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Measuring Plant-Wide Energy Savings

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MEASURING INDUSTRIAL ENERGY SAVINGS

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Abstract

This paper presents a general method for measuring industrial energy savings and demonstrates the method using a case study from an actual industrial energy assessment. The method uses regression models to characterize baseline energy use. It takes into account changes in weather and production, and can use sub-metered data or whole plant utility billing data. In addition to calculating overall savings, the method is also able to disaggregate savings into components, which provides additional insight into the effectiveness of the individual savings measures. Although the method incorporates search techniques and multi-variable least-squares regression, it is easily implemented using data analysis software.

The case study compared expected, unadjusted and weather-adjusted savings from six recommendations to reduce fuel use. The study demonstrates the importance of adjusting for weather variation between the pre- and post-retrofit periods. It also demonstrated the limitations of the engineering models when used to estimate savings.

Introduction

The decision to spend money to reduce energy expenditures frequently depends on the expected savings. Decision makers must then weigh the expected savings with several other issues. These issues include the availability of capital, competing investments, the synergy of the proposed retrofit with other strategic initiatives, and, not insignificantly, the certainty that the expected savings will be realized.

This uncertainty about whether the expected savings will be realized depends largely on the type of retrofit. In some cases, it is relatively easy to verify expected savings; for example, expected energy savings from a lighting upgrade can be easily verified by measuring the power draw of lighting fixtures before and after a lighting upgrade. A history of verified savings reduces the uncertainty about future lighting recommendations and encourages this type of energy efficiency retrofit. In other cases, however, the retrofit may occur on a component of a larger system, and the energy use of the component may be difficult or impossible to meter. Moreover, the energy use may also be a function of weather and/or production, which frequently changes between the pre- and post retrofit periods. In these cases, it is more difficult to measure energy savings and, as a consequence, savings are seldom verified.

This lack of verification hurts the effort to maximize industrial energy efficiency. In some cases, retrofit measures which would realize the expected savings are not implemented since there is no history of successful verification. In other cases, retrofits that do not achieve the expected savings get implemented, which wastes resources that may have been directed to more effective measures. Both of these problems could be minimized by systematically measuring savings, and comparing expected and measured savings. The information could guide the selection of future retrofits, improve methods to calculate expected savings, and improve utilization of capital resources.

This paper presents a general method for measuring industrial energy savings and demonstrates the method using a case study from an actual industrial energy assessment. The method takes into account changes in weather and production, and can use sub-metered data or whole plant utility billing data.

The case study involves an energy assessment by the University of Dayton Industrial Assessment Center (UD-IAC). The UD-IAC is one of twenty-six Industrial Assessment Centers at universities throughout the United States (DOE, 2006). Each center is funded by the United States Department of Energy Industrial Technologies Program to perform about 25 energy assessments per year for mid-sized industries, at no cost to the industrial client. Each assessment identifies energy, waste, and productivity cost saving opportunities, and quantifies the expected savings, implementation cost and simple payback of each opportunity. This information is delivered to the client in a report summarizing current energy and production practices and the savings opportunities identified during the assessment.

About one year after each assessment, the client is called and asked which, if any, of the recommendations were implemented. At that time, the client is also asked if they believe the estimate of savings and implementation costs were accurate. Based on this information, the quantity of implemented savings is recorded. For example, from 2001 to 2004, about 49% of the cost savings identified by the UD-IAC were implemented.

However, even more information about the effectiveness of these energy conservation assessments could be derived if the savings could be measured. Numerous efforts have been made to develop standard protocols for measuring savings. For example, the National Association of Energy Service Contractors developed protocols for the measurement of retrofit savings in 1992. In 1994, the US Department of Energy initiated an effort that resulted in publication of the North American Energy Measurement and Verification Protocols (USDOE, 1996a) and, later, the International Performance, Measurement and Verification Protocols (EVO, 2002). The U.S. Federal Energy Management Program developed their own set of Measurement and Verification Guidelines for Federal Energy Projects (USDOE, 1996b). ASHRAE published its guideline, Measurement of Energy and Demand Savings, in 2002 (ASHRAE, 2002).

