# Improving Energy Retrofit Decisions by Including Uncertainty in the Energy Modelling Process

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ABSTRACT: Currently, many investment decisions concerning energy retrofits are made directly based on the outcomes of energy simulations. However, there are various uncertainties inherent in the energy retrofit assessment process, both at the energy simulation and life cycle cost analysis (LCCA) levels, which can result in inaccuracy of energy performance forecasts and therefore, inappropriate investment decisions.
Through a case study, this paper presents a procedure for deriving and including the uncertainty associated with various factors in energy retrofit option assessment and clearly demonstrates how to generate probability distributions for final financial outcomes required for investment decision-making such as Net Present Value (NPV) and Internal Rate of Return (IRR). These distributions provide decision makers with more insight into the risks associated with achieving the expected outcomes. The simulation process proposed in this paper could be used by modelers to improve the level of confidence associated with simulation outcomes and enhance the quality of investment decisions concerning energy retrofit.
An existing office building is selected and multiple calibrated energy base models are developed to evaluate a combination of lighting controls as a new energy retrofit option. The paper demonstrates the calibration process of the base models and a LCCA of the lighting controls package. Analysis was conducted to examine how evaluating retrofit options with multiple base models could impact the financial outcomes and improve the final investment decisions. The financial metrics are compared with the results of modeling using a single base model. The results show that this approach could have the potential to  and may alter a retrofit decision from 'no go' to 'go'.

KEYWORDS: Energy Retrofits, Energy Simulation, Investment Decision-making, Risk and Uncertainty

## INTRODUCTION

As summarized by Bozorgi and Jones (2010), evidence suggests that there is inaccuracy/error associated with energy modeling forecasts and in some cases the models are not a good predictor of project energy performance (pp. 3/15-13/16). The accuracy of model prediction is greatly dependable on the accuracy of inputs. In the context of existing buildings, the level of uncertainty associated with simulation inputs is typically higher, because the systems may not performed as they specified or designed. Therefore, there is always some uncertainty associated with projecting the energy use based on design assumptions. It is critical for decision makers to consider the inaccuracy/error of modeling forecasts to avoid overestimating or underestimating the building energy performance (Bozorgi & Jones, 2010).
In this analysis, ranges and probability distributions are suggested to be used instead of single-point estimates in order to introduce various sources of uncertainty and articulate the risks associated with achieving the expected energy performance outcomes. By providing more insight into risk, the proposed process will improve the reliability of energy modeling outcomes and also the confidence level of decision-makers in their decision-making process. As a result, the quality of investment decisions concerning energy retrofit options will increase (Bozorgi & Jones, 2010).
Calibration of a base model is a critical part of the simulation process of existing buildings for the purpose of evaluating energy retrofit options. Existing buildings are typically modeled based on the necessary data and information obtained from available plans and construction details, specification books, and operating schedules. The results of initial simulations usually indicate that despite the careful attention in creating the models, the actual measured energy use is different from what was projected by models. This discrepancy is primarily due to the significant uncertainty or error associated with the simulation inputs (Pan, Huang, & Wu, 2007, Westphal & Lamberts, 2005).
Accordingly, through conducting a case study on an existing office building, this paper aims to derive the various sources of uncertainty inherent in the energy retrofit analysis and numerically demonstrate a procedure for including those uncertainty factors into the modeling process in order to communicate more

reliable outcomes to the decision-makers. The analysis shows how various potential risk and uncertainty might impact the final financial outcomes, and therefore, the investment decisions. The paper present a calibration process and explains how to create a reliable model to serve as a base case for evaluating the energy performance and generating distributions of energy performance indicators, resulting from selecting a new retrofit option. It also describes a LCCA process of the selected retrofit option and demonstrates how to generate distributions of financial performance indicators such as NPV and IRR.

Unlike the common practice of calibration, this study developed multiple acceptable base models for evaluating the selected energy retrofit option to account for inaccuracy of base models in generating the distribution of outcomes. Energy retrofit options are typically evaluated based on a calibrated energy base model. The acceptability of these base models are determined based on their forecasts error indicators. However, there might be several base models within the acceptable ranges that have different inputs, outputs, and error indicators. These base models could produce different outcomes when evaluating the performance of new retrofit options due to interactive modeling effects of retrofit options inputs. Thus, a sub-analysis was conducted to compare the estimated financial outcomes with the results of modeling using a single base model. The hypothesis here is that considering the inaccuracy of a base model could improve the level of confidence associated with simulation outcomes and enhance the quality of investment decisions regarding green retrofits. This analysis tests this hypothesis towards the broader goal of assisting decision-makers to make more informed decisions about investing in green retrofits. The results explain whether or not the impacts of modeling new retrofit options using different base models are significant enough to encourage modelers to put extra time and effort into running additional simulations.
It is important to note that this paper is mainly concerned with demonstrating the process of calibration and generation of distributions of outcomes and not the accuracy of final numeric results. The accuracy of outcomes is limited to the quality of assumptions and information that was obtained through literature, researcher’s professional judgments, expert interview, and questionnaires.

