Using Billing Analysis Techniques to Estimate Realized Demand Savings for Commercial and Industrial DSM Programs

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In the past, little work has been done to quantify the actual realized demand savings of commercial and industrial DSM programs, using billing data. Typically, energy savings are quantified using billing analysis techniques, but demand savings are estimated using engineering estimates, simulation models, or load research data. This approach often leads to a mis-estimation of demand savings.

Often, commercial and industrial customers are billed based on their kW demand. With this billing data and the appropriate billing analysis techniques, actual demand savings can be estimated using billing models. The result is more accurate and realistic estimates of program demand savings.

This paper presents the results of using billing analysis to estimate the actual realized demand savings for Boston Edison Company's (BECo) small commercial and industrial DSM program. The billing models measure the average monthly demand savings that are being realized. Adjustment factors developed from load research data are applied to the average savings to derive realized peak, coincident peak, and non-coincident peak savings.

INTRODUCTION

In the past, demand savings have been estimated by using engineering estimates, simulation models, load research data, or metering. Engineering estimates of savings are often based on generic estimates of the savings energy conservation measures will achieve. Engineering estimates often assume that the measures are operating constantly, and all of the measures stay in place. The weakness of using this method is that there is no verification that these assumptions are realistic. Simulation modeling, such as DOE2, uses the engineering estimates as the basis for the model. Thus, if these assumptions are not realistic the results of the simulation model will not be accurate. Simulation models also need large amounts of data in order to produce accurate results. Load research data often are used with the estimates of energy savings achieved by a commercial/industrial program. This technique is based on the assumption that the amount of demand savings achieved is consistently equal to some ratio of energy savings. This assumption is not always accurate. All three of these methods are based on assumptions and do not verify what is actually occurring.

Metering is another technique used to estimate demand savings. Metering provides data on actual operating patterns and actual demand savings if pre-metering and post-metering are employed. However, this technique can be extremely expensive, and thus, often is not a viable option.

The billing analysis technique is a cost-effective alternative that captures actual energy consumption or demand at the customer level. The billing models use program participants' actual billing data, and therefore, model what is actually occurring. Billing analysis techniques have been used largely in the past to quantify energy savings. Every electricity customer is billed based on kWh usage; thus, billing data regarding kWh usage has been available for most DSM programs. This makes billing analysis an available option to use to estimate energy savings.

Most commercial/industrial customers are billed based on their kWh usage and kW demand. All large commercial/industrial customers are billed this way, and a majority of small commercial/industrial customers are billed based on both kWh and kW. For these customers, billing data based on kW demand is available, and therefore, billing analysis techniques can be applied to estimate actual demand savings.

Scope

The methodology used to estimate demand savings for a small commercial/industrial DSM program is presented in this paper. The results of using the methodology discussed to estimate the demand savings for BECo's small commercial/industrial DSM program also will be given. Finally, the advantages and disadvantages of using billing models to estimate demand savings will be presented, along with areas of additional research.

METHODOLOGY

The key to isolating program demand savings in billing analyses is to properly model customer demand. Program savings are often difficult to isolate because they are relatively small when compared to overall customer demand. Therefore, it is necessary to account for as much variation in kW demand as possible to help separate program demand savings from other confounding effects on demand. A sequence of steps aimed at enhancing this process has been devised.

The first step is to segment customers by business category and estimate separate billing models for each category. By segmenting the customers into specific business sectors, some of the variation in the billing data that is caused by the different electricity needs and consumption patterns by different business or industries will be removed. One sector, such as schools, has a higher peak demand in the winter while another sector, such as manufacturing, has higher peak demand in the summer. If these two industries were modeled together, it would be much more difficult to isolate those business-specific effects.

The next step in this process is to isolate some of the customer-specific variation in kW demand. The vast majority of variation in kW demand results from differences in business size and electric intensity. Analysis of Covariance (ANCOVA) models are used to capture these differences.[1] The model uses pre-installation demand as a control for post-installation consumption. The independent variables used in the ANCOVA models to estimate the dependent variable are quantitative variables and fixed effects variables. Each customer is treated as a separate effect in the ANCOVA models. The customer-specific variable is used to account for the wide variation found in the base consumption between customers in commercial and industrial analyses. Interactions between the customer-specific variable and the weather variables are used in these models to capture customer-specific responses to heating and/or cooling needs.

