CASE STUDIES IN USING WHOLE BUILDING INTERVAL DATA TO DETERMINE ANNUALIZED ELECTRICAL SAVINGS

Mark Effinger
Engineer

James Anthony
Engineer

Lia Webster
Senior Engineer

Portland Energy Conservation, Inc
Portland, OR USA

ABSTRACT

Whole building interval analysis to determine savings from energy reduction measures is addressed by IPMVP Option C, ASHRAE Guideline 14 and is also presented in a 2008 guideline from the California Commissioning Collaborative. The whole building analysis has typically focused on the avoided energy use method; although a normalized savings method is also described in Guideline-14 and IPMVP.

Using the normalized method might allow for the determination of annual savings when less than a year of post-implementation data is collected. The reduced time required to determine annual savings via the normalized savings method might appeal to energy conservation programs. However, details and rules for applying normalized savings are not yet detailed in the guidelines.

The case studies presented in this paper use the normalized savings method to determine annual savings. Savings uncertainty for the normalized method is determined and presented after slight modifications to the formulas described in ASHRAE Guideline 14. The effects of reduced post-implementation monitoring periods are also investigated.

INTRODUCTION

The use of whole building data to develop energy models as a method to ascertain energy savings has been researched for many years. This method has been detailed in the IPMVP Option C, ASHRAE Guideline 14 (GL14), and was used extensively in the Texas LoanSTAR program. The California Commissioning Collaborative (CCC) has also recently published procedures for using this method in the "Guidelines for Verifying Existing Building Commissioning Project Savings Using Interval Data Energy Models". Despite the extensive research into this M&V method, and availability of guidelines, the wide-spread adoption has not yet taken hold in utility programs.

One of the largest obstacles preventing adoption of Option C is the length of monitoring time required to develop reliable regression models. Also, to be IPMVP adherent, both pre- and post-implementation data must be collected over a period that covers the full reporting period (IPMVP, 2007). As such, the determination of annual energy savings for weather-dependent energy efficiency measures can require a monitoring period of an entire year for each phase of the project (baseline and post-implementation). Since it is more common that a year of historical baseline interval data is available at the start of the project, the length of the post-implementation phase is typically the point of contention. A year delay to determine project savings might not be desired or even possible in certain energy efficiency programs.

One possible method to reduce the length of time required to determine annual savings is to create a post-implementation regression model when less than a year of data is collected. The baseline and post-implementation models can be applied to a common base, such as TMY temperature data to determine the normalized annual average savings (Reddy, 2000). This paper presents the experience gained from applying IPMVP's Option C to determine normalized savings on two existing building commissioning projects.

Utilizing previous studies and guidelines, a method for determining the fractional savings uncertainty in normalized savings estimates is developed. This uncertainty analysis is applied to the annualized energy savings based on normalized weather data for a large commercial office building and a grocery store. The impact on savings and uncertainty from the various monitoring period lengths used to develop the post-implementation models is investigated.

BACKGROUND

The focus from previous research and guidelines on determining energy savings from whole building energy meters has been directed toward "avoided energy use." The avoided energy use method requires the development of a regression model from measured baseline data. The regression model is then used to project the building energy performance into the post-implementation period as if no change were made to the building. The independent driving variables are measured in the post-implementation period and used as inputs for the baseline model. Measured energy use is compared with the regression model results and savings are defined as the difference between the adjusted baseline model prediction and the actual post-implementation energy measurements.

The normalized savings method uses the same baseline regression development as the avoided energy use method. However, for normalized savings, measured post-implementation data is used to develop a post-implementation regression. Baseline and post-implementation regressions are driven by the same input, TMY3 temperature data for this study, and savings result from the difference between the results of the two regressions.

Depending on project requirements, an establishment of savings uncertainty might be an important component of reported savings. The avoided energy use method typically introduces uncertainty in the form of regression error from an imperfect baseline model. Measurement error from the post-implementation period should be applied to the overall uncertainty calculation, but when the measured data are taken from utility grade meters, the error is assumed to be zero. In the normalized approach, an additional uncertainty is present in the form of regression error from the post-implementation energy model. This uncertainty should be addressed when annual avoided savings are reported.

GL-14 mentions the normalized savings method as a measurement option, but then states that the main focus and process development was based on the avoided energy use method. No clear direction has been provided to address the overall uncertainty when the normalized savings method is used, so one was developed and is outlined herein.

The case studies presented in this paper will use the well established avoided energy use as a base of comparison to investigate the impact on total savings when a normal average data set (TMY3) is used. The impacts on savings and uncertainty due to post-implementation regressions with monitoring lengths less than one year were also investigated. It is important to note that when annual savings are calculated using less than 12 months of post-installation data, the results are no longer IPMVP adherent (CCC, 2008).

METHODOLOGY

The buildings selected for this study are a large office located in Southern California and a large sized grocery store located in Northern California. A year's worth of utility data, in 15 minute intervals, was collected for each baseline and post-implementation period. The analysis interval desired for this analysis was hourly, since determining peak demand savings is a priority for many California retro-commissioning projects. In order to extract peak demand savings, the smaller data intervals are required (Katipamula, 1994).