A principle method for measuring savings, which is included in all of the protocols shown above, relies on regression models. The regression method of measuring savings has been widely used in the residential and commercial building sectors (see for example: Fels, 1986, Kissock et al., 1998). However, this method can be extended to measure savings in the industrial sector. This paper gives a brief review of the regression method for measuring savings, discusses the extension of the method to measure industrial energy savings, and demonstrates the method with a case study.

REGRESSION METHOD FOR MEASURING SAVINGS

Perhaps the simplest method of measuring retrofit energy savings is to directly compare energy consumption in the pre- and post-retrofit periods. Savings measured using direct comparison of pre- and post-retrofit energy consumption are sometimes called "unadjusted" savings. This method implicitly assumes that the change in energy consumption between the pre-retrofit and post-retrofit periods is caused solely by the retrofit. However, energy consumption in most industrial facilities is also influenced by weather conditions and the level of production—both of which may change between the pre- and post-retrofit periods. If these changes are not accounted for, savings determined by this simple method will be erroneous.

One way to account for these changes is to develop a weather and production-dependent regression model of pre-retrofit energy use. The savings can then be calculated as the difference between the post-retrofit energy consumption predicted by the pre-retrofit model $\hat{E}_{\mathrm{Pr}e}$ and measured energy consumption during the post-retrofit period E_{Meas}. The procedure to calculate savings is summarized by:

$$S = \sum_{j=1}^{m} (\hat{E}_{\mathrm{Pr}e,j} - E_{Meas,j}) \qquad (1)$$

where m is the number post-retrofit measurements.

The pre-retrofit regression model is sometimes called a baseline model. Savings measured using a baseline model, are called "adjusted" savings if the baseline model can be adjusted to account for the weather and production conditions in the post retrofit period. Adjusted savings are much more accurate than unadjusted savings, and should be used whenever the energy use data used to measure savings is weather and/or production dependent. Two types of baseline regression models that are appropriate for measuring industrial energy savings are described below.

<u>Multi-Variable Change-Point Models</u>

In most industrial facilities, the weather dependence of energy use can be accurately described using a three-parameter change-point model. Three-parameter change point models describe the common situation when cooling (heating) begins when the air temperature is more (less) than some balance-point temperature. For example, consider the common situation where electricity is used for both air conditioning and process-related tasks such as lighting and air compression. During cold weather, no air conditioning is necessary, but electricity is still used for process purposes. As the air temperature increases above some balance-point temperature, air conditioning electricity use increases as the outside air temperature increases (Figure 1a). The regression coefficient β_1 describes non-weather dependent electricity use, and the regression coefficient β_2 describes the rate of increase of electricity use with increasing temperature, and the regression coefficient β_3 describes the change-point temperature where weather-dependent electricity use begins. This type of model is called a three-parameter cooling

(3PC) change point model. Similarly, when fuel is used from space conditioning and process-related tasks, fuel use can be modeled by a three-parameter heating (3PH) change point model (Figure 1b).

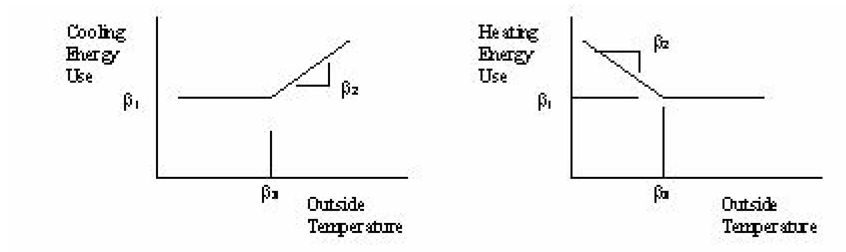

Figure 1. a) 3P-cooing and b) 3P-heating regression models.