## 1.0. ENERGY SIMULATION AND CALIBRATION PROCESS

As mentioned earlier, a thorough calibration process requires on-site measurements, surveys and interviews with occupants, etc. However, in this case study, the model was made as reliable as possible based on the available drawings and interviews with the owner representative and the property manager. No measurement or experimental study was performed for collecting the actual data other than actual utility records. The subsequent steps were followed in order to arrive at a reliable model:

1) The initial model was set up in eQuest (QUick Energy Simulation Tool) based on the data collected from the architectural and mechanical drawings, construction details, researcher’s visit, pictures, and interview with the owner representative who was also an occupant in the building. The annual and monthly electricity consumptions were calculated based on the initial model. The building is all electric and there is no gas usage. A Typical Meteorological Year (TMY) file was used in the simulation process and not the actual weather file of 2009 for which the modeled consumptions was compared with. This could be one of the sources of inaccuracy associated with modeling outputs.

2) The actual annual and monthly electricity usage (KWh) was gathered by looking at 12 months of electricity bills in 2009. Adjustments were then made to those estimates in order to correspond to the calendar months. Utility records are not normally first of the month to last of the month, the simulation outcomes from energy modeling, however, are first of the month to last of the month. Two possible procedures for dealing with this include: if available, sum the daily simulation values to correspond to the measured records; or normalize the measured records to correspond to the simulated monthly values (weighted average approaches). This could be another potential source of inaccuracy associated with the modeling outputs. In this case, the weighted averages of actual electricity records were estimated to correspond to the calendar months.

3) The actual weighted average electricity usages were compared with those predicted by the simulation model, and the annual and monthly Mean Bias Error (EER) % and Coefficient of Variation of the Root-Mean-Squared Error (CV RMSE)—error indicators—were calculated by formulas presented in Equation 1:

$$\mathrm{ERR}_{\mathrm{month}}\,(\%) = \left[\frac{(M-S)_{\mathrm{month}}}{M_{\mathrm{month}}}\right] \times 100\% \qquad (1)$$

$$\mathrm{ERR}_{\mathrm{year}}\,(\%) = \sum\nolimits_{\mathrm{year}} \left[\frac{\mathrm{ERR}_{\mathrm{month}}}{N_{\mathrm{month}}}\right] \qquad (2)$$

where $M$: measured electricity (kWh) or fuel consumption; $S$: simulated electricity (kWh) or fuel consumption; $N_{\mathrm{month}}$: number of utility bills in the year.

$$\mathrm{CV}\,(\mathrm{RSME}_{\mathrm{month}})\,(\%) = \left[\frac{\mathrm{RSME}_{\mathrm{month}}}{A_{\mathrm{month}}}\right] \times 100\%$$

$$\mathrm{RSME}_{\mathrm{month}} = \left\{\frac{\left[\sum_{\mathrm{month}}(M-S)^2_{\mathrm{month}}\right]}{N_{\mathrm{month}}}\right\}^{1/2}$$

$$A_{\mathrm{month}} = \left[\frac{\sum(M_{\mathrm{month}})}{N_{\mathrm{month}}}\right]$$

where RMSE: root-mean-squared monthly error; $A_{\mathrm{month}}$: mean of the monthly utility bills.

Equation 1: EER and RSME formulas (Pan, et al., 2007)

The calculated EER% and CV RMSE% were checked to see if they fall in any of the three accepted tolerances for data calibration suggested by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) 14, International Performance Measurement and Verification Protocol (IPMVP), and Federal Energy Management Program (FEMP) (presented in Table 1):

**Table 1:** Acceptable tolerance for monthly data calibration. Source: (Pan, et al., 2007)

| *Index* | *ASHRAE 14 (%)* | *IPMVP (%)* | *FEMP (%)* |
|---|---|---|---|
| ERR month | ±5 | ±20 | ±15 |
| ERR year | - | - | ±10 |
| CV (RMSE month) | ±15 | ±5 | ±10 |

The error percentages of the initial model did not agree well with the above acceptable ranges, and therefore, the initial model was not appropriate for evaluating the new retrofit options.