Ambient conditions and TMY3 data were collected from the nearest NOAA station. The date stamps between the weather data and interval data were aligned using the Universal Translator processing tool (available free at utonline.org).

Once the data conditioning was complete, an analysis was conducted to identify the independent variable or variables that drive the building energy use. Microsoft Excel was used to perform multi-variable linear regressions on the outside air ambient dry bulb and ambient wet bulb temperatures as well as the humidity ratio to determine if one variable or the other had a stronger correlation to electrical consumption. Production level data was not available for these two projects. Outside air dry bulb temperature proved to be the strongest available contributor and was chosen for the development of the energy models for the two buildings in this case study.

Energy Explorer, a software tool developed by Dr. Kissock from the University of Dayton, Ohio, was used to develop and evaluate potential change-point regressions models. Background on variable change-point models can be found in ASHRAE Research Project 1050, or in the 2008 CCC guidelines. The statistical tests from Energy Explorer indicated that a 2-parameter model (linear) regression was acceptable for the large office project. A 4-parameter regression model was the best fit for the grocery store energy use profile.

STATISTICAL METHODS

In existing guidelines, there are two primary approaches to evaluate the uncertainty resulting from whole building energy regression models. The method described in IPMVP applies traditional regression statistics to evaluate the validity of the regression model(s) and to calculate relative precision. The GL14 approach follows a procedure to calculate fractional savings uncertainty of avoided energy savings. Both methods require the establishment of a confidence interval. GL14 requires a confidence interval of at least 68% for compliance.

The fractional savings uncertainty methodology accounts for potential autocorrelation errors which might be present and significant with shorter data intervals. Autocorrelation is a statistical metric that defines how much a particular point is dependent on the previous value. High autocorrelation indicates a systematic error that will transfer to the final savings estimate. Since the fractional uncertainty was developed to include the effects of autocorrelation, this method is the basis for this analysis.

ENERGY SAVINGS CALCULATION METHODS

Currently, the existing guidelines focus on the avoided energy use method, where savings are calculated in the following manor:

$$E_{save,j} = \hat{E}_{pre,j} - E_{meas,j} \tag{E-1}$$

Where:

$E_{save,j}$ is the avoided energy use (savings) that occurred over time interval *j*.

$\hat{E}_{pre,j}$ is the total predicted energy use that would have occurred over time interval *j* if the project had not been performed. This value is determined by a regression model developed from the baseline project data.

$E_{meas,j}$ is the total measured energy consumption that occurred over time interval *j* of the post-implementation period.

For the normalized savings method, a post-implementation regression is used in place of the measured data. As such, normalized energy savings are determined by equation E-2.

$$E_{save,normalized} = \hat{E}_{pre} - \hat{E}_{post} \tag{E-2}$$

Where:

$\hat{E}_{post,}$ is the total predicted energy use of the post-implementation period as determined by a post-implementation regression.

Fractional Savings Uncertainty

Fractional savings uncertainty was first developed and presented in 2000 (Reddy, Claridge). It was intended to be used as a metric to help select appropriate regression models for avoided energy use calculations. The metric shifts the focus from the evaluation of the regression to the uncertainty associated with the final savings estimate.

Fractional savings uncertainty was adopted by ASHRAE GL14 (GL14) and is also used in the CCC guideline. Information regarding the full development of fractional savings uncertainty, along with examples, can be found in these two sources. The CCC guideline defines the metric as "…the ratio of the expected uncertainty in the savings to the total savings" which is shown in Equation E-3.

$$\text{Fractional Savings Uncertainty} = \frac{\Delta E_{save}}{E_{save}} \tag{E-3}$$

Where:

ΔE_{save} is the uncertainty of the savings

The fractional savings uncertainty equation, as given in GL14, is presented by equation E-4.

$$\frac{\Delta E_{save}}{E_{save}} = t \cdot \frac{1.26 \cdot CV \left[\frac{n}{n'} \left(1 + \frac{2}{n'} \right) \frac{1}{m} \right]^{1/2}}{F} \tag{E-4}$$

Where:

1.26 is a coefficient based on numeric trials that simplifies matrix algebra related to regression error (Reddy and Claridge, 2000)

t is the t-statistic evaluated at a given confidence interval

F is the ratio of energy savings to baseline energy use

n is the number of data-points used to develop the regression model

n' is the adjusted number of independent observations that accounts for autocorrelation

m is the number of data points expected in the post project measurement period

CV is the coefficient of variation root-mean-squared-error.