These basic change-point models can be easily extended to include the dependence of energy use on the quantity of production by adding an additional regression coefficient. The functional forms for best-fit multi-variable three-parameter change-point models for cooling (3PC-MVR) and heating (3PH-MVR), respectively, are:

$$Y_c = \beta_1 + \beta_2 (X_1 - \beta_3)^{+} + \beta_4 X_2 \quad (2)$$

$$Y_h = \beta_1 - \beta_2 (\beta_3 - X_1)^{+} + \beta_4 X_2 \quad (3)$$

where β_1 is the constant term, β_2 is the temperature-dependent slope term, β_3 is the temperature change-point, and β_4 is the production dependent term. X_1 is outdoor air temperature and X_2 is a metric of the level of production. The ( )+ and $( )^{-}$ notations indicate that the values of the parenthetic term shall be set to zero when they are negative and positive respectively.

In Equations 2 and 3, the β_1 term represents energy use that is independent of both weather and production. The $\beta_2 (X_1 - \beta_3)^{+}$ or $- \beta_2 (\beta_3 - X_1)^{+}$ term represents weather-dependent energy use. And the $\beta_4 X_2$ term represents production-dependent energy use. Thus, this simple regression equation can statistically disaggregate energy use into components. The interpretation and use of this disaggreation technique is called Lean Energy Analysis (Kissock and Seryak, 2004a; Kissock and Seryak, 2004b; Seryak and Kissock, 2005).

Several algorithms have been proposed for determining the best-fit coefficients in piecewise regressions such as Equations 2 and 3. A simple and robust method uses a two-stage grid search. The first step is to identify minimum and maximum values of X1, and to divide the interval defined by these values into ten increments of width dx. Next, the minimum value of X1 is selected as the initial value of β_3 and the model is regressed against the data to find β_1, β_2 , β_4 and RMSE. The value of β_3 is then incremented by dx and the regression is repeated until β_3 has traversed the entire range of possible X values.

The value of β_3 that results in the lowest RMSE is selected as the initial best-fit change-point. This method is then repeated using a finer grid of width 2 dx, centered about the initial best-fit value of β_3 (Kissock et al., 2003). For discussions of the uncertainty of savings determined using regression models see Kissock et al. (1993) and Reddy et al., (1998).

This method has been incorporated in several software tools for measuring savings. One tool is the ASHRAE Inverse Modeling Toolkit (Kissock et al., 2002, Haberl et al., 2003), which supports ASHRAE Guideline 2002-14. Another tool is ETracker (Kissock, 1997; Kissock, 1999) which is free software used to support the EPA Energy Star Buildings program. Another tool is Energy Explorer (Kissock, 2005), which is used in the analysis that follows.

<u>Multi-variable Variable-Base Degree-Day Models</u>

Multi-variable variable-base degree-day (VBDD-MVR) models can also be developed that yield similar results. The use of VBDD models to measure savings traces its origin to the PRInceton Scorekeeping Method (PRISM), which has been widely used in the evaluation of residential energy conservation programs (Fels, 1986; Fels and Keating, 1993; Fels et al., 1995). Sonderegger (1997; 1998) extended the method to include additional variables, such as production.

The forms of multi-variable VBDD models are shown below:

$$Y = \beta_1 + \beta_2 \, HDD(\beta_3) + \beta_4 X_2 \quad (4)$$

$$Y = \beta_1 + \beta_2 \, CDD(\beta_3) + \beta_4 X_2 \quad (5)$$

where β_1 is the constant term, β_2 is the slope term, $HDD(\beta_3)$ and $CDD(\beta_3)$ are the number of heating and cooling degree-days, respectively, in each energy data period calculated with base temperature β_3, and β_4 is the production-dependent term. X_2 is a metric of the level of production. The number of heating and cooling degree-days in each energy data period of n days is:

$$HDD(\beta_3) = \sum_{i=1}^{n} (\beta_3 - T_i)^+ \quad (6)$$

$$CDD(\beta_3) = \sum_{i=1}^{n} (T_i - \beta_3)^+ \quad (7)$$

where T_i is the average daily temperature.

