



Conference paper

**A generalized method for estimation of industrial energy savings from capital and behavioral programs**

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**ABSTRACT**

In 2005, NEEA engaged the food processing industry in the Northwest with a behavior based program called Continuous Energy Improvement (CEI). Industrial energy efficiency programs have historically been limited to large capital projects because savings from behavioral elements are difficult to measure. The challenge is to calculate a robust estimate of all program energy savings, not just those associated with capital projects.

A generalized linear regression model based on intervention analysis methodology was developed to capture total energy savings. This model allows the separation of capital savings to yield savings uniquely attributable to the behavioral program.

The intervention model and the resulting calculated savings were both validated by an independent Evaluation Measurement and Verification (EM&V) validation contractor. Actual 2006-2010 validated savings from CEI behavior change was 3% per year for both electric and natural gas. This paper will present the technical foundations of the model and discuss the resulting analysis.

## INTRODUCTION

The concept of continuous improvement is well established in industrial practice. Quality improvement programs like Motorola's Six Sigma evolved into more holistic approaches such as Lean Manufacturing. Along the way, manufacturers have systematically improved virtually every aspect of their cost structure. The notable exception is energy consumption.

In 2005, NEEA launched an industrial energy efficiency program called Continuous Energy Improvement (CEI). The program created and deployed a holistic energy management system in selected industrial facilities. Companies were provided tools and training to integrate energy management into daily operations. Key elements of the program included executive support, widespread employee training, the creation of an energy team and energy champion, selection of energy projects based on return on investment, and creating the infrastructure to manage energy costs as a controllable expense.

Industrial energy efficiency programs are traditionally focused on the installation of large new capital projects or capital retrofitted for efficiency. This is because the Measurement and Verification (M&V) activities required to demonstrate the energy saved are reasonably well established. The status quo or baseline is easily observable, the measure is well defined and easily observable, and therefore the calculation of energy savings is straight forward via established protocols.

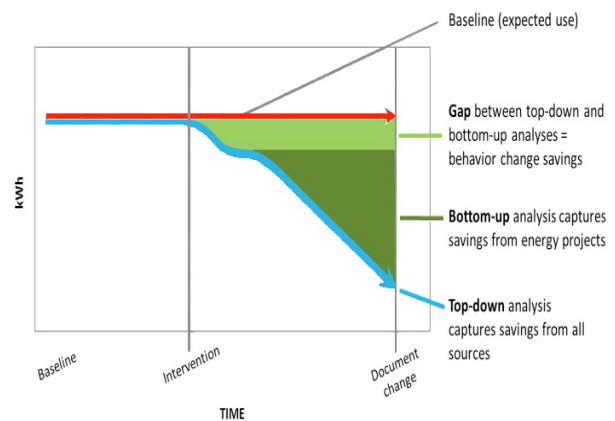
CEI is unique by applying an ongoing structured management system throughout the entire facility. Attitudes, behaviors, policies, and procedures are systematically addressed over time. As such, the fundamental change agent is behavioral. How do you measure (in kWh) the cumulative impact of increased employee awareness, modified work or maintenance procedures, the deployment of a real-time energy dashboard, regular management review, or an energy team efforts to focus scarce resources on the projects with the highest energy savings potential?

Strategic energy management systems can lead to real savings that impact a company's energy costs and therefore its market competitiveness. However, many of the benefits are not directly observable. The methodologies developed in this paper allow these "hidden" benefits to be identified and captured so that total savings is visible to corporate leadership.

The measurement of behavioral based programs is different than capital programs in at least two respects. Capital projects are discrete events whose impact on energy consumption is (1) directly observable and (2) immediately measurable. Behavioral programs, such as CEI, are processes deployed over a long period of time and whose impacts on energy consumption are difficult (or impossible) to directly observe or measure. Regardless, we will utilize the same measurement methodologies generally accepted for capital projects: 1) Establish a baseline energy consumption 2) Implement the measure (intervention) 3) Observe the energy consumption for a period of time 4) Estimate the change in energy consumption.

