Elements of Defensible Regression-Based Energy Models for Monitoring and Reporting Energy Savings in Industrial Energy Efficiency Operation and Maintenance Projects

Todd Amundson, Steve Brooks and Jennifer Eskil, Bonneville Power Administration
Steve Martin and Steve Mulqueen, Energy Smart Industrial

ABSTRACT

Utility-sponsored operation and maintenance (O&M) based energy efficiency programs rely on consistent and defensible methodologies for developing energy models that provide the basis for quantifying savings results. Without the ability to accurately distinguish the effects of O&M-type improvements from changes in production, ambient conditions, or other energy driver variables, individual initiatives may succumb to a lack of management support or skepticism of reported savings on the part of program evaluators. This paper outlines six major steps to develop defensible regression-based energy models for monitoring and reporting energy savings in industrial energy efficiency programs. The paper explains several valuable lessons learned during the model development process for a large industrial facility. The paper then compares differences in model coefficients and fractional savings uncertainty between models created with daily and monthly time resolution for two large industrial facilities. The results show that, for large industrial facilities, the prediction capability and the estimated fractional savings uncertainty are greatly improved when using defensible modeling techniques and models with daily time resolution.

Introduction

Since 2010, the Energy Management (EM) components of the Bonneville Power Administration's Energy Smart Industrial (ESI) program have actively monitored and reported energy savings from operation and maintenance (O&M) improvements for 41 industrial facilities. The facilities, spread over 19 public utility service areas, have a combined annual electrical load of over 200 aMW. Energy savings resulting from O&M improvements for each project are quantified using the avoided savings approach, a method that draws from Superior Energy Performance (SEP) Measurement and Verification Protocol for Industry (SEP 2012), International Performance Measurement and Verification Protocol (IPMVP) Option C (IPMVP 2012) and ASHRAE Guideline 14-2002 (ASHRAE 2002). In 2012, a third party conducted an impact evaluation that provided an independent assessment of the statistical modeling methods and analysis techniques used to quantify energy savings from 17 pilot engagements. Using an alternative statistical method, the evaluation demonstrated close agreement in the savings results for 15 of 17 projects, and yielded a realization rate of 88% on 8,278 MWh of O&M electrical energy savings (Ochsner et al. 2013).

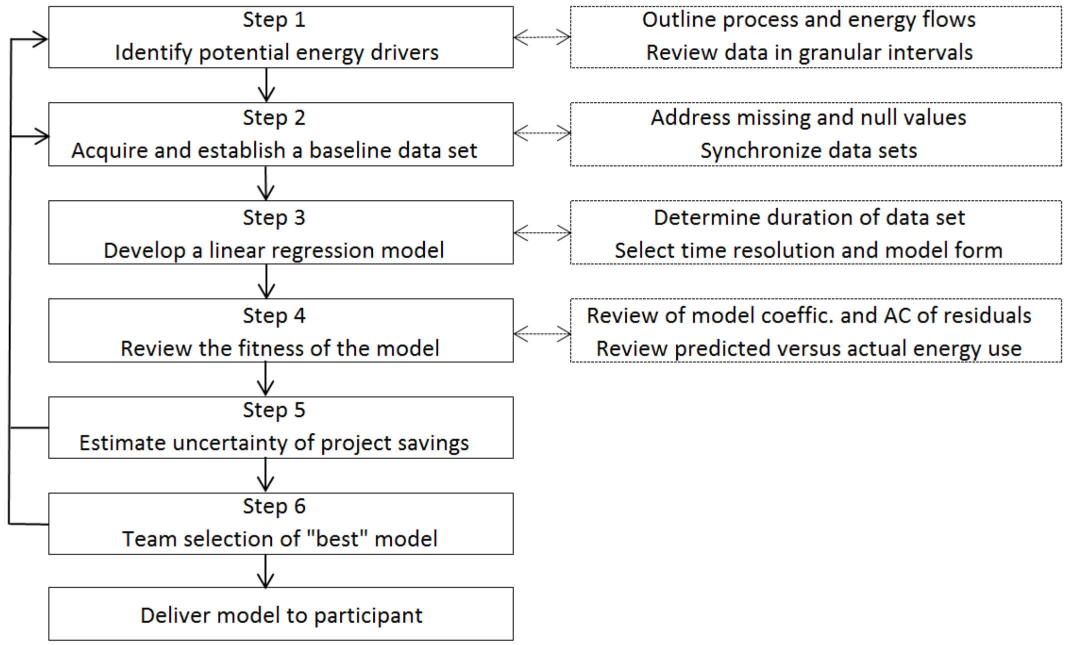
This paper begins by outlining six major steps that the ESI Energy Performance Tracking (EPT) team has found beneficial in developing linear regression models for sub-system and plant-wide energy use in industrial facilities. The resulting models provide robust prediction capabilities to track energy savings during project implementation and to defend those savings during project evaluation. The ESI Monitoring, Tracking, and Reporting (MT&R) Reference Guide (ESI EPT Team 2012) further details this methodology.