Buildings vary in terms of size, insulation, design and uses, and therefore, they have different heating and cooling needs. These differences can be captured by using customer-specific weather reactions. To accomplish this, daily weather data are matched to each customer's billing cycle. The dependent variable for the demand model is the customer's peak demand in the billing cycle. Peak demand is likely to be tied to the hottest or coldest day in the billing period. Therefore, the two weather variables are defined as the maximum high in the billing period for the cooling response and the minimum high in the billing period for the heating response.

The statistically adjusted engineering (SAE) model specification is used to capture the savings estimate. In these models, the engineering estimates were used to capture program savings. This approach acts to differentiate the savings which each customer will actually achieve. The variation between program participants that occurs in the savings estimate as a result of size, quantity and use differences is reduced. As previously discussed, the pre-installation period is used as a control for the post-installation period. The coefficient of the engineering estimate of savings variable represents the percentage of estimate savings which can be observed in the bills. This is referred to as the ''realization rate''.

The SAE model specification is often used. However, another specification that also can be used is the installation indicator model. The demand savings is estimated directly with a zero/one indicator variable. In instances, where engineering estimates of savings are inaccurate or inconsistent, this model specification may yield a more precise estimate of demand savings. However, this model may yield an imprecise estimate of demand savings if the model contains different customers with dramatically different savings levels.

The SAE model used to estimate kW demand savings is similar to the following:

$$Y_{ij} = \beta_j + \beta_{maxj}*MaxH_{ij} + \beta_{minj}*MinH_{ij} + \beta_{save}*EES_j.$$

Y_{ij} = the peak kW demand in billing period i, for customer j,

β_j = customer j's base peak demand,

β_{maxj} = customer j's demand response to the hottest day in a billing period,

β_{minj} = customer j's demand response to the coldest day in a billing period,

$MaxH_{ij}$ = the maximum daily high temperature in billing period i,

$MinH_{ij}$ = the minimum daily high temperature in billing period i,

β_{save} = demand savings, in the form of a realization rate,

EES_{ij} = customer j's engineering estimate of savings in post-installation month i, 0 otherwise.

Weather related savings and non-weather related savings can be estimated separately in a billing model. The program savings for the weather related measures would be interacted with weather variables. For example, heating measures would be interacted with the minimum high temperature in the billing period.

The billing models do not estimate the overall peak savings of installing measures, rather, the models measure the average monthly demand savings that is being realized. To derive realizations rates of the peak, coincident peak, and non-coincident peak savings, adjustment factors have to be developed. Load research data are used to develop these adjustment factors, and then the adjustment factors are applied to the average monthly demand savings estimated by the models. These factors should be developed for each commercial/industrial customer segment analyzed in the billing models.

RESULTS

BECo's Small Commercial and Industrial (C/I) Retrofit Program offers incentives for the installation of energy efficient electro-technologies by non-residential electric customers with a peak demand of less than 150 kW. The program measures are divided in two categories: Level 1 measures include the most prescriptive measures, such as lighting, HVAC, and water heating measures, and Level 2 measures include more comprehensive applications pertaining to advanced HVAC, motors, advanced lighting systems, energy management systems, and refrigeration.

For this Small C/I DSM program, realized demand savings were estimated. To estimate the kW demand savings for small commercial/industrial customers, separate billing models were estimated for the twelve different business categories. The results for one of the business categories is discussed within this paper. Offices were the most common facility type of participants in BECo's small C/I DSM program; thus, the results of this model are discussed.

The model employed a customer-specific constant and a customer-specific reaction to heating and cooling needs. Demand is instantaneous, and therefore, is likely to be tied to the hottest or coldest day in a period. Thus, the maximum high temperature during the billing period was used to capture the cooling needs and the minimum high temperature during the billing period was used to capture heating needs. The savings were captured with the SAE model specification. The model estimated separate realized demand savings for Level 1 and Level 2 program measures.