The difference comes in the implementation of the protocol. In traditional capital M&V, the baseline and estimation of savings are separate processes. At the facility level, industrial data is typically at monthly intervals. This generally leads to very small sample sizes and a high degree of uncertainty in the baseline models and forecasts. This paper develops a methodology where establishment of the baseline and calculation of whole facility energy savings is accomplished via a single multiple linear regression model.

A whole facility estimate is often referred to as "Top-Down" statistical assessment. Capital projects implemented during the intervention time period are evaluated using traditional "Bottom-Up" M&V. The net savings associated with the behavioral program is then the whole facility savings estimate minus those attributable to capital projects as shown in Figure 1.



**Figure 1 Energy Savings from Behavior Change**

This methodology has advantages over forecasting consumption from a modeled baseline in at least three respects:

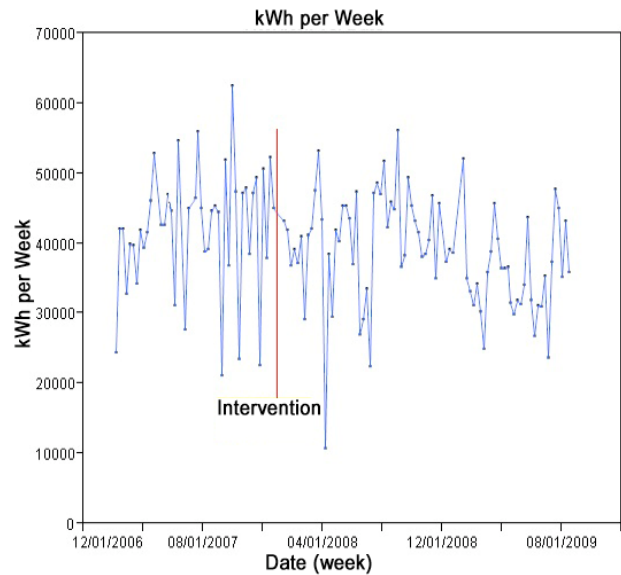
- 1) It is unlikely that all of the elements impacting industrial energy consumption will be observed in the typical short baseline period. When forecasting forward, it is not possible to separate the impact of the intervention from the impact of un-modeled energy drivers not observed in the baseline period.
- 2) Using all of the available data in the modeling process increases the number of degrees of freedom associated with the mean square error. This results in an enhanced ability to detect any meaningful impact on energy consumption resulting from an energy efficiency program.
- 3) This methodology eliminates the issue (generally not acknowledged or addressed) of the growth of uncertainty as a serially correlated time series, modeled from minimal data, is forecasted beyond the time period of the baseline data.

We will show that this methodology provides a robust means to estimate total savings and subtracts savings we directly observed to estimate the savings that we can't observe. While relatively straightforward in theory, there are many challenges to implementing this methodology in practice. In the process of model development, we will address some of these issues.

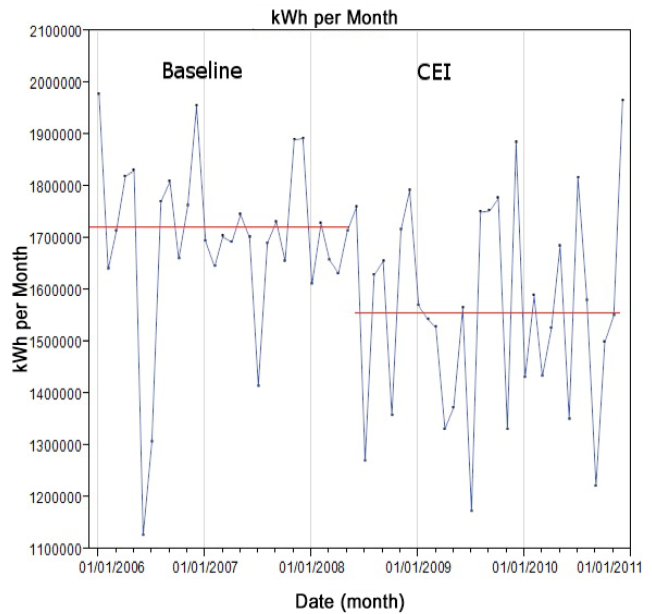
### **MODEL DEVELOPMENT**

The drivers of industrial energy consumption are widely varied and typically industry dependent. Commonly included are manufacturing production and weather; it is important to be aware of other factors that drive energy consumption in developing a robust model to assess the impact of an intervention.

