A Novel Approach to the Evaluation of Lighting Programs: The National Grid Energy Initiative Lighting Program

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ABSTRACT

This paper describes the innovative methodology employed in the evaluation of National Grid's Energy Initiative program for 2000 and 2001. Previously, Statistically Adjusted Engineering (SAE) models have been used in such evaluations, introducing the potential for biased results when the model inputs (i.e., engineering estimates of savings) had measurement error. Other approaches used building simulation models on either a sample of or the entire participant population. The benefit of a building simulation model is that it customizes savings estimates to specific buildings and incorporates post-installation conditions. Frequently, a building simulation model is used on a sample of the participant population due to budget constraints. If the circumstances experienced by the population differ from that of the sample, the model may produce biased results when extrapolated to the population. Using an SAE model on the results from a building simulation model for a sample achieves the joint goals of limiting the cost of data collection and verifying the reasonableness of the sample results. While engineering models and building simulations have been used in isolation in the past, this represents the first time that they had been married into a single, integrated evaluative tool.

Significant results were found in both stages of the analysis. The building simulation modeling (Phase I) produced a realization rate larger than 100%, indicating that the company's initial savings estimates were low. The second phase SAE modeling indicated that the building simulation modeling may have overstated that bias. Overall, the Program achieved a realization rate of 86.5%.

Introduction

The prescriptive lighting measures of the Energy Initiative Program assist commercial, industrial, and governmental customers within the New England region of the National Grid service territory (Massachusetts Electric Company, Nantucket Electric Company, The Narragansett Electric Company, and Granite State Electric Company) in installing a comprehensive list of retrofit lighting measures (energy conservation measures or ECMs). The Program encompassed 1,242 participants that installed a total of 281,935 measures for a total expected savings of 83,590 MWh for 2000 and 2001.

The Program has offered either customized incentives for qualifying energy-efficient measures based on the value of load reduction or pre-calculated rebates for a wide range of prescriptive measures since 1989.

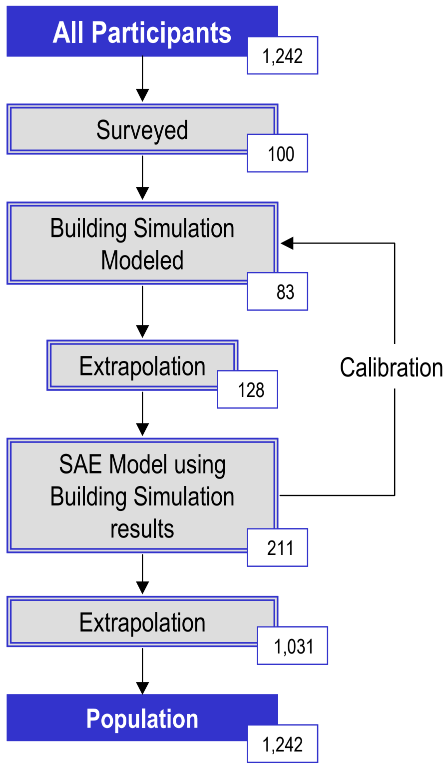
Methodology

As shown in Figure 1, this evaluation utilized the following methods:

1. Telephone survey of 100 participants to obtain buildings' characteristics and any related changes since measure installation
2. Engineering simulation utilizing the surveyed sample of 90 participants, representing a range of building types, were modeled with 83 yielding viable results

3. Strategically Adjusted Engineering (SAE) model utilizing the engineering estimates from Step 2 extrapolated to a sample of 211 (the 83 modeled and an additional 128 with sufficient billing data) participating buildings with sufficient billing data
4. Readjusted engineering estimates from Step 3 were extrapolated to the remaining population of 1,031 participants, yielding estimated savings for all 1,242 Program participants

Figure 1: Methodology



Though the Program has been evaluated many times since its inception, recent evaluations have centered on SAE models. An SAE model uses energy consumption as the dependent variable and weather and ECM expected savings as the primary independent variables. There are potential difficulties associated with SAE modeling, including the assumption that its inputs are measured without error. If this assumption is violated, the results of the model may be biased.

Though we had used SAE models in previous evaluations, our methodology in evaluating the 2000 and 2001 Energy Initiative Prescriptive Lighting Programs took this approach one step further, prefacing the SAE modeling with a building simulation model. This was done for two reasons: first, to alleviate the potential bias with the SAE model discussed above and, second, to reduce the cost of data collection using a building simulation model in isolation. If a building simulation model is used on the entire population, the cost of acquiring data may be prohibitive (often a sample is modeled and the results are then extrapolated to the population). Further, extrapolating modeled results without verification may yield unreasonable values for non-modeled sites or the population.