The adjusted number of independent observations during the baseline period due to autocorrelation is given by equation E-5

$$n' = n \cdot \frac{1-\rho}{1+\rho} \tag{E-5}$$

Where:

ρ is autocorrelation coefficient defined as the square root of the coefficient of determination, R^2, between the model residuals and the residuals shifted by a single time increment

The ratio of energy savings to baseline energy use for the normalized savings method is given by equation E-6.

$$F = \frac{\hat{E}_{pre} - \hat{E}_{post}}{\hat{E}_{pre}} \tag{E-6}$$

The original form of the fractional savings uncertainty (E-4) is not readily suited for use with normalized savings. As developed, E-4 assumes only the baseline regression error will impact the final savings uncertainty. Substituting equations E-2 and E-6 into the fractional savings uncertainty formula, produces the following results:

$$\frac{\Delta E}{\hat{E}_{pre} - \hat{E}_{post}} = \frac{t * 1.26 \cdot CV \cdot \left[\frac{n}{n'} \cdot \left(1 + \frac{2}{n'}\right) \cdot \frac{1}{m} \right]^{1/2}}{\frac{\hat{E}_{pre} - \hat{E}_{post}}{\hat{E}_{pre}}} \quad \text{(E-7)}$$

Solving equation E-7 for the regression uncertainty, ΔE, yields an equation that can be applied to each regression, baseline and post-implementation, independently as shown by equations E-8 and E-9.

$$\Delta E_{pre} = t \cdot 1.26 \cdot CV_{pre} \cdot \left[\frac{n}{n'} \cdot \left(1 + \frac{2}{n'}\right) \cdot \frac{1}{m} \right]^{1/2} \cdot \hat{E}_{pre} \quad \text{(E-8)}$$

$$\Delta E_{post} = t \cdot 1.26 \cdot CV_{post} \cdot \left[\frac{n}{n'} \cdot \left(1 + \frac{2}{n'}\right) \cdot \frac{1}{m} \right]^{1/2} \cdot \hat{E}_{post} \quad \text{(E-9)}$$

The variable m in equations E-8 and E-9 originally refers to the number of measured post-implementation data. Since the regressions in the following case studies will use TMY3 temperature data as the driving variable, m is interpreted as the number of TMY3 points (8760 for hourly models and 365 for daily models). The variable m will be the same value in both equations whereas n and n' will depend on each regression.

Once uncertainty is determined for each independent regression, a single combined uncertainty value can be calculated and reported for the final savings using the standard additive error equation shown by equation E-10.

$$\Delta E_{total} = \sqrt{\Delta E_{pre}^{\ 2} + \Delta E_{post}^{\ 2}} \quad \text{(E-10)}$$

The combined uncertainty can then be applied to the normalized savings value using the original fractional savings uncertainty from equation E-3. As mentioned earlier, uncertainty due to measurement error has been excluded.

Application to Case Studies

Data from the two case studies were utilized to evaluate the savings resulting from the projects. The avoided energy use approach was first used to develop a point of comparison for the normalized models. The original fractional savings uncertainty method was also applied to use as a base of comparison.

Large Office Analysis

The large office included in this study contains over 300,000 ft^2 (27,870 m^2) of conditioned space and is located in Southern California. As part of a retro-commissioning process, two identified measures were implemented: duct static pressure reset and supply fan scheduling.

As mentioned earlier, the desired analysis period was hourly intervals. Unfortunately, the hourly large office regressions did not pass a GL14 stipulation that net determination bias of the regression model does not exceed 0.005%. The net determination bias compares the ratio of total predicted and total measured values. The hourly data was rolled into average daily temperature and daily energy use. The results using daily intervals now produce a net determination bias less than 0.005%. GL-14 also stipulates that fractional uncertainty shall not exceed 50% at the 68% confidence level (e.g. 10% ± 2.5%). The 68% confidence interval is quite low so 95% confidence was chosen for this analysis.

Avoided energy use method:

Regression models were developed for baseline and post installation periods. The results are shown in Figure 1. A simple linear regression provided as good a fit as the more complicated change-point models and was chosen for this analysis. A noticeable improvement in the models was observed when the data was separated by day type (e.g. weekday or weekend), but as a main goal of this study was to investigate uncertainty calculations, the analysis was conducted without separating by day type.

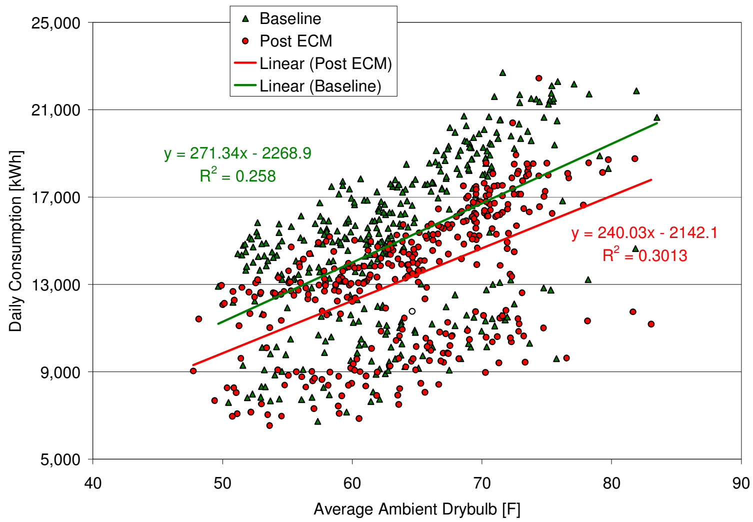

Figure 1: Baseline and post-implementation regression models

Avoided savings:

The actual ambient conditions during the post period consumption were input into the baseline model and the results were compared directly with the measured post period. These results are shown in Table 1.