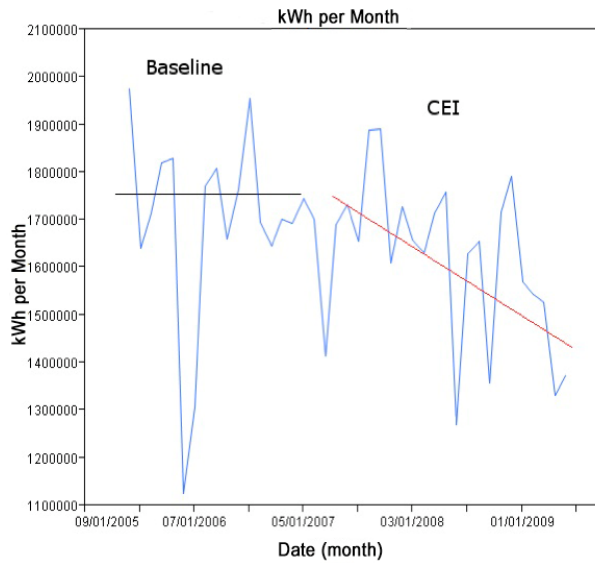
The challenge is to create a generalized model specification that is sufficiently flexible to accommodate a wide variety of industrial energy consumption patterns, be able to effectively detect the impact of an energy program intervention, and be simple enough for practical implementation. Examples of patterns of industrial energy consumption in response to CEI interventions are shown in Figures 2, 3, and 4.



**Figure 2 No obvious visible change**

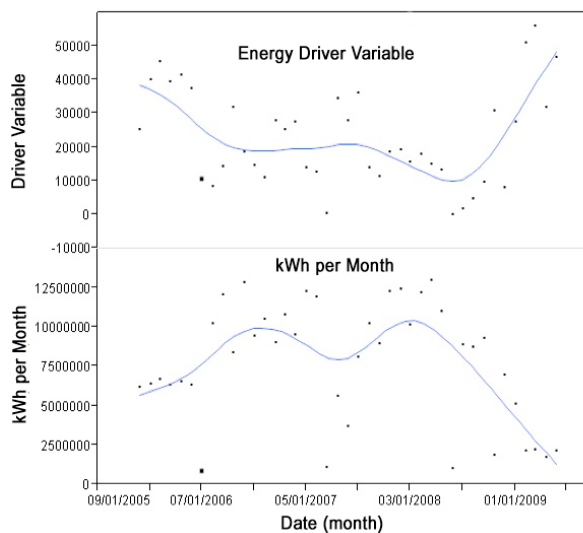


**Figure 3 Distinct Level Change**



**Figure 4 Distinct Trend**

The examples above show situations that are relatively easily modeled. However, industrial energy consumption data often exhibit characteristics that are difficult to adequately model and the drivers of consumption not entirely obvious. The data presented in Figure 5 demonstrate the impact that a “hidden” energy driver can have on consumption. The discovery of these energy drivers is only possible with the appropriate understanding of specific facilities manufacturing processes.



**Figure 5 Example Energy Driver**

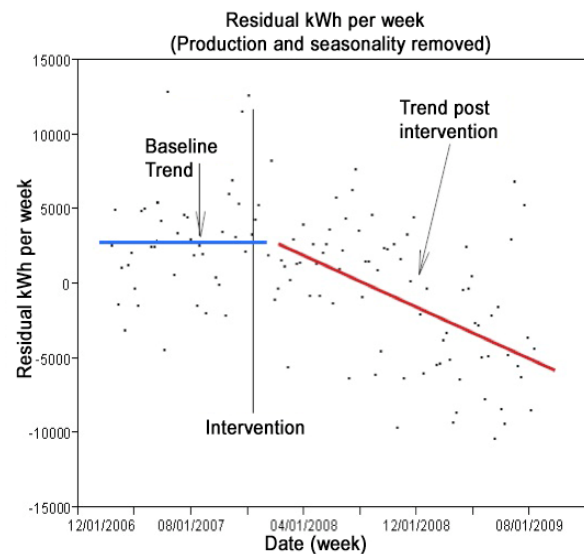
While production volume and weather are often the primary drivers of consumption, it is important to

be aware of the impact that other variables have on the consumption of the source under analysis. Incorrect inferences on the efficacy of energy programs can be made without explicitly accounting for these variables in the model.