The results of the demand model are shown in Table 1.[2] Fifty-three percent of Boston Edison's demand savings estimate is realized for Level 1 measures and eighty-four percent of the demand savings estimate is realized for Level 2. These values underestimate the peak savings, because they represent the average monthly demand savings values, not the peak savings in the summer or the peak savings in the winter. An adjustment is used to estimate the peak, coincident peak, and non-coincident peak savings for the models and the probability of coincident demand with the utility.

To estimate the peak savings, Boston Edison's load research data were used to develop adjustment factors to the average monthly demand realization rates. The load research data were based on the average small commercial/industrial customer, so the adjustments are identical for each business sector. As previously discussed, the adjustments were developed by comparing the peak amount in question with the average monthly peak for small commercial/industrial customers. The peak adjustment was derived by calculating the ratio of the highest monthly demand to the average monthly demand for prototypical small C/I customers. Table 2 displays the gross kW savings, realized kW savings, peak kW savings, and off-peak kW savings.

The coincident and non-coincident peak adjustments were also derived. The utility summer and winter coincident peak adjustments were derived by calculating the ratio of the prototypical small C/I customer's demand at the utility's summer coincident peak to the average monthly demand for a prototypical small C/I customer and the ratio of the prototypical C/I customer's demand at the utility's winter coincident peak to the average monthly demand of a prototypical small C/I customer. The summer and winter non-coincident peak adjustments were derived by calculating the ratio of the prototypical small C/I customer's demand at the utility's summer non-coincident peak to the average monthly demand for a prototypical small C/I customer and the ratio of the prototypical small C/I customer's demand at the utility's winter non-coincident peak to the average monthly demand. The equations for these adjustment factors are shown below. These adjustment factors were then applied to the customer's savings estimates to determine the coincident and non-coincident savings estimates.

Summer Coincident Adjustment = Prototypical small C/I customer's demand at the utility's summer coincident peak / average monthly demand for a prototypical small C/I customer;

Winter Coincident Adjustment = Prototypical small C/I customer's demand at the utility's winter coincident peak / average monthly demand for a prototypical small C/I customer;

Summer Non-Coincident Adjustment = Prototypical small C/I customer's demand at the utility's summer non-coincident peak / average monthly demand for a prototypical small C/I customer;

Winter Non-Coincident Adjustment = Prototypical small C/I customer's demand at the utility's winter non-coincident peak / average monthly demand for a prototypical small C/I customer;

Table 1. Office Demand Savings Model

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	467.0	12,412,379.3	26,579.0	336.04	0.0001
Error	4,215.0	333,387.6	79.1		
Uncorrected Total	4,682.0	12,745,766.9			

R-Square	C.V.	Root MSE
0.954066	25.98	8.89

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Account	155	12,148,658.9	78,378.4	990.93	0.0001
MaxHigh*Account	155	201,583.6	1,300.5	16.44	0.0001
MinHigh*Account	155	18,361.3	118.5	1.50	0.0001
kWsave*Level	2	43,775.6	21,887.8	276.73	0.0001

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Account	155	205,977.7	1,328.9	16.80	0.0001
MaxHigh*Account	155	19,203.8	123.9	1.57	0.0001
MinHigh*Account	155	17,021.4	109.8	1.39	0.0013
kWsave*Level	2	43,775.6	21,887.8	276.73	0.0001

Coefficient of Savings Estimate	Coefficient	t-Statistic	Pr > t	Std Err of Est
Level 1 Measures	−0.531386	−17.38	0.0001	0.03058287
Level 2 Measures	−0.8355569	−15.86	0.0001	0.05268174

90% Confidence Intervals

Level 1 Measures	(48%–58%)
Level 2 Measures	(75%–92%)

Source: Cambridge Systematics, Inc. 1995, 3–16.

ALTERNATIVES

In alternative techniques, the demand savings which occur are not specifically measured. Billing models can be used to estimate actual demand savings for those customers who are billed based on kW demand. Billing models are based on actual billing data, rather than assumptions on how the energy conservation measures perform or how often the measures are in operation. Thus, the result of the billing models is a more realistic estimate of program demand savings than the techniques more commonly used in the past.