While engineering models and building simulations have been used in isolation in the past, this represents the first time that they had been married into a single, integrated evaluative tool. Though described as a linear process, in reality, the approach was used iteratively with each process feeding the other. The following were the steps taken:

1. Ninety participants were modeled using engineering simulation models with 83 yielding viable results
2. Initial planning estimates of energy consumption were adjusted for this modeling
3. Adjusted expected savings were extrapolated to a group of participants for whom we had sufficient billing histories (n=211)
4. SAE model was run on for this group using the adjusted engineering estimates
5. Sites with apparent anomalies were revisited and rerun

Data Collection

Company Data. National Grid provided the following data:

- ***Program tracking***, including customer-specific information for measures installed, predicted kWh savings, and vendor information
- ***Consumption data***, including monthly billing data from January 1999 through March 2002
- ***Account information***, including details such as Standard Industrial Code, location, and rate code for all customers who participated, as well as those who may have been eligible for the Program

Customer Survey. To conduct engineering simulations of each building, the evaluation required more-detailed data than were available from National Grid's records. Quantec conducted a phone survey of 100 Program participants. Data collected included building characteristics (e.g., total square footage), primary business type (office, retail, large office, warehouse, manufacturing), space or water heat fuel type, presence of air conditioning, operating hours, and changes in building operations or operating hours since installation.

Survey Sample Frame. Initially, the population of Program participants was screened for viable candidates for the engineering simulation. Participants with incomplete billing data or tenant changes, and those that had either participated in other programs or installed nonlighting Program measures were eliminated. Others were eliminated for participating in a concurrent Free Rider/Spillover study.[1] The remaining participants were randomly sorted and surveyed until 100 responses were gathered.

Building Simulation Modeling and Results

For this portion of the evaluation, the building simulation model was employed. The model uses historical billing information to produce estimates of long-term energy savings. It also enables examination of the energy savings on a measure-by-measure basis. The building simulation model provides information on whether a realization rate that deviates from 100% is due to customer behavior or problems with the engineering estimates developed for the Program.

The building simulation model includes a set of calculations based on performance curves that duplicate DOE-2 results. The model's methodology, however, is very different from that of DOE-2. While DOE-2 produces detailed hourly simulations, the building simulation model computes monthly energy consumption based on average daily temperatures, equipment, and operations. We assembled simulation models of the facilities and calibrated them so that the predicted energy consumption matched the post-installation year utility bills. This is the as-built as-operated model, representing the

[1] The Free Rider/Spillover survey used a random sample, as did the current survey. Therefore no bias was introduced by leaving out these participants.

baseline. The building simulation model can be calibrated to pre-installation consumption to create a baseline, with ECMs "added" to that baseline to determine savings. Alternatively, it can be calibrated to the post-installation consumption to create a baseline with ECMs "removed" to determine savings.

Savings were computed as the difference in energy consumption between the two models (calibrated post and calibrated post minus ECMs) when operated under typical weather conditions. Savings for individual measures were also estimated through specific modeling runs in which one measure at a time was removed from the baseline model. Interactive effects (between lighting and space cooling) often lead to total modeled savings for all the measures being more than the sum of individual measures. Although 100 surveys were completed, only 90 were modeled due to inconsistencies in the data,[2] with 83 yielding viable results.

Estimate Site Savings for Individual ECMs. Using Program tracking and account information from National Grid, additional survey data, and the building simulation model software, each participant's measure type was analyzed, and adjusted savings were calculated.

Table 1 shows an example (for one site) of how the planning kWh savings estimates for each ECM were compared to the adjusted savings estimates and how the realization rates were computed. In this example, the total modeled kWh savings estimate for the site was 3,809 kWh, compared to the planning savings estimate of 3,566 kWh for a realization rate of 106.8%.

Table 1: Example of Calculated Savings by Measure

Measure Type	Initial Program Estimate (kWh)	Adjusted Savings (kWh)	Realization Rates
Fluorescent Systems	2,537	2,706	106.7%
LED signs	1,029	1,103	107.2%
Site Total	***3,566***	***3,809***	***106.8%***

Compute Individual ECM Realization Rates. As Table 1 illustrates, planned and modeled savings were used to calculate an adjustment factor or realization rate for the expected energy savings for each ECM installed at each site. For example, modeled savings from the LED signs at this site were estimated to be 107.2% of planning savings.