A common barrier to modeling industrial energy consumption is the availability and integrity of data. There may be many variables that impact energy consumption and the ability to acquire data for all of the variables during the baseline and intervention periods can be a challenge. Most industrial facilities do not have the data management systems or discipline to keep sufficient records over a 4 or 5 year period; especially if they didn't know in advance those data would be important.

Consider again the data presented in Figure 2. Casual observation doesn't reveal any indication that the CEI intervention had any impact on energy consumption. Further analysis using total production output and weather failed to indicate any energy savings. However, the company was convinced that the CEI program was very beneficial resulting in real energy savings.

Further investigation revealed that the factory produced three distinct products. The energy consumed in the production of each product type is distinctly different. Therefore, it is the amount of each product type produced in each period, not just total production that drives energy consumption. Data on the three products was obtained and the model refit producing the residual plot shown in Figure 6.



**Figure 6 Residual Plot Showing Trend**

In this case, the intuition of the energy team was correct. The implementation did indeed result in energy savings. However, it took a relatively sophisticated model supported by the appropriate data to demonstrate the savings.

The examples shown above are characteristic of the patterns seen in industrial energy consumption data. Any generalized methodology must be able to accommodate a wide variety of energy drivers and energy consumption patterns. Assuming that the appropriate variables have been identified and that the data is available, the model specification must be able to:

- 1) Segregate baseline and intervention periods
- 2) Accommodate variable(s) that drive energy consumption independent of the intervention under study
- 3) Accommodate an intervention effect observed as a step change in energy consumption
- 4) Accommodate an intervention effect observed as a change in consumption trend

### **MODEL SPECIFICATION**

The mathematical formulation of the model is presented below. Two forms of the model will be discussed; the first is when the intervention is expected to be observed as a step change in consumption or if the sole interest of the experimenter is to determine the total energy savings from an intervention. The second form is a more complex special case of the model where the rate of change in energy consumption is of interest.

#### **Intervention Step Model**

This form of the model (Equation 1) estimates the impact of the program intervention by means of an indicator variable to assess the mean per period difference in response (energy consumption) between the baseline period and the intervention period.

Equation (1) Intervention Step Model

$$kWh_i = \beta_0 + \beta_1 Intervention_i + \sum \beta_j EnergyDriver_{ji} + \varepsilon_i$$

Where :

kWh<sub>i</sub> = Total Electricity use per period i

Intervention = Indicator variable  
0 = Before Intervention  
1 = After Intervention

EnergyDriver<sub>j</sub> = Any variable that significantly impacts energy consumption, typically includes production volume and temperature

$\beta_1$  = Estimated impact of intervention per time period

$\beta_j$  = Coefficient for EnergyDriver<sub>j</sub>

$\varepsilon$  = Normally distributed error

i = Time period index

j = Index for the j<sup>th</sup> EnergyDriver, j ranges from 0 to n

If the intervention parameter is not statistically different from zero, it is concluded the intervention had no impact on energy consumption. If it is statistically different from zero, it is concluded that the intervention had an impact on energy consumption. Energy savings is indicated if the parameter is significant AND the sign of the parameter is negative. Total energy impact is estimated by multiplying the value of the parameter by the number of periods post intervention.

If the intervention parameter is significant AND the sign is positive, it would indicate that energy consumption increased after the intervention. This is typically not a desirable outcome of an energy efficiency program. However, such a program can still result in energy savings if it can be shown that that less energy was consumed than would have been if the intervention had not occurred. The second form of the model is capable of detecting savings in an increasing consumption environment.

#### **Intervention Trend Model**

The second form of the model adds some complexity to both the model specification and to the determination of energy savings. Two trend parameters are added to the model to estimate the trend in energy consumption during the baseline period and the trend after the intervention. The differences in the trends are used to assess the impact of the intervention (energy savings).