The paper then details valuable lessons learned from modeling the plant-wide energy use of a large industrial facility, which highlight the need for a methodic and defensible approach to model development. Using actual data from two large industrial facilities, the paper compares model coefficients and estimated fractional savings uncertainty between models created with monthly and daily time resolutions. In contrast to conclusions based on commercial buildings with no production energy drivers (Carpenter et al. 2010), the results show that the effects of production energy drivers on energy use cannot be assumed to be consistent with time. Furthermore, the uncertainty in reported energy savings will be substantially less for models with daily time resolution as opposed to a monthly time resolution. The paper presents select model statistics for seven regression-based models created in the ESI program, including an estimate of fractional savings uncertainty.

Process of Developing a Linear Regression Model

Developing a linear regression model to monitor and report energy savings for industrial energy efficiency O&M projects consistent with SEP and IPMVP protocols is an iterative process. This process requires the practitioner to work with large data sets, to understand the major energy drivers in a facility, and to have a working knowledge of statistics. From the experiences of the EPT team in developing over 40 regression models, the predictive ability of the model depends largely upon the practitioner's ability to navigate this iterative process in a sequential manner. The six major steps outlined in this paper are: 1) identifying potential energy drivers, 2) acquiring and establishing a baseline data set, 3) developing a linear regression model, 4) reviewing model fitness, 5) performing an uncertainty analysis, and 6) selecting the "best" model or alternative direction. Figure 1 provides a graphical representation of these steps, along with sub-steps typically involved in the model development process.

Figure 1. Key Steps In Energy Model Development Process



Before modeling is performed, sufficient time should be spent with steps one and two, identifying potential energy drives and acquiring and establishing a baseline data set. These two steps help avoid modeling errors such as using variables that have no physical relationship to energy use, and using data that contains erroneous observations. After a model is developed, model fitness should be carefully inspected, and then an uncertainty estimate, based on estimated project savings, should be calculated. As possible from the data set, several models deemed acceptable from both the perspective of model fitness and the desired level of uncertainty should be provided for team review so that the "best" model or alternative direction can be selected by a cross-functional group of stakeholders.

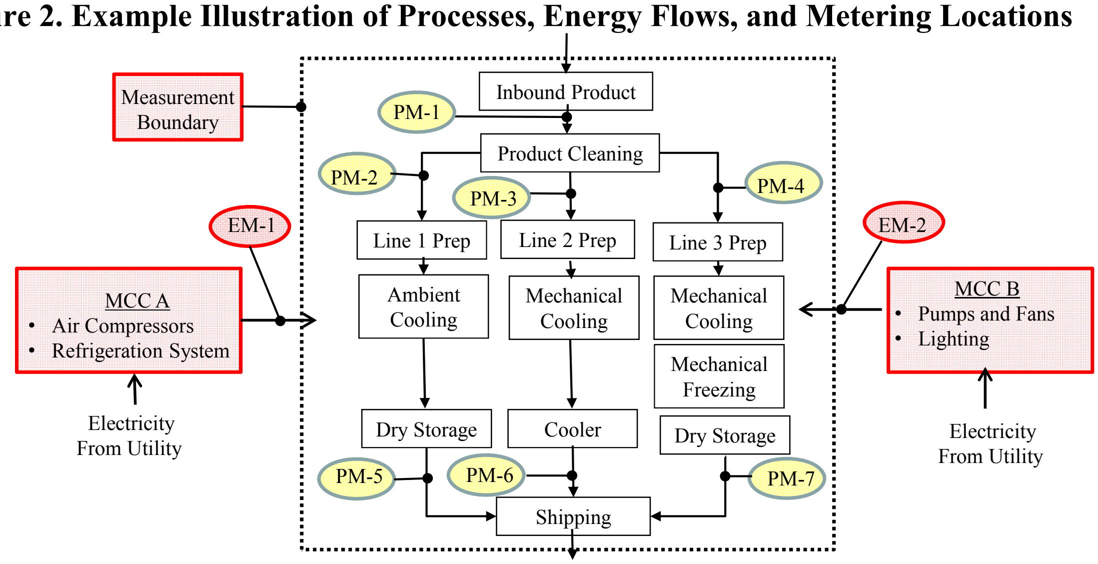
The EPT team, within the context of the ESI program, consists of a three- to five-member body that includes a BPA energy efficiency representative who serves as chairperson, an ESI program manager, and ESI's Energy Performance Tracking engineer. The model developer and various subject matter experts also regularly contribute to the working meetings. This cross-functional structure provides the necessary level of engineering and statistical expertise, while ensuring both BPA and ESI program concerns are represented. The team review also helps ensure that the selected model balances the programmatic requirements for statistical rigor with the practical need to maintain a level of simplicity (or ease of use) that will promote frequent updates by the end user. In select circumstances where the available data does not permit the development of an adequate regression model, team input is instrumental in determining an alternative approach to measuring savings.