4) Further investigation was performed to collect more updated information about the inputs that might have higher impacts on the energy consumption and/or were not clear from the drawings—Information about current Heating, Ventilation, and Air-Conditioning (HVAC) and lighting systems including: types of cooling source; Roof Top Units (RTUs) zoning, etc. Through a survey and a follow up interview with the property manager, most of the needed information was obtained and possible input changes were identified. For example, for thermostat set points which have significant impacts on energy consumption, the property manager could not provide exacts values. She indicated that this has varied significantly in the past.

5) The initial model was calibrated and updated based on the new information from the property manager. The new modeling outputs (KWh) were compared with the actual usages by calculating error indicators—monthly and yearly EER as well as CV (RMSE). The new estimates were much closer to the acceptable ranges suggested by the aforementioned guidelines; however, they were still not within acceptable ranges.

6) The calibration process continued by varying the inputs, which were more uncertain based on our interviews and on-site visits, over reasonable ranges. The input changes included thermostat set points, lighting power density, task lighting and equipment power density, cold deck reset temperature, energy efficiency ratio (EER), minimum air flow, etc. More than 80 models were created and their calculated error indicators were compared with those suggested in Table 1. A model with error indicators that complied with the ranges suggested by FEMP and were very close to those suggested by ASHRAE 14 and IPMVP was selected as the best model. This calibrated model was thought to be sufficiently accurate to serve as a reliable base case for evaluating the new retrofit options.

Figure 1 shows the monthly electricity use as predicted by both the initial and final models. Through an iterative calibration process (creating and testing more than 80 models) the model was improved until they closely matched the actual consumptions. The $\mathrm{EER}_{\mathrm{year}}$ of the best model was zero.

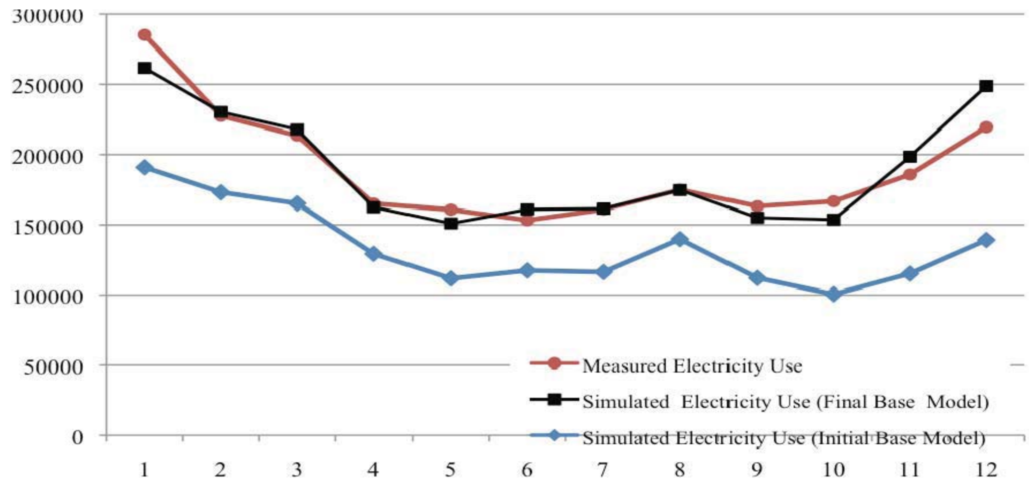


**Figure 1:** The eQuest Model prediction vs. actual consumption. Source: (Author 2012)

7) The next step of the process was to model the retrofit option—lighting control systems—using the calibrated base model. The lighting control systems modeling, LCCA, and a procedure for generating the distribution of final financial outcomes are discussed in the following sections:

## 2.0. FINAL DISTRIBUTION OF ENERGY SAVINGS AND INTERACTION OF BASE MODELS

In current practice and literature, typically, a model that falls in any of the three accepted tolerances for data calibration stated in Table 1 and matches more closely with actual consumption—overall lowest monthly and yearly EER as well as CV $_{RMSE}$—will be used as a base model for existing buildings. New retrofit options will then be entered to this base model to be assessed and compared. However, base models themselves often involve a certain level of inaccuracy as they are typically calibrated based on the final modeling outputs, *which could be results of different inputs*. For example, the predicted energy consumption (KWh) of an energy model with certain assumptions about air conditioner Energy Efficiency Ratio (EER) and lighting power density could be very close to the one with a lower EER but a higher lighting power density assumptions. And both base models might be qualified as acceptable models, based on the aforementioned guidelines, due to their close predicted energy consumptions. In fact, this is very common in the calibration process as selecting a certain/accurate value for some inputs can be difficult in existing buildings.