## Equation (2) Intervention Trend Model

$$kWh_i = \beta_0 + \beta_1 TrendBaseline_i + \beta_2 TrendIntervention_i + \sum \beta_j EnergyDriver_{ji} + \varepsilon_i$$

Where :

$kWh_i$  = Total Electricity use per period i

$TrendBaseline$  = Trend variable that is scaled so the parameter values represent energy consumption change per period.

$TrendIntervention$  = Trend variable that is scaled so the parameter values represent energy consumption change per period.

$EnergyDriver_j$  = Any variable that significantly impacts energy consumption, typically includes production volume and temperature

$\beta_j$  = Coefficient for  $EnergyDriver_j$

$\varepsilon$  = Normally distributed error

i = Time period index

j = Index for the  $j^{th}$   $EnergyDriver$ , j ranges from 0 to n

This form of the model has a more complex method of determining the impact of the intervention. In addition to passing standard regression diagnostics, in this model the ***TrendIntervention*** must also be shown to be statistically significantly less than the ***TrendBaseline***. It is important to note that it does not have to be negative to show energy savings from the intervention, only less than baseline.

Because of the increased complexity, this specification should be used in place of the Intervention Step Model only in cases where:

- 1) The data clearly indicates the intervention resulted in a linear change in energy consumption trend or
- 2) There is significant researcher interest in both the total impact of the intervention and the rate of consumption change or

- 3) Energy consumption has increased from baseline, but at a rate less than what would have occurred without the intervention.

## MODEL APPLICATION

NEEA's CEI program was initiated at 15 facilities from 2005-2008. Data for energy consumption and energy driver variables was collected for the periods prior to and after the CEI intervention at each of the facilities. To adequately model the baseline period, as much historical data was collected as possible. Collecting a sufficiently long baseline data set is particularly important where consumption exhibits significant seasonality or there is the presence of a major un-modeled energy driver. It is desirable to have at least 2 complete seasonal cycles represented in the baseline period.

The first step in developing a facility consumption model is to identify the major energy driver(s). While production output and temperature are common drivers, every facility is unique. Some facilities are driven by raw material input, or by process yield (input/output). Energy drivers can also be cyclical or one-time events such as seasonal variation of the quality of incoming material or a major maintenance event impacting consumption causing an extreme outlier.

The process and statistical best practices for model development and identifying facilities major energy driver(s) is beyond the scope of this paper. Models of the form described in Equations 1 and 2 were developed for each of the 15 CEI facilities to assess the existence of an intervention effect and the magnitude of that effect. Two of these analyses are presented below.

### Intervention Step Model Application

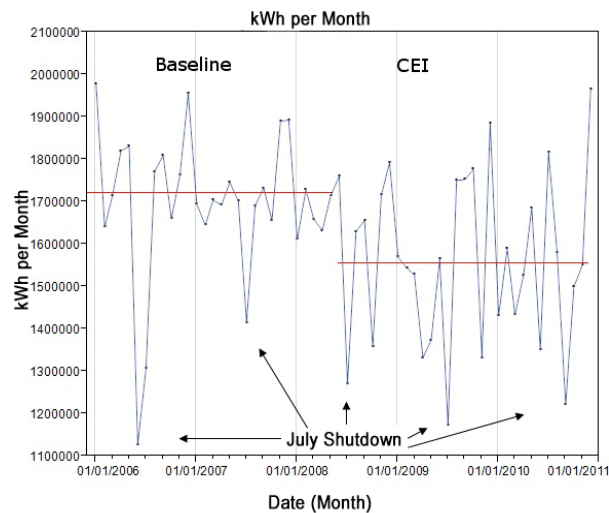
Consider again the data presented in Figure 3. This is a "best case scenario" where the data are relatively easily modeled and the impact of the intervention is directly observable in the raw consumption data. Model development indicated that production output and average temperature were significant energy drivers. The model shown in Equation 3 was fit to the data.