Identifying Potential Energy Drivers (Step 1)

A thorough understanding of the facility and processes is essential to acquiring and establishing a baseline data set of energy use and potential energy drivers. Often, facility personnel have a comprehensive understanding of the process, and invoking this expertise at the beginning of the modeling process can help identify potential energy drivers. When possible, the modeler should conduct a site visit with such facility personnel to understand the plant's major energy drivers. Time spent up front understanding the processes often reduces the time invested in developing numerous models, and ultimately improves the predictability of the final model.

Outline process and energy flows (Step 1, sub-step). A diagram that includes all energy supply streams crossing the measurement boundary and product flows within the measurement boundary is an instrumental aid for the modeling process. This diagram should include all major processes and production meters and depict their location in relationship to the process. Knowledge of all motor control centers (MCCs) that provide energy to equipment within the measurement boundary and the location of the energy meters is essential for the modeling process. A list of all major energy-using equipment associated with each MCC can be valuable. Figure 2 is an example illustration of the process within the measurement boundary, the electrical energy use that crosses the measurement boundary, and the location of the production meters (PM) and electricity meters (EM).

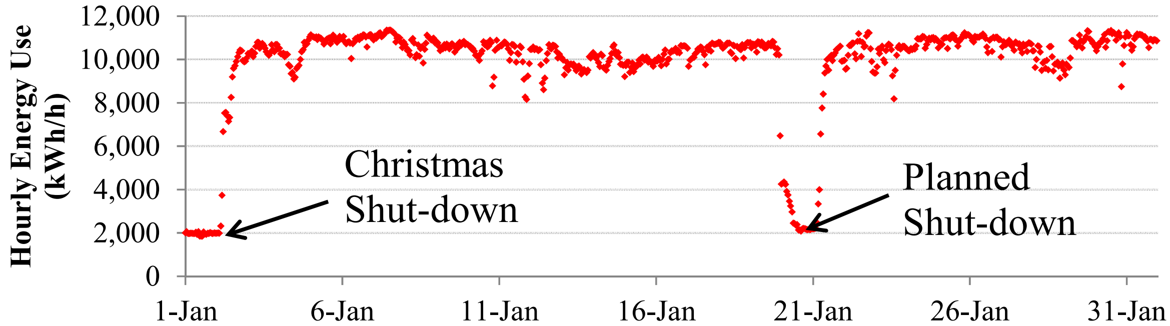
Figure 2. Example Illustration of Processes, Energy Flows, and Metering Locations



Review energy and energy drivers at granular intervals (Step 1, sub-step). A review of energy and production data at hourly or sub-hourly intervals can provide valuable insight into the operation of the plant, including patterns of high energy use and start-up times. Such trends present important opportunities for model improvement and require further investigation to understand key energy drivers.

Figure 3 shows that plant start-up and shut-down times can be determined from a facility's hourly energy use.

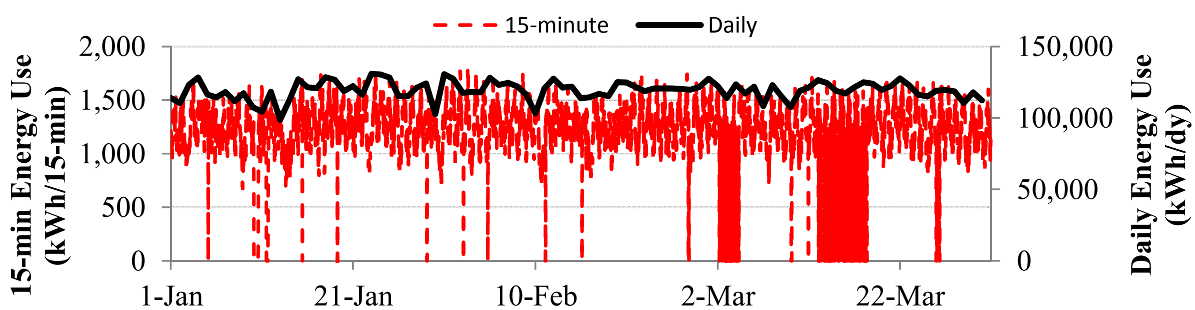
Figure 3. Hourly Facility Energy Use Showing Plant Start-Up and Shut-Down Times



Acquiring and Establishing a Baseline Data Set (Step 2)

Data sets of energy and production often have missing data and erroneous observations, and so data needs to be reviewed for null values and outliers. Many data analysis algorithms often omit null values when aggregating and averaging data. Without this awareness, the modeler may choose to review the data in an aggregated form without considering the underlying mathematical influence of the null values. Figure 4, which represents null values as zero, shows a high frequency of such data points within the five-minute interval data set, but the impact of these values on the daily aggregated summation isn't obvious through casual inspection.