Avoided Energy use (kWh)	690,235
F (savings percentage)	12.7%
Traditional Frac. uncert.	30.7%
Traditional Savings	690,235 ± 105,854

Table 1: Avoided energy use results

Annualized Savings:

Post installation models were developed from the 12 months of post data. TMY3 from a local weather station was averaged to provide a daily value that could be used to drive the baseline and post-implementation regression models. The results are shown in Table 2.

Normalized savings or E_{sav} (kWh)	662,205
F (savings percentage)	12.5%
$\Delta E_{sav,baseline}$ (kWh)	207,086
$\Delta E_{sav,post\ ECM}$ (kWh)	126,978
$\Delta E_{sav,total}$ (kWh)	242,915
Combined Frac. uncert.	36.7%
Project Savings	662,205 ± 121,458

Table 2: Normalized savings results (12 month post)

The slight difference observed between the final savings values from the normalized method and the avoided energy use method is expected. The avoided energy use method is driven by actual measured values during the post monitoring period. The normalized savings method uses TMY3 temperatures, which are averaged over several years. Figure 2 indicates there were differences between the temperature data used for each method. The temperatures in both the baseline and post periods exceeded averages by 2 and 5 percent, respectively.

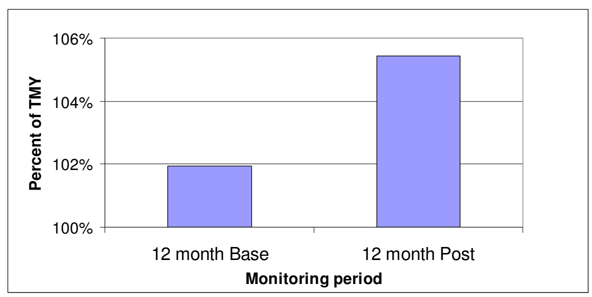

Figure 2: Actual temperature deviation from TMY

The difference in final savings between the avoided energy and normalized methods is within 5% for this case study, with the avoided energy savings higher than normalized as expected due to the temperature deviations. The normalized savings method also has the expected, higher fractional savings uncertainty due to the inclusion of the post-implementation regression uncertainty.

Post monitoring period length impact on final savings:

The results presented to this point have required a year of data collection for each baseline and post-implementation period. When project constraints prohibit a delay of one year to claim annual savings, it might be possible to create post-implementation regression models using less than a year of data. With the shorter post regression model, the savings can be annualized using the normalized savings method. The impact of monitoring length on normalized savings was investigated for this project by developing regression models from data sets of 9, 6 and 3 months of post-implementation data.

The post-implementation period began on June 1st for this particular project. As a result of the actual starting point, the 3-month regression plot contains data from only summer months.

Figure 3 shows a direct comparison between the regressions with various monitoring period lengths. The statistical values of each regression are provided in Table 3. The potential impact of monitoring period length on the predictive ability of the regression can be seen from the data in Figure 3. The 9-month regression overlaps very closely with the original 12 month profile. The 6-month regression has a slightly steeper slope and deviates from the original regression at the extremes of the temperature range. The 3-month regression deviates substantially from all regressions. The deviation of the 3-month post regression plot is likely due to the inclusion of summer months only.

These results are project specific as the shorter monitoring periods around alternate times of year would likely yield different regression profiles.

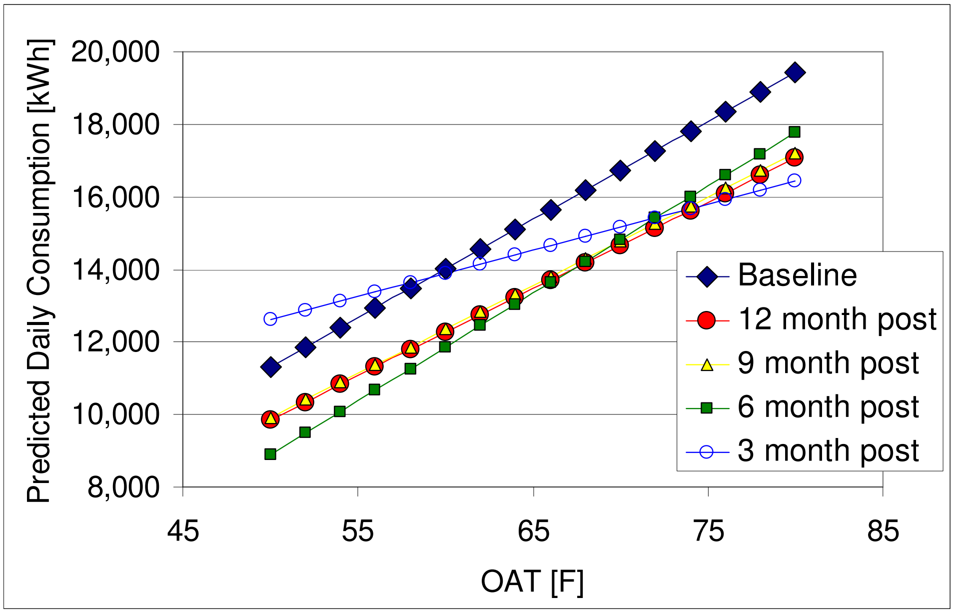

Figure 3: Comparison of post-implementation length on regression development

	Monitoring period	R^2	CV(RMSE)
Avoided Energy Use-Baseline	12 months	0.26	21.1%
Normalized Savings - Post ECM	12 months	0.30	19.4%
	9 months	0.32	19.2%
	6 months	0.18	19.9%
	3 months	0.02	19.4%

Table 3: Statistical values of all regressions

Annual savings were calculated using the original 12-month baseline and each post-period regression. The associated combined fractional savings uncertainty was calculated for each result. A summary of the combined fractional savings results is provided in Table 4 and the final savings for each regression is summarized in Table 5. A graphical representation of the savings, with the associated fractional uncertainty error bars, is provided in Figure 4.

