0.91	0.87	0.85
Wall U value (Btu/h·ft²·°F)	0.09	0.08	0.10
Wall Solar Absorptance	0.63	0.43	0.83
Wall Emissivity	0.91	0.87	0.95
Window U value (Btu/h·ft²·°F)	0.32	0.29	0.36
Window Solar Transmittance	0.22	0.16	0.26
Envelope Heat Capacity (Btu/ft²·°F)	0.81	0.60	1.02
Heating Temperature—Occupied	72	68.5	75.5
Heating Temperature—Unoccupied	65	61.5	68.5
Cooling Temperature—Occupied	70	66.5	73.5
Cooling Temperature—Unoccupied	75	71.5	78.5
Occupancy Density (ft²/person)	208	46	245
Occupant Metabolic Rate (W/person)	80	70	130
Appliance Power Density (W/ft²)	1.63	0.56	3.16
Lighting Power Density (W/ft²)	1.34	1.11	1.58
Cooling System Mean Partial Load Index	0.84	0.83	0.99
Cooling Distribution Loss Factor	0.00	0.00	0.15
DHW System Efficiency	0.91	0.88	0.95
DHW Distribution System Efficiency	0.60	0.54	0.66
Infiltration Rate (ACH)	0.15	0.10	1.25

Identify Dominant Parameters

We applied the Morris method (Morris, 1991) to identify the most influential parameters with respect to their effect on the predicted energy use distribution. This step aims to minimize the role of expert judgment in the selection of calibration parameters. Figure 3 plots elementary and interaction effects of 22 uncertain parameters. The elementary effect refers to the average of the changes in the model outcome as the result of the change in one input value. The interaction effect refers to the standard deviation of the changes. In this example, infiltration rate is the most dominant parameter, followed by appliance power density, heating temperature during the occupied period, and heating temperature during the unoccupied period. We observed that those four parameters have by far the greatest impact on energy use, and selected those four parameters for calibration.
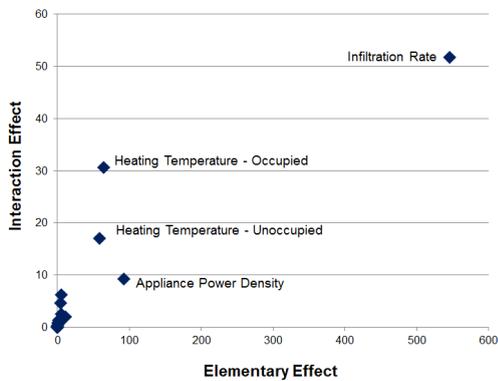
Figure 3 Elementary effects of uncertain parameters

Calibrate Selected Parameters

We calibrated the four dominant parameters in the normative energy model with five-year monthly utility bills. The calibration requires three types of inputs: (1) monthly utility bills, (2) prior density functions of calibration parameters, and (3) energy model outcomes exploring the calibration parameter space. The Latin Hypercube Sampling technique is used to explore the parameter space efficiently with limited samples (Wyss and Jorgensen, 1998).

Figure 4 shows the calibration results (blue histograms) of the four parameters against the prior beliefs (red lines). The posterior distribution of infiltration rate is towards the lower bound, and greatly reduces uncertainty from the prior distribution. In contrast, the appliance power density is likely to be higher than expected. The heating temperature during the occupied hours is likely to be 2°F higher than the expected prior estimate, while that during the unoccupied hours does not change much from the prior estimate.
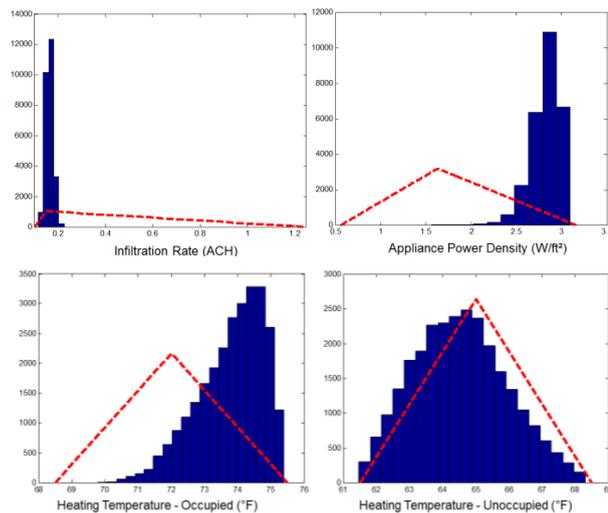