One problem with the billing model is that it measures the realized, average monthly demand savings. To resolve that problem, adjustment factors need to be developed from load research data that can be applied to the average savings to derive the realizations of the peak, coincident peak and non-coincident peak savings. However, load research data are usually not available for each of the specific business seg-

Table 2. Office Program Demand Savings (kW)				
Measure	Gross kW Savings	Realized kW Savings	Peak kW Savings	Off-Peak kW Savings
Level 1	1,467.9	778.0	477.0	301.0
Level 2	324.6	272.7	167.2	105.5

Source: Cambridge Systematics, Inc. 1995, 3–67.

ments modeled using billing analysis techniques. Therefore, load research data will not account for the different energy demand patterns experienced by different business sectors. If load research data are not based on actual energy demand patterns of the specific business sectors then the peak, coincident peak, and non-coincident peak demand savings will not be as accurate or as realistic.

In attempting to improve the estimation of overall peak demand savings, we would suggest further researching the possibility of using a billing model that would interact program savings with peak and off-peak time periods. The model specification would be similar to the one discussed previously in this paper. The dependent variable would still be peak demand in the month. The model would still employ a customer-specific constant to account for base consumption and a customer-specific reaction to heating and cooling needs.

The main difference in approaches would be in the definition of the savings variable. Instead of using just the engineering estimate of savings (SAE), the engineering estimate of savings would be interacted with one/zero indicator variables representing a summer peak period, a winter peak period, and an off-peak period.

The model used to estimate kW demand savings for the three different categories is the following:

$$Y_{ij} = \beta_j + \beta_{maxj}{*}MaxH_{ij} + \beta_{minj}{*}MinH_{ij} + \beta_{save1}{*}EES_{ij}{*}SumPeak + \beta_{save2}{*}EES_{ij}{*}WinPeak + \beta_{save3}{*}EES_{ij}{*}OffPeak.$$

Y_{ij} = the peak kW demand in billing period i, for customer j,

β_j = customer j's base peak demand,

β_{maxj} = customer j's demand response to the hottest day in a billing period,

β_{minj} = customer j's demand response to the coldest day in a billing period,

$MaxH_{ij}$ = the maximum daily high temperature in billing period i,

$MinH_{ij}$ = the minimum daily high temperature in billing period i,

EES_{ij} = customer j's engineering estimate of savings in post-installation month i, 0 otherwise,

β_{save1} = summer peak demand savings, in the form of a realization rate,

SumPeak = 1 if summer peak period, 0 otherwise,

β_{save2} = winter peak demand savings, in the form of a realization rate,

WinPeak = 1 if winter peak period, 0 otherwise,

β_{save3} = off-peak demand savings, in the form of a realization rate,

OffPeak = 1 if off-peak period, 0 otherwise.

The model would estimate the percentage of the engineering estimate of savings that are being realized in the summer peak period, the winter peak period, and the off-peak period. Therefore, adjustment factors would not have to be used to develop peak savings. This would eliminate the potential for measurement error because adjustment factors based on load research data would no longer be necessary. However, adjustment factors still would need to be developed to derive coincident peak and non-coincident peak if this method were used. Again, if the load research data do not accurately represent energy demand patterns, the estimates for coincident peak and non-coincident peak would be less realistic.

A potential problem in estimating this model is the data requirement. When the savings are divided into three periods, one-third of the data is available to estimate that savings value. Separating savings into a summer peak, winter peak and off-peak period would work with the data available for many evaluations. However, there probably would not be enough data to divide savings any further, such as monthly peak demand savings.

CONCLUSION

Billing analysis techniques do have some flaws in estimating realized demand savings. Some of these flaws can be corrected through the use of adjustment factors based on accurate load research data or with additional research. When kW billing data are available, billing analysis techniques produce results that provide realistic and cost-effective estimates of program demand savings.

ENDNOTES

1. Megdal, Lori, Paquette, Eric, and Greer, Jerry. ‘‘The Importance of Using Analysis of Covariance, Diagnostics, and Corrections Within Billing Analysis for Large C&I Customers.’’ Paper presented at the 1995 International Energy Program Evaluation Conference, Chicago, IL., August 22–25.
2. Cambridge Systematics, Inc. 1995. *Small Commercial/ Industrial Retrofit Program Impact Evaluation,* prepared for the Boston Edison Company, Cambridge Systematics, Inc., Cambridge, MA.

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