A simpler method uses degree days with a fixed 65 F base temperature.

$$Y = \beta_1 + \beta_2 \, HDD(T = 65) + \beta_3 X_2 \quad (8)$$

$$Y = \beta_1 + \beta_2 \, CDD(T = 65) + \beta_3 X_2 \quad (9)$$

The loss in accuracy of this method compared to the variable-base degree-day method depends on the deviation between the actual balance-point temperature of the facility and the assumed 65 F balance-point temperature.

Overview Of The Assessment

The use of this method to measure savings is demonstrated by analyzing fuel data before and after an energy assessment of the Staco Energy Products Company in Dayton, Ohio (UD-IAC, 2004). The assessment was performed by the UD-IAC on February 2, 2004. The company employed about 80 people and occupied a 122,000 ft^2 facility. The facility operated about 2,000 hours per year and produced variable transformers, industrial voltage regulators, uninterruptible power supply systems and other power management equipment. During the year from July, 2002 to June, 2003, the facility used 967,061 kWh of electricity, 5,885 mmBtu of diesel fuel and 2,907 mmBtu of natural gas. The diesel fuel was used in a 6.3 mmBtu/hr hot-water boiler dedicated solely to space heating. Natural gas was used in three drying and curing ovens, rated at 0.50 mmBtu/hr, 1.0 mmBtu/hr and 0.55 mmBtu/hr. Total energy expenditures were $140,702.

The assessment generated 17 recommendations addressing electricity, fuel, waste and productivity savings opportunities. These recommendations identified a total of about $97,629 per year in potential savings with a total implementation cost of about $21,121. The estimated simple payback for all recommendations was about 3 months.

On July 25, 2005, Staco was contacted to find out which recommendations had been implemented, and to collect recent utility billing data for measuring savings. According to management, 13 of the 17 recommendations had been implemented. Of the 13 implemented recommendations, six were specific to fuel consumption. Brief descriptions of the six fuel-related assessment recommendations (ARs) that were implemented are shown below:

- <u>AR 1: Run Boiler in Modulation Mode</u>
  The plant employs a hot-water boiler for space heating. The boiler is currently set to run in on/off mode, in which the burner either runs at high fire or turns off in order to maintain the temperature of water in the boiler between two set-points. According to the boiler service technician, the boiler could also be set to run in modulation mode, in which the firing rate is continuously modulated in order to maintain the temperature of water in the boiler. The boiler operates much more efficiently in modulation mode than in on/off mode. We recommend contacting the boiler service technician to switch from on/off to modulation control as soon as possible.

- <u>AR 2: Reduce Night Setback Temperature from 65 F to 60 F</u>
  A hot-water boiler, operating on natural gas, heats the plant during the winter. It is a good practice to reduce the heating set-point temperature when buildings are unoccupied and increase set-point temperature during operating hours. Your plant temperature is already controlled by thermostats set at 70 F during the day

and 65 F on nights and weekends. We recommend reducing night and weekend setback temperature from 65 F to 60 F.

- AR 3: Reduce Air Flow Through Dispatch and Jensen Ovens
  The Dispatch oven is equipped with an exhaust air fan which forces air out of the oven and draws an equal amount of air in through an open grate. The exhaust duct is equipped with a damper, which is currently set to 100% open. The Jensen oven has a similar configuration to the Dispatch oven. If the dampers were partially closed, the quantity of air heated by the oven would be reduced, which would improve the efficiency of the oven and decrease gas use. It is important, though, to maintain enough air flow through the furnace so that fumes emitted by the products do not accumulate inside the furnace and cause an explosive situation. We recommend slightly closing the exhaust dampers to reduce airflow through the Jensen and Dispatch ovens. We recommend that the dampers be closed no more than 25% in order to maintain sufficient airflow though the ovens.