Figure 4 Calibration results for the four parameters
(prior – red, posterior – blue)

Then, we validated the calibrated model against the five-year utility data. Figure 5 compares energy uses calculated from the uncalibrated model and the calibrated model against measured energy uses. The comparisons demonstrate that the calibrated model enhances the reliability of the model by reducing the coefficient of variation of the root mean squre error (CVRMSE) from 0.46 to 0.25.
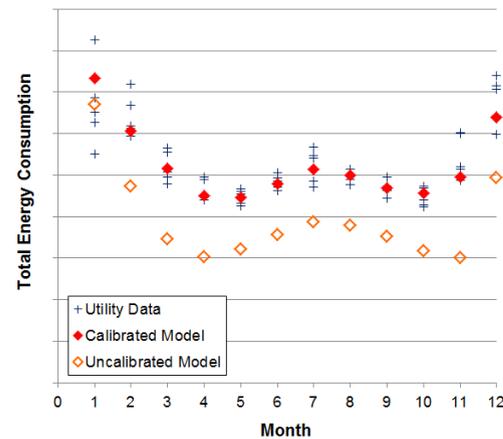

Figure 5 Validation of the calibrated model

Evaluate Retrofit Palettes

We evaluted the effectiveness of the two retrofit palettes specified in Table 2 with respect to energy savings in the example building. We propagated both uncertainties in the calibrated parameters and additional uncertainties associated with the EEMs through the normative model to estimate (1) the energy savings achievable with the retrofit palette and (2) the magnitude of risk associated with those savings. Figure 6 shows a box plot of energy savings from the two retrofit palettes. The bottom and top bars of the box indicate the lower and upper quartiles, and the range between the whiskers includes about 99% of the distribution. The box plot suggests that the possible savings from retrofit palette 1 range between 9% and 12%, while the savings from retrofit pallete 2 fall between 12% and 17%. The performance risks are small for implementing these retrofit palettes in the example building because (1) the EEMs considered contain a relatively small magnitude of uncertainty in their physical properties and (2) the variation in the energy baseline model does not influence the performance of EEMs, so EEMs perform quite consistently regardless of the baseline scenarios obtained from calibration.
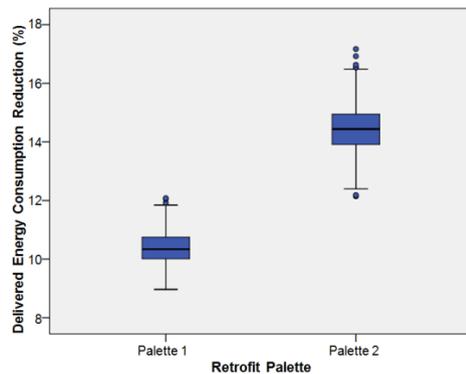
Figure 6 Effects of retrofit palettes on energy saving

DISCUSSION AND FUTURE WORK

This paper presents a scalable analytic method that supports retrofit decision-making at the individual building and aggregate levels. In the method, normative energy modeling is used to forecast the comparative energy use of buildings before and after candidate EEMs are implemented. The methodology allows decision makers to evaluate policy and planning options in the context of the actual building portfolio and informs individual building stakeholders of specific retrofit strategies suited to their buildings and their objectives and risk attitude.

This study is ongoing to develop a web-based retrofit decision-making tool. In order to enhance the strengths of the tool in applications, we need to tackle the following objectives:

1. Scaling the aggregate-level analysis:

   The retrofit analysis method based on normative models tackles scalability with respect to modeling efforts and computational expense. However, collecting building data for each bulding at city or regional scales is still more labor-intensive than desired. In order to reduce the data collection burden, we need to further investigate the possibility of reusing existing data sources. We conducted a sensitivity analysis to evaluate the effects of parameter data that are difficult or impossible to obtain on analysis outcomes and final decisions, and are implementing streamlined data requirements on data collection (Guzowski et al., 2012).

2. Calibrating energy models for the aggregate-level analysis:

   In this study, the aggregate-level analysis is based on normative models without calibration. This approach can be adequate for relative comparisons of different retrofit scenarios. However, this approach is not able to reliably estimate the actual baseline energy uses and forecast energy consumptions after EEM implementation. Hence, if we want to enhance the predictive power of the models, it is necessary to calibrate every model of a building in the portfolio. However, since current calibration approaches are too computationally expensive for this purpose, we should further investigate how to derive correction factors based on a pool of buildings that can properly adjust a model on the basis of measured data without the rigorous calibration process.