Figure 4. Fifteen-Minute Interval Energy Use Depicting Null Values and Daily Energy Use of Same Data Set



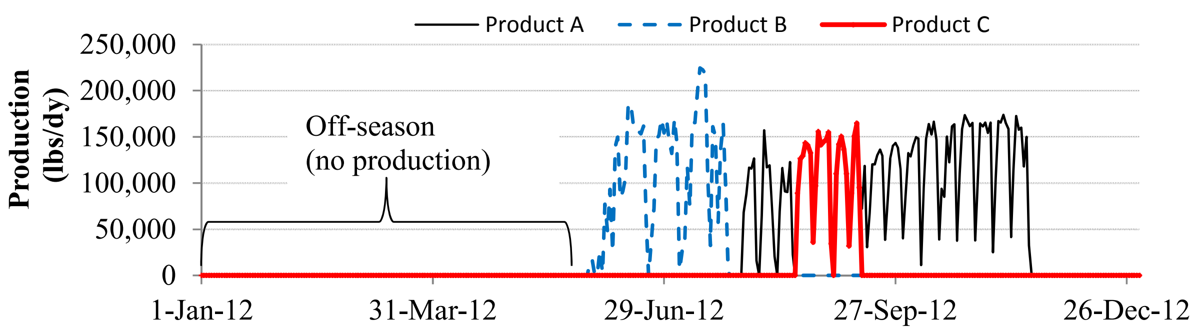
Properly synchronize data sets (Step 2, sub-step). Plants usually record production from the beginning of the process or shift until the end, a time period that is typically different from the beginning and end of the day (e.g., 12 am to 12 am). Thus, it is important to know the start and end times for each production value so that the correct energy use and weather values can be attributed to the defined time periods. Failure to recognize this offset can introduce error into the model, and possibly lead to the erroneous inclusion or exclusion of variables.

Developing a Linear Regression Model (Step 3)

Developing a regression model is an iterative process that should include evaluating all energy drivers and different combinations of these energy drivers. For each model created, the modeler should document the reasons for or against deeming a model as acceptable and why a particular modeling path was chosen. This becomes valuable information when reviewing models both internally and with other stakeholders, such as local utilities, end users, or program evaluators.

Determine duration of data set (Step 3, sub-step). The duration of the data set must be long enough to capture the entire range of production and weather. Baseline periods of less than 12 months are vulnerable to the omission of critical production cycles and often neglect to capture the influence of the full spectrum of ambient conditions. Figure 5 illustrates the production cycles for a fresh-pack vegetable processing facility, and demonstrates how the duration of the data set will impact the variables within the data set and the range of these variables.

Figure 5. One Year of Production for Products A, B, and C



Select time resolution, major energy drivers, and model form (Step 3, sub-step). Time series and x-y graphs of energy use and production greatly aid in the selection of time resolution, major energy drivers, and model form, all of which are typically interrelated and significantly impact the fitness of the model. Typically, the energy use patterns during production and non-production periods can be distinguished using these types of graphs. The energy use of large industrial facilities is often an order of magnitude higher during production periods relative to non-production periods because facility operations are different during these two distinct periods.

For such facilities, it is generally best to develop separate models for production and non-production operations, each with daily time resolution. For facilities that show production to be a less dominant driver of energy use or for batch-type processes, a longer time interval such as weekly may be preferred. Monthly models are generally discouraged because of their poor resolution and their limited usefulness as a proactive management tool.

Likewise, daily models that combine both production and non-production modes through the use of indicator variables are discouraged, as an indicator variable assumes only a phase-shift between these two distinct modes of operation. This can skew the model coefficients, which is important during production periods because the prediction capability of the model can be reduced by including the data during the non-production periods. From an engineering standpoint, operations during non-production periods typically do not influence energy use during production periods, and so these modes of operation should be modeled separately.

The production mode for facilities with large refrigeration or chilled water systems can often be modeled with a three-parameter cooling multi-variable model, as explained in the Inverse Modeling Toolkit (Kissock, Haberl & Claridge 2002). An example of this model is:

$$Ep = Intercept_p + RS\,(Twb - Change\text{-}Point)^+ + Coeff_{P1} \cdot Prod1 + \ldots + Coeff_{Pn} \cdot Prodn \qquad (1)$$