Average the ECM Realization Rates by Building Type and ECM. Next, we aggregated the planned and modeled savings by building type for each ECM, which resulted in the realization rates shown in Table 2 below (frequencies appear in Table 3).

Table 2: Realization Rates by Measure and Building Type

	Office	Retail	Warehse	Manuf.	Other	School	Hospital	Overall
Fluorescent Systems	115.3%	112.0%	98.5%	72.8%	99.4%	105.9%	107.0%	109.8%
CFLs	121.2%		99.0%				98.9%	109.1%
HID Systems	106.7%		95.8%	80.2%	101.0%	101.0%		92.0%
LED exit							107.0%	107.0%
Controls	108.2%	106.0%		97.4%	105.3%	99.4%	103.1%	105.6%
Overall	***114.5%***	***112.0%***	***96.3%***	***76.1%***	***102.0%***	***104.8%***	***104.2%***	***107.7%***

2 In several cases, there were measures associated with a meter that were not actually attached to that meter. This happened despite a great deal of effort expended on the front end to only model sites without data problems.

Table 3: Frequencies by Measure and Building Type

	Office	Retail	Warehse	Manuf.	Other	School	Hospital	Overall
Fluorescent Systems	39	17	2	6	3	3	1	71
CFLs	4		1				1	6
HID Systems	9		4	2	2	4		21
LED exit							1	1
Controls	19	2		1	5	1	2	30
Overall	***71***	***19***	***7***	***9***	***10***	***8***	***5***	***129***

SAE Model & Results

Statistically Adjusted Engineering Model. As discussed above, an SAE model uses energy consumption as the dependent variable and weather and ECM expected savings as the primary independent variables. Prior to installation, ECM expected savings are set to zero. The coefficient of ECM savings can be interpreted as the realization rate for those measures.

Sample. After modeling realization rates with the building simulation model, a sample for the SAE model was chosen. The following filters were applied (representing the 37 sites filtered for "other data anomalies" in Table 4).

- Participants with negative usage for a month (indicating an adjustment from a prior period) were not used (11 participants)
- Outliers (22 participants):
  - Lack of pre-installation billing data
  - Participants with less than 5,000 annual kWh
  - Participants showing multiple locations' installations on a single account, leading to a mismatch between savings estimates and that account's billing history usage
  - Identified as an outlier by residual analysis
- Participants with traffic lights, controls, or controls measures were too few for inclusion in the SAE model. They were removed and analyzed outside of the model (4 participants).

Table 4: Filters for SAE Modeling Sample

	Yes (Number Filtered)	**No** (Number Remaining)
Initial sample		1,242
No billing data (not a current customer)	46	1,196
No billing data during year before or after installation period	14	1,182
Participation in another program	530	652
Installation after June 2001	244	408
Not enough billing data (required 12 months pre-installation and 12 months post-installation)	160	248
Other data anomalies (discussed above)	37	211

A total of 211 participants remained in the SAE sample after the above filters were applied to the participant population. The sample was representative of the number of installations and expected savings for the population.

To allow sufficient sample size for extrapolating realization rates to the SAE model, we combined some measure types. The realization rates appear below.

Table 5: Realization Rates by ECM and Building Type (from the building simulation model)

	Office	Retail	Warehse	Manuf.	Other	School	Hospital	Overall
Interior (CFL & fluorescent)	115.4%	112.0%	98.5%	72.8%	99.4%	105.9%	104.6%	109.8%
HID Systems	106.7%		95.8%	80.2%	101.0%	101.0%		92.0%
LED Exit	108.2%	106.0%		97.4%	105.3%	99.4%	103.1%	105.6%
ETC (controls & traffic)							107.0%	107.0%
Overall	***114.5%***	***112.0%***	***96.3%***	***76.1%***	***102.0%***	***104.8%***	***104.2%***	***107.7%***

The next step was to extrapolate the realization rates from the building simulation modeled participants (as shown in Table 5, above) to the SAE sample. Extrapolation was conducted by ECM and building type. In cases where the building simulation model's realization rates were not available, we used the overall realization rate for that measure type as a proxy.