3. EPC benchmarking of "as-operated" performance:

   Calculation of EPCs is based on the standard scenario of building usage and operation for the energy baseline and the reference values. Accordingly, EPCs rate building energy performance regardless of how the building is actually used. This rating approach is valid if the ranking by "as-operated" performance should be equivalent to the ranking by calculated EPCs. Hence, if we want to benchmark buildings in terms of their "as-used" performance, we need to further investigate the correlation between EPCs and metered energy consumption on the basis of a large basket of buildings with metered data available.

4. Enhancing the individual-level analysis:

   The energy analysis method was developed to reliably predict the effects of candidate EEMs on energy savings and quantify their associated performance risks. To fully support retrofit decision-making, the analysis tool needs to have the following capabilities: First, it should support financial decision-making based on realistic costs, benefits (energy savings, incentives, and other value streams), and risks. To that end, we will integrate the energy analysis method with the financial decision-making tool developed by Argonne National Laboratory. Second, the analysis currently requires some expert judgment, particularly in the uncertainty quantification. To improve the utility of the analytic tool, these computations need to be automated and linked to a database of uncertainty data and feasible EEMs for various types of buildings.

ACKNOWLEDGMENT

REFERENCES

CCAP 2010. Chicago Climate Action Plan. Available from http://www.chicagoclimateaction.org/e

DOE (U.S. Department of Energy) 2009. DOE to fund up to $454 million for Retrofit Ramp-Ups in energy efficiency. Available from http://energy.gov/articles/doe-fund-454-million-retrofit-ramp-ups-energy-efficiency

DOE 2010. Buildings Energy Data Book. Available from http://buildingsdatabook.eren.doe.gov/default.aspx

DOE 2012a. Commercial Building Energy Asset Rating Program. Available from http://www1.eere.energy.gov/buildings/commercial_initiative/assetrating.html

DOE 2012b. Buildings Performance Database. Available from http://www1.eere.energy.gov/buildings/buildingsperformance/

EERE (Energy Efficiency & Renewable Energy) 2012. Better Buildings Challenge. Available from http://www4.eere.energy.gov/challenge/

EIA (U.S. Energy Information Administration) 2003. Commercial Buildings Energy Consumption Survey. Available from http://www.eia.gov/emeu/cbecs/contents.html

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

Granade, H.C., Creyts, J., Derkach, A., Farese, P., Nyquist, S., and Ostrowski, K. 2009. Unlocking Energy Efficiency in the U.S. Economy. McKinsey & Company Report. Available from http://www.mckinsey.com/Client_Service/Electric_Power_and_Natural_Gas/Latest_thinking/Unlocking_energy_efficiency_in_the_US_economy

Hansen, S. J., and Brown, J. W. 2004. *Investment Grade Energy Audit: Making Smart Energy Choices*. Fairmont Press, Inc, Lilburn, GA.

Heo, Y. Choudhary, R., and Augenbroe, G. 2012. Calibration of building energy models for retrofit analysis under uncertainty. *Energy and Buildings*, 47:550-560.

Hogeling, J., and Dijk, D. V. 2008. P60: More information on the set of CEN standards for the EPBD.

IPMVP 2010. International Performance Measurement and Verification Protocol: concepts and options for determining energy and water savings. Volume 1. Available at http://www.nrel.gov/docs/fy02osti/31505.pdf

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

Kokogiannakis, G., Strachan, P., and Clarke, J. 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.

Guzowski, L. B., Graziano, D. J., Heo, Y., and Muehleisen, R. T. 2012. Testing a streamlined project evaluation tool for risk-conscious decision making: the Chicago loop energy efficiency retrofit initiative. Proceedings of the ACEEE Summer Study on Energy Efficiency in Buildings.

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., Zhao, F., and Augenbroe, G. 2011. The use of normative energy calculation beyond building performance rating systems. *Proceedings of the 12th IBPSA Conference*, Sydney Australia

Mills, E. 2009. Building commissioning: a golden opportunity for reducing energy costs and greenhouse gas emissions. *LBNL Report*. Lawrence Berkeley National Laboratory.

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

White House 2011. President Obama's plan to win the future by making American businesses more energy efficient through the "Better Buildings Initiative." Available from http://www.whitehouse.gov/the-press-office/2011/02/03/president-obama-s-plan-win-future-making-american-businesses-more-energy

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

Zhao, F., Martinez-Moyano, I. J., and Augenbroe, G. 2011. Agent-based modeling of commercial building stocks for policy support. *Proceedings of the 12th IBPSA Conference*, Sydney Australia.