	Post period	Fractional Uncertainty
Avoided Energy Use	12 months	30.7%
Normalized Savings	12 months	36.7%
	9 months	42.7%
	6 months	34.2%
	3 months	178.3%

Table 4: Combined fractional savings uncertainty summary

Based on the results of this project, the 3-month post period is the only data set that did not meet the 50% fractional uncertainty requirement of GL-14. A fractional savings uncertainty greater than 100% indicates the uncertainty in the savings greater than the actual savings estimate. As such, the 3 month post regression would not be appropriate to claim savings for this project.

The final energy savings estimates from the 12, 9 and 6 month monitoring periods range from approximately 90% to 112% of the base value determined by the avoided energy use method. The differences in savings observed between the various monitoring period lengths can likely be attributed, at least in part, to the variations in the average temperatures shown in Figure 5.

	Post period	Total Savings (kWh)	% Savings	Project Savings (kWh)
Avoided Energy Use	12 months	690,235	12.7%	690,235 ± 105,854
Normalized Savings	12 months	662,205	12.5%	662,205 ± 121,458
	9 months	627,695	11.8%	627,695 ± 134,092
	6 months	770,793	14.5%	770,793 ± 131,910
	3 months	151,522	2.9%	151,522 ± 135,067

Table 5: Savings summary

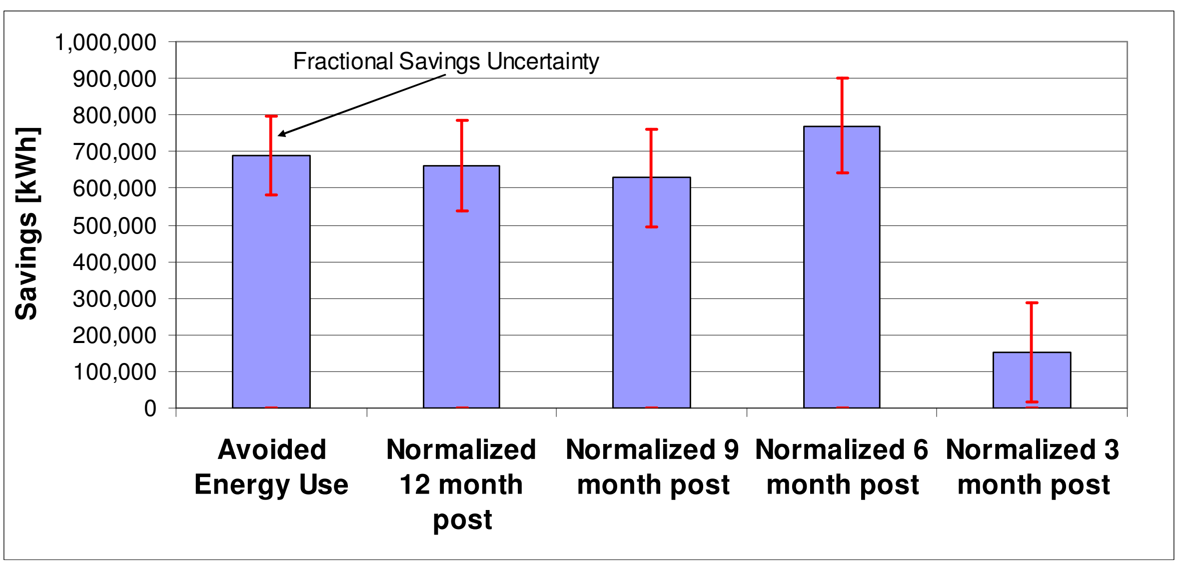

Figure 4: Summary of savings with combined fractional uncertainty

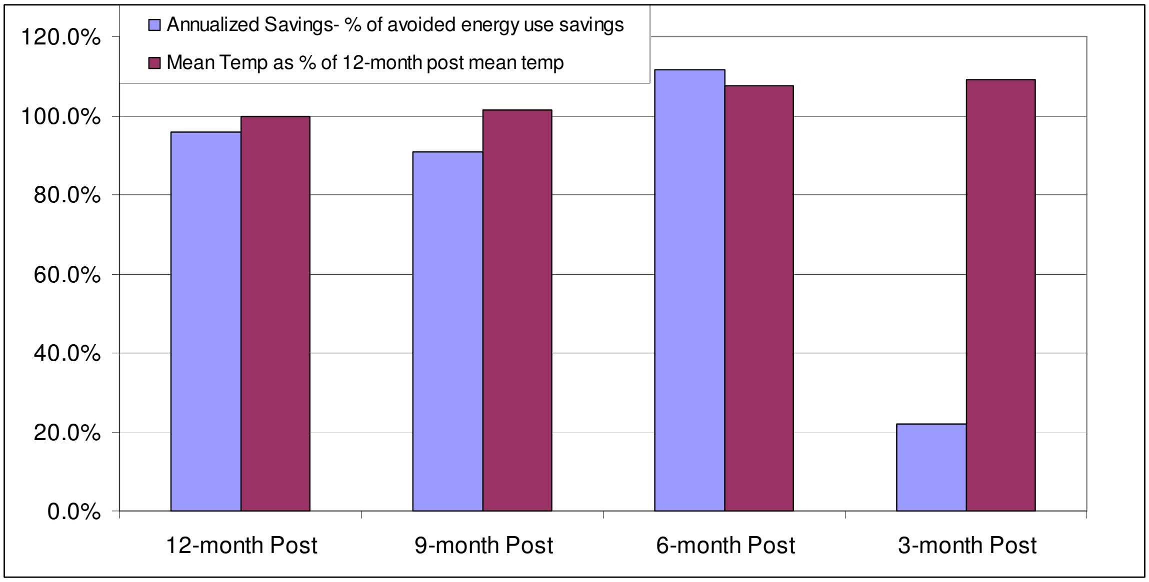

Figure 5: Average Temperature Comparison

The possibility exists that shortened monitoring periods will not capture a representative range of operation and skew the final result, shown particularly by the results of the three-month post-implementation data set. Further research will be required to develop standards or guidance in just how much data is required to achieve a representative data set. Based on this project, a post-implementation monitoring period of nine months is sufficient for a conservative savings estimate. A six month monitoring period can also be argued as a valid representation.

Grocery Store Analysis