Therefore, there might be several base models within the acceptable ranges that have different inputs, outputs, and error indicators. *A model with lowest error indicators is not necessarily the one that replicates the actual performance most accurately*, due to the uncertainty associated with inputs. Furthermore, selecting the lowest error indicators sometimes is not very straightforward, because a model might have a lower EER $_{month}$ for most of the months, but have a higher EER $_{year}$ or CV $_{RMSE}$. It is very important to note that while the final outputs (KWh) of acceptable models might be very close, they could produce different outcomes when evaluating the performance of new retrofit options. This is primarily due to interactive modeling effects of new retrofit options inputs with the base models. Therefore, ignoring the impacts of the variability of inputs for the base models on the outcomes might result in different investment decisions when comparing different retrofit options.

In summary, there are two factors that could influence the distribution/variance of savings associated with new retrofit options in the simulation of existing buildings: 1) ranges of assumptions for new retrofit options and 2) the inaccuracy of base models. In other word, as shown in Figure 2, the final simulation output distribution is the result of interaction between these two factors. In current practice and literature, the second factor, the inaccuracy of base models, is often ignored.

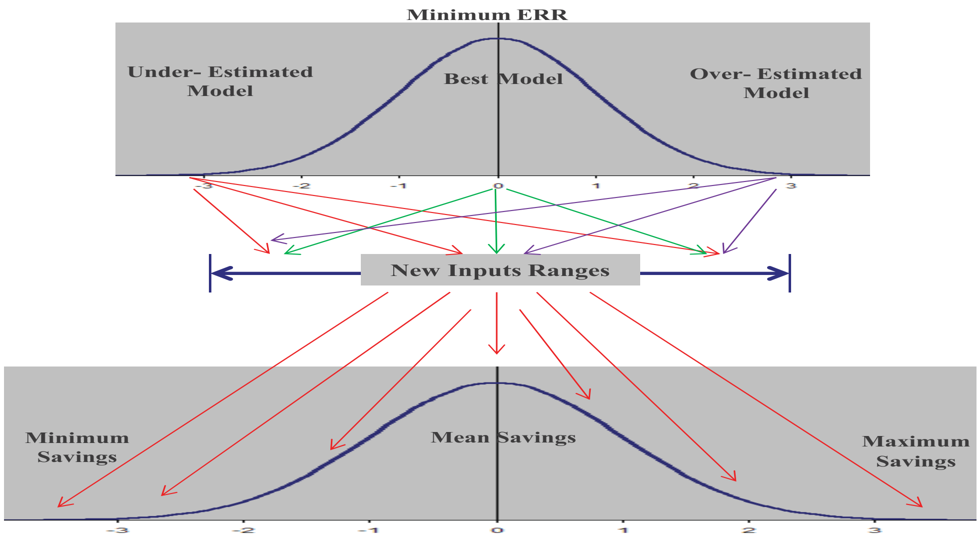


**Figure 2:** Interaction of base model inaccuracy in generating the final simulation outcomes. Source: (Author 2012)

In this paper, lighting control systems were modeled with multiple base models to generate the distribution of energy savings and assess the potential impacts of different base models on simulation outcomes. The objective of this analysis was to understand how this approach could improve the final decisions about retrofit options investment and if the results were worth the effort of running additional scenarios. Might this approach alter the final investment decisions? This is one of the questions that this paper aims to address.

### 2.1 Creating Multiple Base Cases for Evaluating a New Retrofit Option

In order to create a more acceptable model, the seven inputs were selected to be varied over reasonable ranges. These inputs include: four thermostat set points (occupied cooling, occupied heating, unoccupied cooling, and unoccupied heating), cold deck reset temperature, EER of HVAC systems, and Variable Air Volume (VAV) minimum flow. These factors were selected because, based on the interview with the property manager and researchers' professional judgments, they might involve a higher level of uncertainty.
Several base models were created in addition to those built previously and their error indicators were calculated to ensure that they meet the acceptability conditions by the aforementioned guidelines. 22 models were within the acceptable tolerances. Figure 3 shows the distribution of the predicted yearly energy usages of the 22 base models:

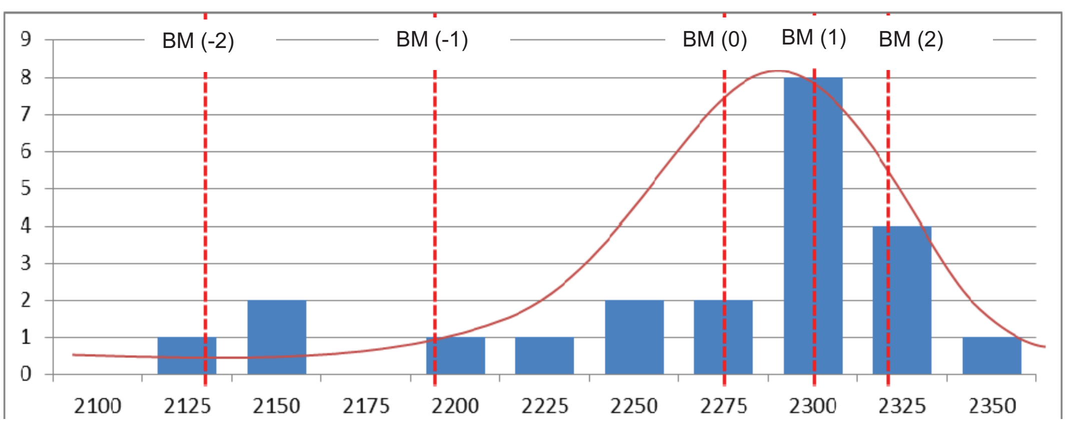


**Figure 3:** The Distribution of Predicted Energy Use (MWh) of 22 Base Models. Source: (Author 2012)

As the distribution of energy consumptions shows, there are some base models (towards the left side) that under-predicted the energy consumption, compared to 2,276.5 MWh consumption of the best base model, and there are others (towards the right side) that over-predicted the consumption. The best model with $EER_{year}$ of 0%, which is presented in Table 2, is close to the mean of the above distribution. Five base models (BM) were then selected from 22 models to be used for evaluating the lighting control option and generating the savings distributions. The five base models, BM (-2), BM (-1), BM (0), BM (+1), and BM (+2), are shown in Figure 3 by dash lines. BM (-2) denotes the base model with lowest predicted energy use, BM (0) the medium, and BM (2) the highest energy use. Their related assumptions, savings, and error indicators are presented in Table 2:

**Table 2:** Five base models assumptions, savings and error indicators. Source: (Author 2012)

| | *BM (-2)* | *BM (-1)* | *BM (0)* | *BM (+1)* | *BM (+2)* |
|---|---|---|---|---|---|
| Yearly energy use prediction (MWh) | 2,130.90 | 2,181.60 | 2,276.50 | 2,291.50 | 2,315.60 |
| EER month | -4.1% to +14.3% | -8.7% to +11.6% | -13.3% to +8.2% | -14.3% to +6.9% | -13.8% to +7.7% |
| EER year | 6.24% | 4.06% | 0.00% | -0.62% | -1.70% |
| CV (RMSE m) | 9.03% | 8.09% | 6.79% | 6.84% | 7.14% |

### 2.2 Accounting for Risks Associated with the Systems Performance - Five Cases for Lighting Control Systems Option

According to a principal at CQI Associate, energy models do not replicate the real world situation, “because those models do not take into account the true investment and cost issues and as well as experience-related issues about them. We have never seen the savings that high [as predicted by model].” There is a certain level of uncertainty associated with each technology which depends on the current level of knowledge of designers or contractors. How innovative is the technology? What is the proven and what is not proven?”

The result of the analysis shows how various potential risk and uncertainty might impact the final financial outcomes, and therefore, the investment decisions. There are several risks associated with the actual performance of lighting control systems. Daylight sensors need to be well calibrated to perform as they are designed, otherwise there might be no savings and low satisfaction by occupants. Occupancy sensors may not be as effective as they are expected to be, if not located properly to cover the area under their control. There is always a risk of poor quality of installation or workmanship—the contractors’ risk. Therefore, in order to demonstrate a process of accounting for the potential risks associated with the performance of the lighting retrofit option in the modeling process, five different cases were developed. Seven factors/variables related to lighting controls performance were identified and their values were varied over defined ranges for creating the five lighting retrofit cases. Case 1 was the best case, case 3 was the most-likely, and case 5 was the worst case. Defining a range for each variable would help to account for some of the risks associated with the option’s performance. If a retrofit option is an innovative technology that the market does not have much experience with, the wider ranges might be defined for its uncertain variables. If it is a proven technology, like the lighting retrofit option in this case, the ranges could be narrower accordingly.