Model. The following SAE model was estimated:

$$ADC_{it} = \beta_1 HDD_{it} + \beta_2 CDD_{it} + \beta_3 ADS_i + \varepsilon_{it}$$

Where:

- ADCit is the average daily consumption (in kWh) by customer i for period t, where t represents the billing month for the participant. Total consumption is divided by the number of days in the period to determine average daily usage.
- HDDit is the average daily heating degree days for those determined to use electric heating. Weather stations are matched by county.[3] Daily HDD[4] readings are matched to the billing cycle and averaged.
- CDDit is the average daily cooling degree days for those determined to use electric cooling. Weather stations are matched by county. Daily CDD[5] readings are matched to the billing cycle and averaged.
- ADSi is the average daily savings for a customer. Pre-installation, this variable is set to zero. Post-installation, this variable is equal to the sum of the building simulation adjusted annual savings (in kWh) for all installed measures, divided by 365.
- β1, β2, and β3 are parameters representing individual impacts of the explanatory variables on ADC. The primary focus of the current analysis is the reduction in ADC due to measure installation, represented by β3, the coefficient of ADS, which can be interpreted as the realization rate associated with EZ Sim adjusted savings.

A fixed-effects specification was needed to account for customer heterogeneity.[6,7] The model was corrected for autocorrelation.[8]

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3 Taunton, MA; Worcester, MA; Providence, RI; Boston, MA; Concord, NH.

4 HDD is defined as 0 if daily average temperature is greater than 65° or 65° minus average daily temperature if that temperature is less than 65°.

5 CDD is defined as 0 if daily average temperature is less than 65° or average daily temperature minus 65° if that temperature is greater than 65°.

We were unable to match a suitable control group with the SAE sample. Program participants tended to have much larger and more stable consumption than the average customer. We modeled control group behavior separately through a stratified sample (by building type, ECM, and State) and found that their energy consumption had actually increased slightly between the pre and post periods. We assumed, therefore, that non-programmatic changes (e.g., changes in the economy, etc.) were small. Also, given this observed increase in consumption, we conclude that, had we had an appropriate control group, our estimates of the Program realization rates would have been higher. Our SAE model is likely on the conservative side.

Attempts to include variables to account for non-Programmatic effects on consumption were unsuccessful. They consistently produced insignificant coefficients and lowered the adjusted R-squared statistic.

Model Estimates. Table 6 shows the estimated coefficients for the Program from the SAE model estimated over the ECM types in aggregate. The model estimated that 90% of the EZ Sim adjusted savings were realized for the 211 participants.

Table 6: SAE Model Results

Variable	Coefficient	Standard Error	T-Statistic
Daily Savings	-0.90	0.956	-8.69
Daily Heating Degree Days	13.64	4.220	14.27
Daily Cooling Degree Days	99.48	0.104	23.58
Model: Adj R-square: 0.134; F-stat: 229.84; N=211 participants with 4,239 billing months			

Results

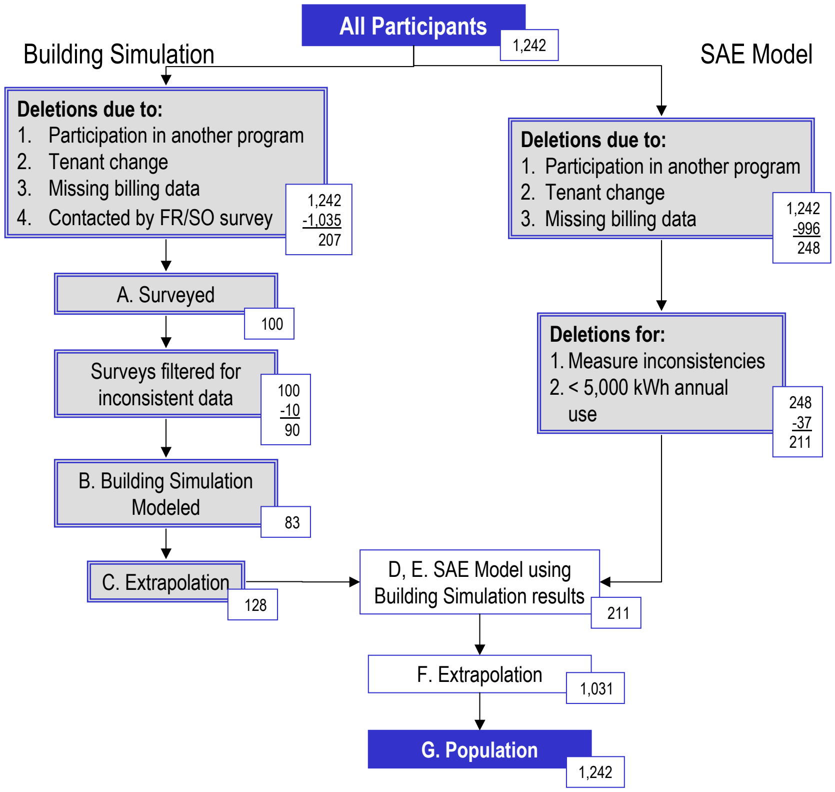
From the initial population of 1,242 Program participants, two parallel paths of data filtering were performed. The figure below illustrates the steps taken. Note that 83 of the building simulation modeled participants were included in the SAE modeling and used for extrapolating to the remaining 128 of the 211 SAE modeled participants.