The grocery store was a large, (greater than 50,000 sqft) supermarket located in Northern California, built during the 1990s. The retro-commissioning project began in late September, 2007, concluding in early December, 2007. The project affected the HVAC system, interior and exterior lighting, and refrigeration system.

Fifteen minute increment utility meter data (kW) was acquired from the utility for a full year prior to the initiation of the project, and was collected throughout the implementation period, as well as a full year after the conclusion of the project. Weather data was collected from the nearest NOAA weather station for these time periods, as well as TMY3 averages. Sales data were not available (or any other potential independent variable). Universal Translator was used to create align the time stamps of hourly weather and power consumption data.

Determining the driving variable:

Microsoft Excel was used to run multivariable regression analysis to correlate the various NOAA weather data to the power data. Ambient dry bulb temperature was found to have the strongest correlation with the hourly kW data.

Model Development:

Regression models for grocery stores typical exhibit a four parameter (4P) change-point model, as do many other buildings (Fels, 1986). Energy Explorer was used to create the 4P change point regression models for the following scenarios:

- Baseline: 1 Year Pre-Project: 9/06 to 9/07
- 1 Year Post Project: 12/07 to 12/08
- 9 Months Post Project: 12/07 to 9/08
- 6 Months Post Project: 12/07 to 6/08
- 3 Months Post Project: 12/07 to 3/08

Figure 6 displays an overlay of the full year data for baseline and post-implementation periods, with the corresponding regression models. This visualization demonstrates how the energy conservation project has reduced overall power and energy consumption. For the avoided energy use calculation method, the savings would be the difference between the 4P (baseline) regression model driven by the post measured OAT values, and the post-implementation scatter points. For the annualized savings method, the savings would be the difference between the two regression models, driven by TMY data.