For example, studies by Lutron Electronics showed a 15% lighting energy savings when personal dimming controls were employed. A saving range of 13%-17% was considered for personal dimming controls to account for uncertainty associated with its related savings. Lighting power density is one of the factors that could have a significant impact on the outcomes of lighting control systems. Also, it could vary significantly based on the occupants’ behavior. Since no tests were conducted in this case study to measure the actual lighting power density, a range of 1.1-1.6 (W/Sq.Ft) was considered to account for this varianceDemand reduction is one of the important benefits of lighting control systems such as daylight sensors. The demand peak (KW) reduction of this option was estimated through eQuest. As described previously, the energy based models in this study were calibrated based on KWh consumptions, so that the predicted KWh matches the actual KWh. They were not calibrated based on their KW prediction. The predicted KW of the best base model (BM0) was compared to the actual values. The $EER_{year}$ was 13.61%. This indicates that the BM0 was over-predicting the annual demand peak by 13.61%. Therefore, in order to account for this inaccuracy in energy models, a multiplier, in a range of 0.8-1, was considered to adjust the KW prediction in each case.

The five lighting retrofit cases were modeled using the five base models, explained in Table 2 through eQuest, which result in a total of 25 energy models/savings estimates. These 25 estimates are used to generate the distributions of energy savings and related financial performance indicators. An excel-based model, a Lighting Control Systems Analytics (LCSA) was then developed for estimating the final lighting controls energy savings and performing economic analyses for each case. This is an analytic tool that could take the KWh and KW estimates from energy models as inputs, and perform a comprehensive analysis to estimate energy savings and financial performance indicators such as simple payback, simple ROI, NPV and IRR as outputs. The assumptions for creating the five lighting cases are primarily based on the researcher's professional judgment and experts' interview.

### 2.3 Distributions of Energy Performance Indicators and Total Energy Cost Savings

In order to estimate the distributions of energy performance indicators, 1) the impacts of daylight harvesting, occupancy sensors, and different lighting power density on energy savings were first calculated by modeling the 25 cases (five cases by five base models) in eQuest; 2) The outputs, including KWh and KW estimates for both lighting and whole building, were taken to the LCSA; 3) The impacts of high-end trimming, personal dimming control, and demand peak adjustment factors were then estimated and incorporated through the LCSA; and 4) The distributions of MWh savings and KW savings, presented in Figure 4 and Figure 5, were generated based on the 25 saving estimates.