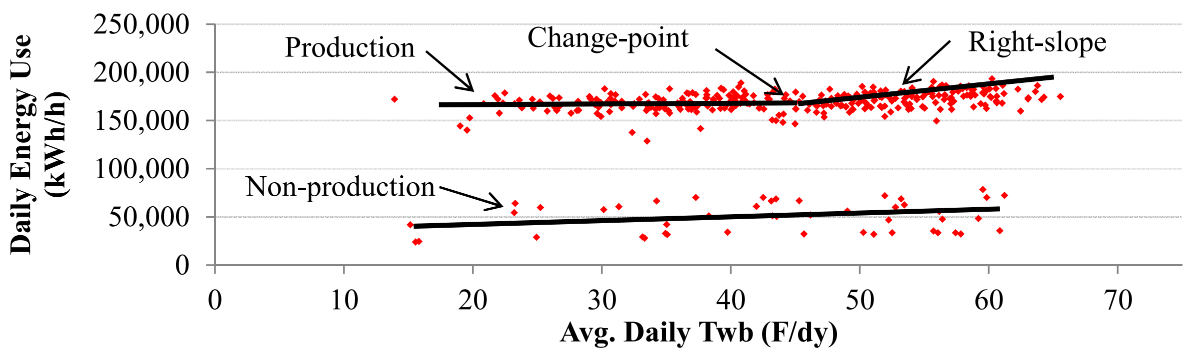
Where electrical energy use during production (Ep), is a function of the right slope (RS), ambient wet-bulb (Twb), and production energy drivers (Prod). The parenthetic quantity is zero for all negative values and the production variables should be limited to only those shown to influence energy use.

Often, a simple linear regression or two-parameter model can be used to correlate electrical energy use during non-production (E_{np}) to ambient wet-bulb temperature as:

$$Enp = Intercept_{np} + Coeff_{np} \cdot Twb \qquad (2)$$

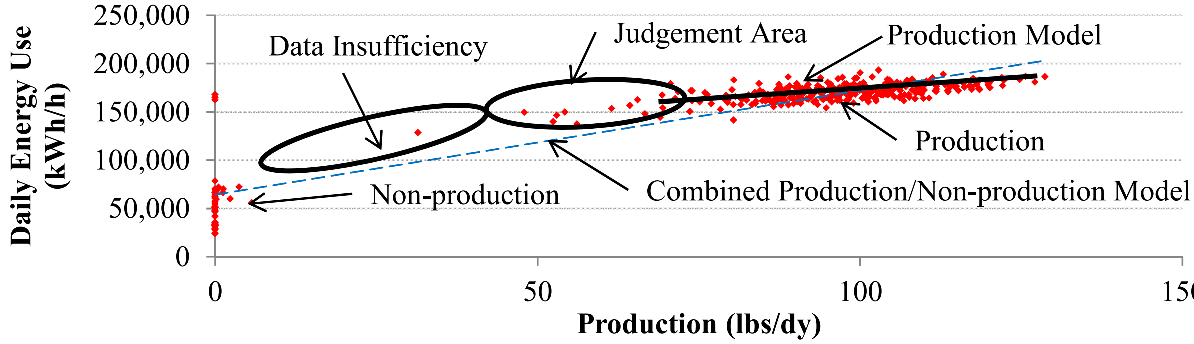
Figure 6 shows that the energy use signatures of a refrigeration-dominated facility between production and non-production periods are vastly different. During production, the energy use signature is in the form of a three-parameter-cooling multi-variable model, and during non-production, energy use is in the form of a two-parameter model.

Figure 6. Energy Use Signature With Respect To Average Daily Wet-Bulb Temperature (Twb) Of a Refrigeration-Dominated Facility during both Production and Non-Production Periods



Valid range of data set (Step 3, sub-step). The range of data used to build the model should be carefully inspected such that observations at the high and low ends of the production range do not leverage or significantly influence the model. In addition, the modeled data should not include large gaps or areas where the data is insufficient. Figure 7 shows an area of the data set where modeling judgment is needed because the data appears to be of a different form. Furthermore, the data set exhibits data insufficiency as the facility transitions between production and non-production periods. Again, Figure 7 shows that a production model can be significantly different from a model that combines both production and non-production operations.

Figure 7. Energy Use Signature With Respect To Production of a Refrigeration-Dominated Facility during both Production and Non-Production Periods



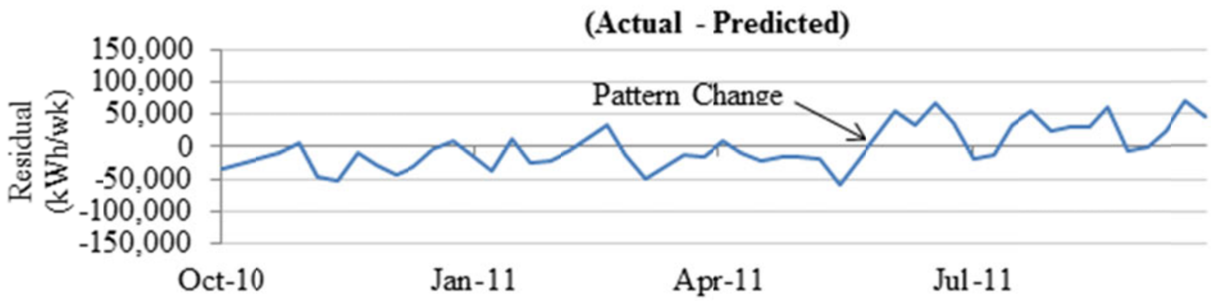
Reviewing the Fitness of the Model (Step 4)