Equation (3)

$$kWh_i = \beta_0 + \beta_1 CEI_i + \beta_2 Temp_i + \beta_3 Output_i + \varepsilon_i$$

A good fit to the model was expected. However, model diagnostics revealed a relatively poor overall fit and the intervention effect that was not statistically significantly different from zero. How could that be when you can “see” the intervention in the data? This can occur when there is an un-modeled energy driver that overwhelms the effect we are attempting to detect.

Further analysis revealed a pattern of extremely low consumption occurring annually every July. Interviews were conducted at the facility to better understand the manufacturing process. The raw material harvest usually starts in late July or early August and can be stored for up to 10 months. Finished goods production is managed so that the raw material is consumed by early July each year. The facility then shuts down for 2-3 weeks of annual facility maintenance in preparation for new raw material. This results in a drastic reduction in energy consumption every July as can be seen in Figure 7.



**Figure 7 Annual July Shutdown Identified**

This represents a state of operation that is not adequately modeled by simple production output (partial months output plus energy consumed during facility maintenance period). To account for the impact of this annual maintenance cycle an indicator variable estimating the impact of the maintenance cycle was added to the model

Equation (4)

$$kWh_t = \beta_0 + \beta_1 CEI_t + \beta_2 Temp_t + \beta_3 July_t + \beta_4 Output_t + \varepsilon_t$$

The output of the updated regression model is shown in the tables below.

### Summary of Fit

RSquare	0.703176
RSquare Adj	0.681588
Root Mean Square Error	112524.3
Mean of Response	1626876
Observations (or Sum Wgts)	60

### Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	1.6498e+12	4.124e+11	32.5737
Error	55	6.9639e+11	1.266e+10	<b>Prob &gt; F</b>
C. Total	59	2.3461e+12		<.0001*

### Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	1538158.1	106022.7	14.51	<.0001*
ATemp	-122.164	935.0993	-0.13	0.8965
July	-332303.2	46578.04	-7.13	<.0001*
CEI2008-10	-78562.37	30451.44	-2.58	0.0126*
Production	0.0406714	0.017074	2.38	0.0207*

The revised model results in an acceptable overall fit to the data and the intervention effect is both significantly different from zero and negative. For the Intervention Step form of the model this is all that must be shown to demonstrate that energy savings have occurred.

The data set contains 36 post intervention observations. The estimate of the energy savings resulting from the intervention is then 36 times the value of the intervention parameter. The point estimate and 90% Confidence Intervals of the energy savings for the example are shown in Table 1.

**Table 1 Estimated Savings 2008-2010 (kWh) from example 1 Intervention Step Model**

Point Estimate $36 * 78562.4 = 2,828,245$ kWh
90% Confidence Interval ( <b>1,024,911</b> < kWh Savings < <b>4,631,580</b> )

## Intervention Trend Model Application

To demonstrate the Intervention Trend model we will return to the data presented in Figure 2. The facility manufactures three separate products. Each product is manufactured using unique processes and only shares the final packaging step. During the facility characterization it was determined that each product required significantly different amounts of energy to produce. The volume of each product produced varied unpredictably from period to period.

Since only total facility energy consumption was available, it was essential that production volume by product was available. This is because the specific ratio of the three products is what drives energy consumption, not just total production volume. Preliminary modeling using production volume of the three products and temperature resulted in the residuals shown in Figure 6. Because of the distinct linear trend exhibited post intervention the model shown in Equation 5 was fit to the data.

Equation (5)

$$kWh_i = \beta_0 + \beta_1 TrendBaseline_i + \beta_2 TrendCEI_i + \beta_3 Temp_i + \sum \beta_j Product_{ji} + \varepsilon_i$$

The output of the regression model is shown in the tables below.

Summary of Fit	
RSquare	0.74908
RSquare Adj	0.736212
Root Mean Square Error	4249.044
Mean of Response	39965.45
Observations (or Sum Wgts)	124

Analysis of Variance				
Sum of				
Source	DF	Squares	Mean Square	F Ratio
Model	6	6306098837	1.051e+9	58.2140
Error	117	2112361677	18054373	<b>Prob &gt; F</b>
C. Total	123	8418460515		<.0001*

## Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	9389.5455	2649.827	3.54	0.0006*
Temp	282.64545	37.5897	7.52	<.0001*
Trend Baseline	39.535006	34.82398	1.14	0.2586
Trend CEI	-74.80843	16.91069	-4.42	<.0001*
Product 1	0.0135482	0.004114	3.29	0.0013*
Product 2	0.0273847	0.002103	13.02	<.0001*
Product 3	0.0446901	0.003251	13.75	<.0001*

In this form of the model it is not sufficient (or even required) that the intervention parameter be statistically different from zero and negative. What must be shown is that the **TrendIntervention** is statistically significantly less than **TrendBaseline**. An energy efficiency program need not result in an absolute reduction in consumption to be successful; it only needs to show less energy was used than if the intervention had not occurred. This is accomplished via a standard hypothesis test shown below.

H<sub>0</sub>: Trend Baseline = Trend CEI  
(CEI had no effect on energy consumption)

H<sub>1</sub>: Trend Baseline ≠ Trend CEI  
(CEI did have an effect on energy consumption)

$$t = \frac{TrendBaseline - TrendCEI}{\sqrt{Var(TrendBaseline) + Var(TrendCEI)}} = \frac{39.5 - (-74.8)}{\sqrt{34.8^2 + 16.9^2}} = 2.95 \quad Prob>|t| < .001$$

The assertion that Trend Baseline and Trend CEI are equal is rejected in favor of the alternate hypothesis. It is therefore concluded that the CEI initiative at had a statistically significant impact on energy consumption and that there is evidence supporting that this resulted in a reduction in energy consumption.

The calculation of energy savings for this form of the model is somewhat different than the Intervention Step Model. In the Step model, the amount of savings is constant for each period after the intervention. However, in the Intervention Trend model, the savings are changing (increasing) for each successive intervention period. The calculation for total savings for the Intervention Trend model is shown in Equation 6 and estimated savings shown in Table 2.

Equation (6)

$$TotalSavings = \sum_{i=1}^{n1} i * (\beta_{Baseline} - \beta_{CEI})$$

Where n1 is the number of periods post intervention.

**Table 2 Estimated Savings from example 2 Intervention Trend Model**

Estimated Savings (kWh) through 86 weeks of intervention
$\sum_{i=1}^{86} i * (39.5 - (-74.8)) = 427,596 \text{ kWh}$
90% Confidence Interval ( 189,521 < kWh Savings < 665,671)

### Savings Attributable to Behavior Change

The two application examples demonstrate the results of modeling industrial energy consumption using the methodologies presented herein. The process used for model development at the other 13 facilities was identical. The methodologies, data analysis, and estimated total energy savings were evaluated and validated by a third party EM&V evaluator.

The estimated energy savings from this modeling represent total energy savings from all sources: both capital and as a result of the behavioral intervention. As shown in Figure 1, the energy savings of the behavioral program can be calculated by subtracting the energy savings of discrete physical projects from the total facility energy savings.

Equation (7)

$$Behavior\ Savings = Total\ Savings - Physical\ Savings$$

As a standard part of the CEI engagement, each facility maintained a comprehensive list of operations and maintenance improvements and capital projects completed during the intervention period. Engineering calculations were made at the time of implementation based on International Performance Measurement & Verification Protocol (IPMVP) M&V protocols. The third party evaluator then visited facilities to independently validate the engineering calculations and resulting estimates of energy saved during the intervention period.

CEI project data management, engineering calculations, applicability of the International Performance Measurement and Verification Protocol (IPMVP) Option C, and the process of independent validation of savings are beyond the scope of this paper. For complete information the reader is referred to “NEEA Market Progress Evaluation Report #6: Evaluation of NEEA’s Industrial Initiative (E11-220)” prepared by the Cadmus Group, Inc. and released on 2/08/11. The document can be found at the following url:

<http://neea.org/research/reports/E11-220A.pdf>

Tables 3 and 4 summarize the validated savings from the document and are updated to reflect validated savings through 2010. The reader should be aware of two items when examining the tables: 1) the third party evaluator referred to the behavioral savings derived per Equation (7) as “Net-Top Down Savings” and 2) the unit of energy savings are in Average Megawatts (aMW). This is a summary unit of measure used in the Northwest and is equal to a megawatt year or 8,760,000 kilowatt hours.