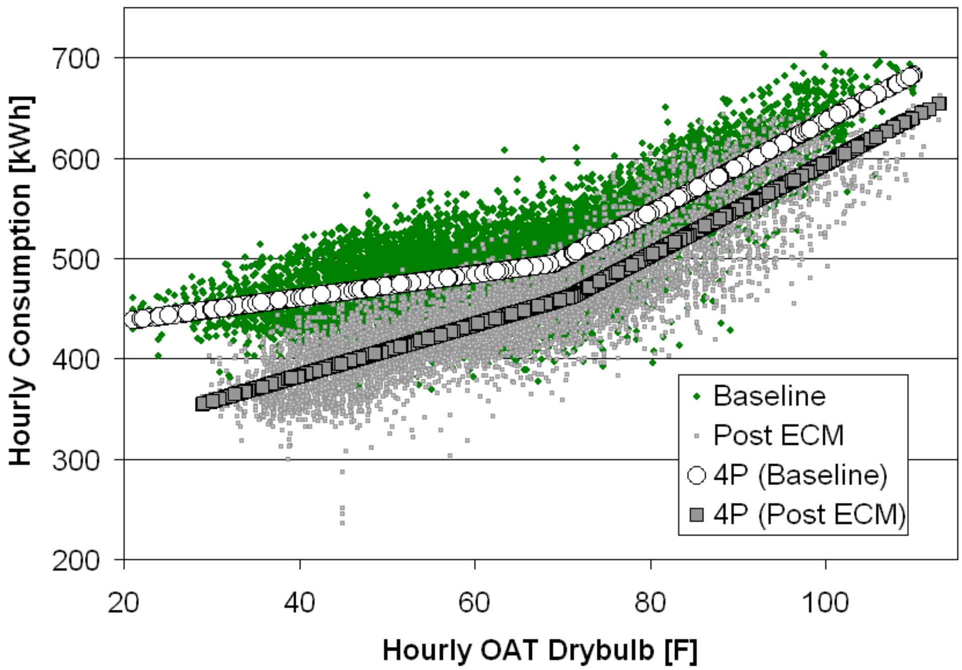

Figure 6 - Grocery Pre and Post Scatter Plots

Figure 7 shows a direct comparison between the regressions with various monitoring period lengths. The statistical values of each regression are provided in Table 6. All of the post period models predict lower hourly consumption values at each temperature, as expected. All of the post period models have a steeper slope than the baseline model in the low temperature section, indicating that the energy conservation measure is taking advantage of the extra cooling capacity at low temperatures, as provided by the refrigeration floating head pressure adjustment.

The one year post, 9 month post, and 6 month post period models all show similar behavior to the baseline model in that they have a similar change-point value, as well as a similar high temperature slope. The 3 month post period model varies from the other models greatly, in that its change-point is much lower, and its high temperature section has a lower slope than the low temperature section. This behavior is probably due to the fact that the 3 month post-implementation monitoring period occurred only during winter months, resulting in low average temperatures. The lack of higher ambient temperature data did not allow an accurate high temperature slope.

The 9 month post period model demonstrates similar behavior to the 1 year post period model, almost completely overlapping the 1 year model. The 6 month post period model is relatively close to the 1 year post period model, while the 3 month post period model varies greatly at the mid and high temperature sections.

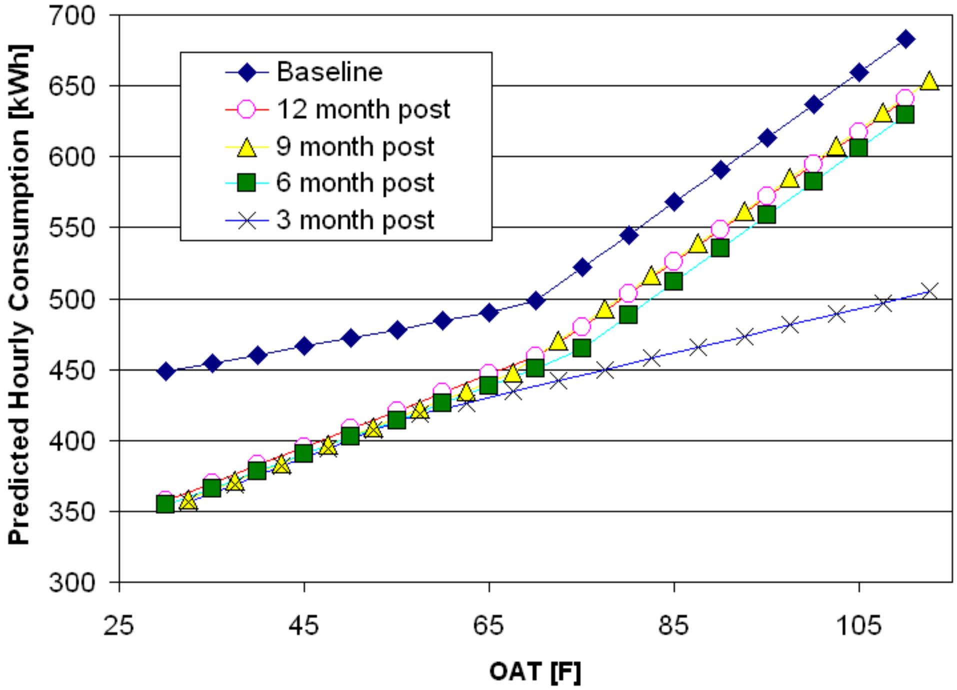

Figure 7 - Grocery Regression Models

	Monitoring Period	R^2	CV(RMSE)
Avoided Energy Use - Baseline	12 months	0.70	6.00%
Avoided Energy Use - Post ECM	12 months	N/A	N/A
Normalized Savings - Post ECM	12 months	0.79	6.5%
	9 months	0.83	6.4%
	6 months	0.74	5.4%
	3 months	0.39	6.0%

Table 6 - Statistics for Grocery Regression Models

The main goals of this study was to develop a method to determine annualized fractional savings uncertainty and understand the effect of modifying the post project monitoring duration on the savings calculation. Figure 8 displays the final savings estimates, as well as the fractional savings uncertainty for the various savings calculations. The fractional savings uncertainty values were calculated at the 95% confidence level.