After a linear regression model has been developed, the fitness of the model should be reviewed. This review needs to encompass a broader evaluation of statistical indicators than a mere criteria check of goodness-of-fit statistics, such as the coefficient of determination, R^2, and the coefficient of variation of the root mean square error, CV-RMSE. As previous authors have explained (Reddy & Claridge 2000), R^2 and CV-RMSE have limitations, and selection of models based solely on a cut-off criterion can be arbitrary and often misleading.

Review of model coefficients (Step 4, sub-step). The first step in this process should be an engineering evaluation of the relative magnitude of the model coefficients. If model coefficients indicate that energy use decreases as production increases (e.g., a negative coefficient), then the reason for this occurrence must be determined. Further investigation is also needed if a less energy-intensive process results in a larger impact on energy use than a highly intensive energy process.

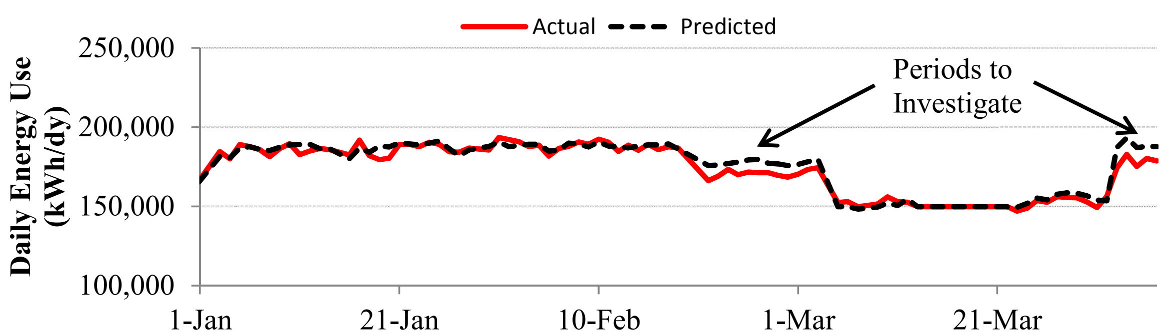
Review of residuals (Step 4, sub-step). The underlying assumption of a regression model is that the residuals (actual energy use minus the energy use predicted by the model) are normally and independently distributed with an average value of zero. From an applications standpoint, reviewing the residuals can help identify not only outliers, but model weaknesses and process changes as well. Three graph types considered important when reviewing residuals are: 1) a time series of residuals, 2) an x-y plot of each independent variable versus the residuals, and 3) a histogram of residuals. Of the three graphs, the EPT team has found the time series of residuals most useful in identifying model inadequacies, often as a result of process changes. As an example, Figure 8 shows a shift in the residual pattern near the latter part of the baseline period, indicating a process change or disruption that isn't described by the selected variables. Left unaddressed, this issue within the baseline period has the potential to ultimately bias the savings estimate for the project.

Figure 8. Example of a Time Series of Residuals



Review predicted versus actual energy use (Step 4, sub-step). Similar to a review of the residuals, reviewing the predicted and actual energy use in both a time series plot and x-y plot can help identify areas of the model to investigate. Figure 9 shows two distinct areas where the model is over-predicting energy use. These areas should be investigated to determine the root cause.

Figure 9. Example of a Time Series Plot of Actual and Predicted Energy Use



Quantify auto-correlation coefficient of residuals (Step 4, sub-step). The operation of industrial facilities often exhibits a time series pattern, such as a similar production operation for an extended period of time. Such operations can lead to a residual pattern with few sign changes, resulting in positively auto-correlated residuals. Positive auto-correlation underestimates the standard errors of the coefficients and thereby inflates the statistical significance of model coefficients. This may lead the practitioner to include variables in the model that are not truly energy drivers. The auto-correlation coefficient of residuals, p, can be calculated from the model's residuals (e) as (Montgomery, Peck & Vining 2012):

$$p = \frac{\sum_{t=2}^{n} (e_{t-1})e_t}{\sum_{t=1}^{n} (e_t)2} \tag{3}$$

On several projects, the EPT team has used transformations to reduce auto-correlation, but all attempts have been unsuccessful. To this point, only a more thorough data review and understanding of the process have provided the insight necessary to address auto-correlation by identifying other relevant variables, or aggregating the data to a more appropriate time interval.