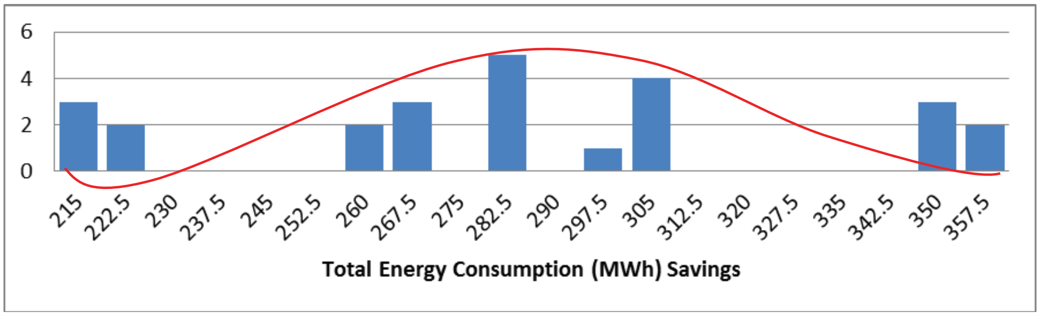


**Figure 4:** The Distribution of Energy Consumption Savings (MWh) .Source: (Author 2012)

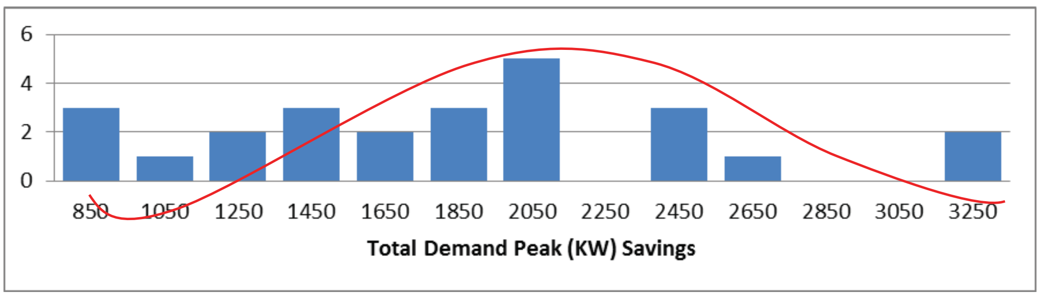


**Figure 5:** The Distribution of Peak Demand Savings (KW). Source: (Author 2012)

## 3.0. FINANCIAL ANALYSIS

### 3.1 Simple Cost-Based Analysis

The entire capital costs data for lighting control systems including equipment and installation costs were obtained from Lutron Electronics. Capital costs could vary significantly based on the building characteristics, number of existing lighting fixtures, users' expectations, lighting contractors, etc. For the purpose of this analysis, five capital cost estimates were developed for the lighting retrofit cases 1-5 to account for the potential uncertainty associated with cost approximation suggested by Lutron Electronics. The utility provider for the building provides incentives for lighting equipment replacements / retrofits and lighting control systems. The total incentives were estimated for the five cases based on assumed ranges for numbers of sensors and ballasts and were subtracted from the total capital costs to calculate the total investment costs.

### 3.2 Life Cycle Cost Analysis (LCCA)

Cash flows for a period of 20 years were developed. NPVs and IRRs were estimated over four time horizons of 5, 10, 15, and 20 years to show the financial performance of the lighting retrofit over various life cycles. The costs of lighting replacements at the end of their useful life (UL) cycle were included in the cash flows for two conditions. The two conditions are 1) When a lighting retrofit option is undertaken and new control systems are installed— the replacement costs can negatively impact the cash flow at the end of the new systems useful life 2) When no lighting retrofit is undertaken and existing lighting fixtures will be replaced with similar models—the costs can positively impact the cash flow at the end of the remaining useful life of the existing lighting fixtures. Distributions of NPVs and IRRs over various periods of 5, 10, 15, and 20 years were generated. Table 3 shows a summary of statistics of financial outcomes:

**Table 3:** Min, Max, Mean, and Standard Deviation of Financial Outcomes. Source: (Author 2012)

| *Financial Metrics* | *Min* | *Max* | *Average* | *Standard Deviation* |
|---|---|---|---|---|
| Total $ Savings | $26,975 | $49,829 | $38,163 | $6,656 |
| Simple Paybacks | 5.6 | 10.4 | 7.7 | 1.4 |
| Simple ROI | 9.62% | 17.89% | 13.35% | 2.41% |
| 5-Year NPV | ($152,667) | $22,199 | ($78,550) | $61,199 |
| 10-Year NPV | ($28,430) | $225,171 | $97,429 | $68,462 |
| 15-Year NPV | ($3,390) | $334,067 | $150,239 | $101,059 |
| 20-Year NPV | $53,661 | $478,213 | $249,254 | $129,192 |
| 5-Year IRR | -23% | 11% | -8% | 12% |
| 10-Year IRR | 9% | 27% | 17% | 5% |
| 15-Year IRR | 9% | 29% | 18% | 6% |
| 20-Year IRR | 12% | 30% | 20% | 5% |

### 3.4 Interpretation of Distributions of Final Outputs

Probability distributions provide information about the probability of achieving the estimated outcomes. Based on the empirical rule if a distribution is approximately normal then the probability is about 68.26 percent of the estimates will lie within one standard deviation of the mean (mathematically, $\mu \pm \sigma$, where $\mu$ is the arithmetic mean), about 95.44 percent will be within two standard deviations ($\mu \pm 2\sigma$), and about 99.74 percent will lie within three standard deviations ($\mu \pm 3\sigma$) (Ott & Longnecker, 2001)

The distributions of NPVs in this scenario are approximately normal, and therefore, the following information could be understood from the distribution of average 5-year NVP:

- There is about 68% chance that the 5-year NVP falls between -$139,749 and -$17,351.
- There is about 95% chance that the 5-year NVP falls between -$200,948 and +$43,848.
- There is about 99.5% chance that the 5-year NVP falls between -$262,147 and +$105,047.
- There is less than 13% chance that the 5-year NVP is positive.
- There is about 84%chance that the 5-year NVP is not less than -$17,351.
- There is about 2% that that the 5-year NVP is higher than +$43,848

The above information provides investment decision-makers with more insight into risk associated with achieving the expected financial outcomes. As a result, decision-makers would be able to make more informed decisions concerning investing in green retrofit options.