6 It is reasonable to believe that the data behave differently across participants but similarly for each participant. Therefore, treating the billing data for each participant separately is appropriate. A fixed-effects model accomplishes this by allowing the model to estimate each participant separately using differential intercepts for customer heterogeneity.

7 Attempts to include monthly and building-specific dummy variables were unsuccessful, as was modeling savings by measure type or grouped measure type.

8 Autocorrelation indicates that observations of a variable across time are correlated with one another. It is common in time series data (such as the billing analysis used in the current study). It causes a model to be inefficient and test statistics to be unreliable. We corrected for autocorrelation by using an AUTOREG procedure as opposed to the typical OLS regression procedure. The AUTOREG augments the OLS model with an autoregressive model for the random error, thereby accounting for the autocorrelation of the errors.

Figure 2: Participant Filtering



In order to estimate the final Program impacts, the following steps were taken:

A. Surveyed 100 Customers
B. Modeled 90 customers using a building simulation model
C. Extrapolated building simulation realization rates by ECM and building type for 83 of the participants to a sample of 211 customers that did not participate in other programs, did not have tenant changes, and had complete billing data
D. Ran SAE model using 211 customers and estimated an overall realization rate
E. Applied the SAE-derived realization rate of 90.3% to individual ECM/building type adjusted savings estimates
F. Used the verified savings to extrapolate to remaining population
G. Compared the SAE verified savings to initial estimated savings for the participant population

The overall realization rate for the Program is 86.5%. Breakdowns by measure type, building type, and state are shown in Tables 7 through 9.[9]

[9] Though the simple product of the realization rates from building simulation modeling and SAE modeling yields 107.7%*90%=97%, extrapolating to the participant population, which had a slightly different ECM/building type mixture than either sample brought the aggregate realization rate down to 86.5%.

Table 7: Program Savings by Measure Type

	Initial Program Estimate (kWh)	Final Verified Savings (kWh)	Realization Rate
Fluorescent Systems	55,732,173	49,143,549	88.2%
CFLs	2,825,431	2,849,791	100.9%
HID Systems	17,449,340	12,696,858	72.8%
LED exit	3,420,239	3,659,656	107.0%
Controls	53,200	57,173	107.5%
Controls – Other	3,509,694	3,288,650	93.7%
Traffic lights	600,668	645,528	107.5%
Total	***83,590,745***	***72,341,205***	***86.5%***

Table 8: Program Savings by Building Type

	Initial Program Estimate (kWh)	Final Verified Savings (kWh)	Realization Rate
Office	17,674,361	18,261,523	103.3%
Retail	12,582,339	12,398,424	98.5%
Warehouse	1,913,731	1,787,709	93.4%
Manufacturing	32,752,614	22,139,438	67.6%
Hospital	5,275,584	5,065,271	96.0%
School	9,851,970	9,396,324	95.4%
Other	3,540,145	3,292,515	93.0%
Total	***83,590,745***	***72,341,205***	***86.5%***

Table 9: Program Savings by State

	Initial Program Estimate (kWh)	Final Verified Savings (kWh)	Realization Rate
MA	51,928,545	44,178,969	85.1%
NH	1,032,626	1,030,142	99.8%
RI	30,629,574	27,132,093	88.6%
Total	***83,590,745***	***72,341,205***	***86.5%***

Conclusions

The evaluation of National Grid's Energy Initiative Program utilized a combination of traditional SAE modeling and a building simulation model. The Program achieved an overall realization rate of 86.5%. The combined approach achieved its dual purposes of: 1) reducing the measurement bias associated with SAE models and 2) utilized the SAE modeling to verify the applicability of extrapolating the building-simulation modeled sample to the population. The combined approach also lowered the cost of data collection significantly. In isolation, it appears that the SAE model was underestimating and the building simulation was overestimating savings, however in combination, the two approaches yield a realization rate that is unbiased, cost effective, and robust.