Estimate Uncertainty of Estimated Project Savings (Step 5)

Typically, industrial energy efficiency O&M projects have multiple stakeholders who all, to a varying degree, have a vested interest in the confidence and uncertainty of the project's energy savings. Therefore, estimating the uncertainty of the estimated project savings provides an objective framework to judge competing models in a manner consistent with the interests of the multiple stakeholders. Before the project begins, reasonable estimates of the uncertainty of project savings can be made based on estimated project savings, a value typically obtained from engineering calculations. To this point, estimates of uncertainty of project savings have been calculated based on procedures outlined by ASHRAE Guideline 14.

Team Selection of "Best" Model or Determination of Alternate Path (Step 6)

After a model is developed, model fitness should be carefully inspected, and then an uncertainty estimate, based on estimated project savings, should be calculated. As possible from the data set, several models deemed acceptable from both the perspective of model fitness and the desired level of uncertainty should be provided for team review so that the "best" model or alternative direction can be selected by a cross-functional group of stakeholders.

The EPT team actively communicates with various stakeholders during model development to ensure the "best" model selected contains the right balance of model predictability and complexity. Model selection is typically guided by model fitness and fractional savings uncertainty, but other stakeholder interests such as the usability of the model must also be considered. In the event that a correlation of facility energy use cannot be determined, input from the team is valuable in deciding how energy savings will be measured for a given project. Documenting statistics for model fitness and fractional savings uncertainty is important for internal team review, as well as review with the various stakeholders, as shown in Table 1.

Table 1. Example Table Showing Model Selection Based On Fractional Savings Uncertainty At 80% Confidence for an Estimated Project Savings Of 3%

Trial #	% CV-RMSE	Model Parameters	Actual Baseline Observations	Auto-correlation	Savings Observations	Fractional Savings Uncertainty (%)
1	4.1%	7	300	0.14	300	15.7%
2	3.8%	8	300	0.02	300	12.8%
3	3.7%	7	300	0.01	300	12.4%

Lessons Learned from a Large Industrial End User

At the beginning of the ESI program, a regression model was created for a large food processor with annual energy use of approximately 60 million kWh/yr. The refrigeration system uses approximately 50% of facility energy use, while the pumping, conveying, compressed air, and lighting systems use the remaining 50%. Early in the savings period, the plant suspected that an additional production variable, one not included in the model, influenced facility energy use and asked the Team to re-evaluate the model. During the re-evaluation, several notable corrections were made to the model.

First, a subject matter expert at the plant was invoked, and through conversations with this individual, the Team learned that daily production was counted from 7 am to 7 am, not 12 am to 12 am. Second, a more thorough understanding of the process resulted in identifying a new variable that served a proxy for process yield, which was a key driver of facility energy use. Third, the form of the model was changed based on information obtained from the subject matter expert and experiences gained from other projects since the development of this model. Originally, an indicator variable for production (PI) was used to model both production and non-production operations with a single model. The model had the following form:

$$Et = \text{Intercept} + \text{Coeff}_1 \cdot \text{Twb} + \text{Coeff}_2 \cdot \text{Prod} - \text{Coeff}_3 \cdot \text{Prod}^2 + \text{Coeff}_4 \cdot \text{PI} \quad (4)$$

The revised model was separated into two distinct models; a production model and a non-production model. The production model took the form of Equation 1 and the non-production model took the form of Equation 2. Table 2 shows that relative to the original model, R^2 decreased, but so did the %CV-RMSE, and consequently the fractional savings uncertainty. The decrease in R^2 resulted from a decrease in the slope of the data, and the decrease in CV-RMSE resulted in from a decrease in the spread of the data. This illustrates how selecting models based solely on the statistics of R^2 and CV-RMSE can be misleading.

Table 2. Model Improvement after Implementing Current Methodology

Model	Data Frequency	R^2	% CV-RMSE	Auto-correlation	Fractional Savings Uncertainty (%)
Original	Daily	0.92	7.8%	0.25	30.6%
Rev, Prod Only	Daily	0.83	2.3%	0.23	9.7%

Lessons Learned from Daily Time Interval Models

Additional hardware and software requirements make regression models with daily time resolution more expensive to construct than regression models on a monthly resolution. Furthermore, other authors (Carpenter et al. 2010) have shown that when outdoor air temperature is the sole energy driver, daily and monthly models for these types of facilities yield nearly the same result. Therefore, the additional costs incurred to develop a regression model with a daily resolution may seem unwarranted. Our experience indicates that the additional time and complexity of daily resolution are needed to reduce the uncertainty to a level that allows the model to detect energy reduction in the range of 3-5%. Typically, the majority of additional time is incurred for data acquisition and management, rather than the modeling process itself.