## 4.0. DISCUSSION ON USING MULTIPLE BASE MODELS FOR SIMULATING RETROFIT OPTIONS

The hypothesis here is that considering the inaccuracy of a base model in the modeling process could improve the level of confidence associated with simulation outcomes and enhance the quality of investment decisions regarding green retrofits. This sub-analytic attempts to test this hypothesis towards the broader goal of assisting decision-makers to make more informed decisions about investing in green retrofits.

In order to measure the impacts of simulation with multiple base models on financial outcomes, the low-end and high-end impacts were estimated by comparing the minimum and maximum of each financial outcome to related average value of the best model (BM0). The assumption was that the retrofit options would be modeled using the best model (BM0), if multiple base models would not be used.

Table 4 shows the impacts, both absolute values and percentages, on different financial indicators:**T**

The results of the analysis show that including inaccuracy of base models could have the potential to impact the financial outcomes and influence the investment decisions. There were few conditions in the NPV analyses, 10-year and 15-year NPV, where one case has a negative NPV with the best case (BM0) but positive NPVs with other base models. Thus, if an investor bases her/his decision on the result of modeling with a single base model, she/he would not agree to invest in the lighting controls option. The 4% increase in a 5-year IRR or $16,625 in a 5-year NPV could alter an investment decision from ‘no go’ to ‘go’.

It should be noted that many factors might play roles in the magnitude of impacts. Factors include level of calibration, type of retrofit options, investors return’ horizons, building characteristics, or level of analysis. Accordingly, the inaccuracy of base models could potentially impact the investment decisions at the property level, when selecting the retrofit options. It could alter an investment decision from ‘no go’ to ‘go’.

Table 4: **Impacts of simulating by multiple base models on financial outcomes Source: (Author 2012)**

| *Financial Indicator* | *(Min - BM0)* | *(Max - BM0)* | *Low-End Impact* | *High-End Impact* |
|---|---|---|---|---|
| Total $ Savings | -$744 | $3,563 | *-2%* | *13%* |
| Simple Paybacks | -1.2 | 0.2 | *-12%* | *2%* |
| Simple ROI | -0.3% | 1.3% | *-2%* | *13%* |
| 5-Year NPV | -$3,596 | $16,625 | *-38%* | *136%* |
| 10-Year NPV | $0 | $65,771 | *0%* | *253%* |
| 15-Year NPV | -$9,181 | $39,206 | *-334%* | *2708%* |
| 20-Year NPV | -$11,334 | $46,742 | *-10%* | *79%* |
| 5-Year IRR | -1% | 4% | *-17%* | *74%* |
| 10-Year IRR | -1% | 2% | *-3%* | *25%* |
| 15-Year IRR | -1% | 3% | *-4%* | *32%* |
| 20-Year IRR | -1% | 2% | *-2%* | *20%* |

Therefore, if the lighting controls option was only modeled using one calibrated base model:

- The total savings could have been underestimated by 13% ($3,563) or overestimated by 2% ($744).
- The Simple Payback could have been underestimated by 2% (0.2 year) or overestimated by 12% (1.2 years).
- The 5-year NPV could have been underestimated by 136% ($16,625) or overestimated by 38% ($3,596).
- The 5-year IRR could have been underestimated by 74% (4%) or overestimated by 1% (17%).

## CONCLUSION

Decision-makers often rely on the results of the energy simulation when making investment decisions about energy retrofit options. Thus, it is important for modelers/consultants to examine potential strategies to improve the reliability and level of confidence associated with simulation outcomes to ultimately enhance the quality of investment decisions. Towards achieving this objective, this paper presents how to define and include ranges for uncertain factors in the energy retrofit assessment process and explains how to generate distributions of outcomes to communicate risk associated with achieving the expected outcome. The proposed process is numerically demonstrated through a case study on evaluating a combination of lighting controls package for an existing office building.

When simulating a new retrofit option in an existing building, there are two factors that could influence the distribution/variance of savings associated with the retrofit option: 1) ranges of assumptions for new retrofit options and 2) the inaccuracy of base models. The final simulation output distribution is the result of interaction between these two factors. In current practice and literature, the second factor, the inaccuracy of base models, is often ignored. The analysis shows that considering the inaccuracy of a base model in the modeling process could improve the level of confidence associated with simulation outcomes and enhance the quality of investment decisions regarding green retrofits. It could alter an investment decision from ‘no go’ to ‘go’. However, the result of this single analysis cannot be generalized. Therefore, depending on the level of analysis, modelers are encouraged to consider the inaccuracy of a base model in addition to the uncertainties associated with each retrofit option when making investment recommendations about green retrofits to decision-makers.

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