**Table 3 Total Validated Electric Savings (aMW) (2006–2010)**

Year	O&M + Capital (aMW)	Net Top-Down (aMW)	Total Electric Savings (aMW)
2006	0.65	0.22	0.869
2007	0.841	0.461	1.303
2008	3.002	0.563	3.565
2009	1.548	0.579	2.126
2010	2.012	1.138	3.150
Total	8.053	2.961	11.013

**Table 4 Total Validated Gas Savings (2006–2010)**

Year	O&M (therms)	Net Top-Down (therms)	Total Gas Savings (therms)
2006	0	73,666	73,666
2007	0	131,378	131,378
2008	1,057,414	967,701	2,025,115
2009	20,600	1,879,095	1,899,695
2010	1,211,150	1,658,478	2,869,628
Total	2,289,164	4,710,318	6,999,482

The result of the model development and the ensuing validation process has been the empirical demonstration of 25,938,360 kWh electricity and 4,710,318 therms of natural gas savings from behavior change. *These are energy savings directly attributable to the behavior change elements of the CEI program from 2006-2010.* Total energy savings including capital savings were 96,473,880 kWh of electricity and ~7,000,000 therms of natural gas.

To put these savings into perspective, they represent an annual savings of 3.07% for electric consumption and 2.89% for natural gas consumption. This is a very important auxiliary discovery: *Over a 5 year period at 15 different facilities, the rate of energy savings resulting from a holistic strategic energy management system appears to be fuel source independent.*

### **Conclusion**

This paper has presented the foundation, specification, and validated application examples of a generalized methodology for the estimation of energy savings from industrial programs with behavioral and capital elements. In developing the foundation for the model, a cursory discussion of some of the issues associated energy consumption analysis was presented. It is hoped that the reader has gained some appreciation of the complexity of modeling industrial energy consumption and potential issues associated with “one size fits all” approaches.

The breadth of potential modeling scenarios were consolidated into two generalized model forms based on the manner in which the impact of the intervention was observed (Step or Trend). These two forms have proven to provide adequate modeling

across a wide variety of applications and across multiple fuel sources. The end result was the validated demonstration of energy savings resulting from the behavioral component of an industrial energy efficiency program.

This methodology has advantages over forecasting consumption from a modeled baseline in at least three respects:

- 1) It is unlikely that all of the elements impacting industrial energy consumption will be observed in the typical short baseline period. When forecasting forward, it is not possible to separate the impact of the intervention from the impact of un-modeled energy drivers not observed in the baseline period.
- 2) Using all of the available data in the modeling process increases the number of degrees of freedom associated with the mean square error. This results in an enhanced ability to detect any meaningful impact on energy consumption resulting from an energy efficiency program.
- 3) This methodology eliminates the issue (generally not acknowledged or addressed) of the growth of uncertainty as a serially correlated time series, modeled from minimal data, is forecasted beyond the time period of the baseline data.

Among the primary challenges in modeling energy consumption is the availability and integrity of relevant data. Particularly difficult is obtaining sufficient historical data on energy drivers for a viable baseline. While this methodology addresses some of the issues associated with baseline estimation, it does not eliminate the need for sufficient pre-intervention data to be able to assess the impact of an intervention.

Strategic energy management programs such as CEI, help companies develop the data management practices necessary to manage energy as a controllable expense. While this paper presented applications of the methodology in an industrial environment. There is nothing in the model formulation or the data requirements to prevent the use of this methodology to assess the impact of behavioral programs in any sector.

## **About the Author**

Joining NEEA in 2009, Robert Luneski is the Technical Manager for the Industrial and Agricultural Sector and is responsible for the measurement the energy savings from NEEA's industrial energy efficiency programs. Robert has a broad range of experience in the application of statistical methods in industrial manufacturing. For 25 years, he managed manufacturing process, analysis, and systems engineering functions at a major global manufacturer and has taught Statistics at Portland State University.

Robert has BS degrees in Decision Science and Mathematics from the University of Oregon and a Master's degree in Statistics from the University of Wisconsin. He is currently working with Pacific Northwest National Laboratory to extend this work to include the diffusion of innovation in the estimation of energy savings from industrial programs.