Two models were developed in order to investigate the differences between models created on a daily and monthly time resolution for large industrial facilities. Models of a daily time resolution were constructed from production periods and are assumed to be invalid for non-production conditions. The models on a monthly time resolution were created by aggregating production and energy use and averaging temperature of the entire data set, which is on a daily time resolution, to monthly values. Energy and production were then divided by the number of days in the month and a weighted regression was performed as outlined in ASHRAE Guideline 14 using the analysis tool Energy Explorer (Kissock 2010). Each model took the form of Equation 1, a three-parameter cooling multi-variable model. Although each model had additional production variables, only one production variable is shown for illustration purposes as the other variables provided essentially the same information.

As shown in Table 3**Error! Reference source not found.**, only the temperature change-point coefficient was similar for both daily and monthly models. As pointed out by previous authors (Carpenter et al. 2010), this is likely a result of a similar distribution of temperature effects throughout time. However, in large industrial facilities, production is typically the primary energy driver. Thus, model effects are usually dominated by the production mode, and these effects are typically not evenly distributed throughout time. This can lead to significant differences in model coefficients and model fitness.

The fractional savings uncertainty (FSU) is typically much larger for models with monthly time resolution as opposed to daily, resulting from substantially fewer data points. When the uncertainty that accompanies the reported energy savings for a project is large, skepticism rises about the true savings value. For Model 4 in Table 3, the FSU for a monthly model is reasonable, but this is driven by a lofty expectation of project savings. However, if actual project savings are a modest 2.8%, then the FSU for a monthly model grows to 82.8%, while the FSU for a daily model is within 20% uncertainty. In other words, for the monthly model, the uncertainty may be nearly as large as the reported savings.

Table 3. Comparison of Models with Time Resolutions of Daily and Monthly, FSU Is Provided For An 80% Confidence Level

Model # Subsector	Resolution	R2	%CV-RMSE	Intercept	RS	Change-point	Prod. 1 Coeff	Est. Savings	FSU (%)
Model #4 Food Proc.	Daily, prod only	0.84	3.9%	45,999	205	36.2	4.7	10.5%	4.8%
	Monthly, all	0.89	4.1%	22,782	126	32.6	22.77	10.5%	22.1%
	% Difference	-	-	50%	39%	10%	-381%		
Model #6 High Tech	Daily, prod only	0.89	1.6%	80,702	931	55.0	685.8	5.9%	8.3%
	Monthly, all	0.78	7.2%	53,179	1,696	54.2	1830	5.9%	67.0%
	% Difference	-	-	34%	-82%	1%	-167%		

Model Development Results from Selected Participants

Table 4 shows statistics for model fitness, R^2, CV, and auto-correlation, and estimated fractional savings uncertainty expected based on estimated projected savings for seven ESI program participants. The results show that with a methodic and rigorous approach, models with good fitness and relatively low uncertainty can be developed. For this select group of models, the estimated fractional savings uncertainty at 80% confidence is estimated to be less than 20%. However, instances have occurred in which data sets provided models with substantially lesser fitness. At this time, we do not believe that model fitness should be a barrier to program participation.

Table 4. Model Statistics from Selected Participants, FSU Is Provided For An 80% CL

Model No.	Sector	Time Interval	R^2	% CV RMSE	Model Parameters	Actual Baseline Observations	Auto-correlation	Estimated Savings Observations	Estimated Project Savings (%)	FSU (%)
1	Food Processing	Daily	0.83	2.3%	6	225	0.23	300	2.8%	9.8%
2	Food Processing	Daily	0.91	2.3%	10	228	0.65	300	4.8%	10.1%
3	Food Processing	Daily	0.93	2.1%	8	281	0.47	281	10.5%	3.3%
4	Food Processing	Daily	0.84	3.9%	6	275	0.27	275	10.5%	4.8%
5	Food Processing	Daily	0.85	3.1%	7	153	0.06	280	6.2%	5.2%
6	High Tech	Weekly	0.89	1.6%	4	50	0.23	50	5.9%	8.3%
7	Pulp & Paper	Daily	0.94	3.3%	3	142	0.18	300	3.1%	12.1%

Summary and Conclusions

This paper outlined a six-step procedure that the ESI EPT Team has found beneficial to the development of linear regression models for sub-system and plant-wide energy use in industrial facilities. The procedure outlined in these six steps demonstrated close agreement in the savings estimates for 15 of 17 projects evaluated by an independent third party in 2012. The paper provided several key lessons learned from modeling the energy use of a large industrial facility.

Regression-based models created with a daily time resolution were shown to provide an estimated fractional savings uncertainty of less than 20%, with 80% confidence. For the same confidence level, the fractional savings uncertainty exceeded 20% for those models created with a monthly time resolution. The results show that for linear regression models used to model sub-system and plant-wide energy use in industrial facilities, the prediction capability and the estimated fractional savings uncertainty are greatly improved when using defensible modeling techniques and models with daily time resolution. Further work seeks to improve the methodology used to estimate fractional savings uncertainty. These results, along with energy savings achieved for each project, will then be used to provide a cost benefit analysis between models with daily and monthly time resolution.

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