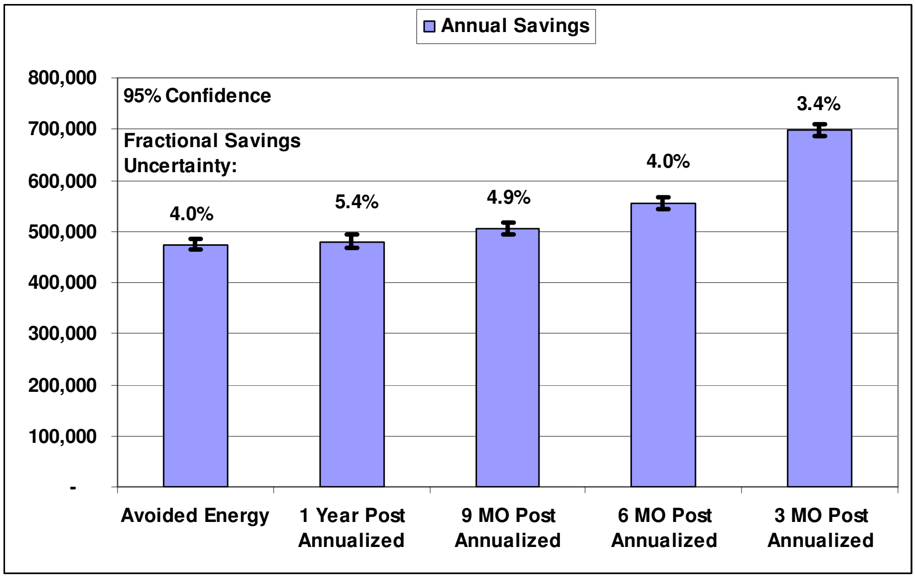

Figure 8 - Grocery Annualized Savings and Uncertainty vs. Method

	Post Period	Fractional Savings Uncertainty @ 95%	Project Savings at 95%
Avoided Energy Use	12 months	4.0%	473,975 ± 9,480
Normalized Savings	12 months	5.4%	479,274 ± 12,940
	9 months	4.9%	504,569 ± 12,362
	6 months	4.0%	554,080 ± 11,082
	3 months	3.4%	698,278 ± 11,871

Table 7 - Grocer Savings and Uncertainty vs. Method

The annualized savings for all post period length regressions range from 101% to 147% of the avoided energy base established at the start of the investigation. If the 3-month post period regression was removed from the comparison, the higher limit of the savings range decreases to 117% of the avoided energy use method.

To better understand the effect of the monitoring period temperature characteristics, Figure 9 displays a comparison of average temperature during the monitoring periods and the calculated annualized savings. The annualized savings are normalized by the avoided energy use savings and the mean temperatures are normalized by the average measured temperature during the 1 year post-implementation period.

Figure 9 indicates that as the mean ambient temperature deviates from the 1 year post period mean temperature, the estimated savings increase. This is likely because the 3-month period develops a regression model that only explains one half of the change-point model, exhibiting an almost linear behavior. The 3- month model appears to be accurate for the low temperature range of the post period, on one side of the change-point. However, if the model is extrapolated to the high side of the change point, there will be a large difference between the baseline and the post period model, regardless of which half is accurately defined. This is demonstrated in Figure 7.

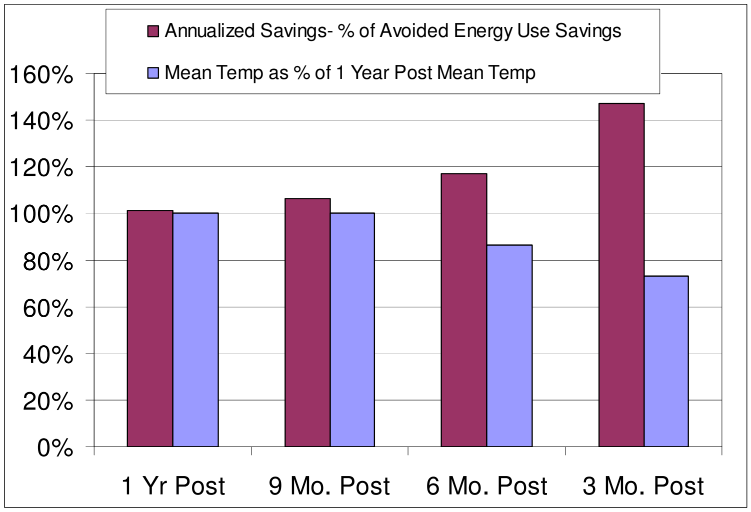

Figure 9 - Grocery Mean Temp and Annualized Savings

CONCLUSIONS

Whole building energy meter analysis was used to analyze savings for a large office and a large grocery store. The fractional savings uncertainty equation, which was developed only for the avoided energy use method, was modified to apply to independent regressions that are required for the normalized savings method. The strategy presented in this paper provides a means to quantify uncertainty in savings that are developed from separate regression models.

The modified fractional savings uncertainty allows for an estimation of error based on regression characteristics, but does not predict the possible estimation errors caused by reduced monitoring periods. These bias errors might be present if data is not collected over full operating cycles but is still used to extrapolate annual savings. ASHRAE has recently approved funding for RP-1404 which will develop protocols for short term monitoring of whole building performance.

For now, the two projects analyzed in this case study indicate that a 3 month post-monitoring period provides inadequate results or annual savings estimates. A post-implementation monitoring period of 9 months aligns closely with the annual data in both projects. Deviations from annual savings begin to develop in both projects when the post monitoring period is reduced to 6 months. The large office normalized savings range is between 90% and 112% of the base avoided energy use when post-implementation monitoring regressions at least 6 months of post-implementation data is used. The large grocery normalized savings range is between 101% and 117% when at least 6 months of post-implementation data is used. Further research is needed to determine if these results are project specific or a finding that can be extrapolated to future projects.

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