- AR 4: Turn Off Exhaust Fans on IR Oven When Not in Use
  An infrared (IR) oven is used to dry painted cases for variable transformers and uninterruptible power supplies. Two fans on the roof exhaust fumes from the painted products as they pass through the IR oven. According to management, the oven operates 75 percent of the time, but the fans run the entire shift. The volume of air exhausted by these fans must be made up by infiltration through other areas of the building. In the winter, this increases the plant heating load. Off-delay timers can be used to turn off exhaust fans when IR ovens are not used. Off-delay timers wait a given period of time before shutting off to ensure that all toxic fumes are exhausted. We recommend installing an off-delay timer to turn off the exhaust fans on the IR oven when it is not being used.

- AR 5: Shut Off Boiler at the Beginning of May
  According to maintenance's boiler logging book, the boiler is fired up on September 29th and is shut off on June 4th. The logging book indicated that the boiler only ran for about 16 hours during the between May 1st and June 4th. Since the boiler runs in on/off control, it is most likely firing to make up for the heat it loses through cyclic air purging, drift heat loses, and heat losses through its shell. Most of the natural gas heat going to the boiler during May and June is probably not used for space heating but instead wasted. We recommend shutting the boiler off at the beginning of May each year rather than at the beginning of June.

- AR 6: Reduce Excess Combustion Air in Boiler
  During our visit, we measured the temperature and quantity of excess air in the exhaust gasses of the primary boiler. The exhaust gasses contained about 29% more air than is required for combustion. The ideal amount of excess air is about 10%. We recommend asking your boiler maintenance contractor to reduce the quantity of combustion air supplied to the boiler so that the boiler operates at 10% excess air at high fire.

The estimated savings and implementation cost of each recommendation are shown in Table 1. Total estimated fuel savings were 2,696 mmBtu per year.

Table 1. Estimated savings and implementation cost of the six implemented fuel-related recommendations.

Assessment Recommendation	Annual Savings		Project Cost	Simple Payback
	Fuel (mmBtu)	Dollars		
AR 1: Run Boiler in Modulation Mode	985	$7,720	None	Immediate
AR 2: Reduce Night Setback Temperature from 65 F to 60 F	900	$7,056	None	Immediate
AR 3: Reduce Air Flow Through Dispatch and Jensen Ovens	327	$1,575	None	Immediate
AR 4: Turn Off Exhaust Fans on IR Oven When Not in Use	291	$2,281	$175	1 month
AR 5: Shut Off Boiler at the Beginning of May	100	$784	None	Immediate
AR 6: Reduce Excess Combustion Air in Boiler	93	$729	None	Immediate
Total	**2,696**	**$20,145**	**None**	**Immediate**

Unadjusted Savings

Table 2 shows monthly fuel use, an indicator of monthly sales, and average outdoor air temperature data for pre- and post-retrofit periods. The date of each record is the meter-reading date. The fuel use data were compiled from utility bills, and represent the total energy from both natural gas and diesel fuels. Due to the variety of products produced, sales data were the best metric of production available. The sales data were lagged by one month, since sales in one month influenced production during the next month when production restocked depleted inventory. The average outdoor air temperature for each period was calculated using average daily temperatures from the UD/EPA Average Daily Temperature Archive, which posts average daily temperatures for 324 cities around the world from 1995 to present (Kissock, 1999b). -99 is used as a no-data flag.

Table 2. Monthly fuel use, an indicator of monthly sales, and average outdoor air temperature data from the pre-retrofit (8/20/2002-7/21/2003) and post-retrofit (8/18/2003-7/19/2005) periods respectively.

Month	Day	Year	NG (mmBtu/day)	Diesel (mmBtu/day)	Fuel (mmBtu/day)	ProdLag1 ($/day)	Toa (F)
8	20	2002	6.5	0.0	6.5	-99	77.0
9	19	2002	7.2	0.0	7.2	28	73.1
10	18	2002	9.3	7.9	17.2	27	59.3
11	18	2002	10.0	15.8	25.9	29	43.4
12	16	2002	10.8	33.7	44.5	25	31.1
1	20	2003	6.8	51.8	58.5	28	28.5
2	19	2003	9.1	41.1	50.2	18	22.4
3	19	2003	8.6	24.7	33.3	16	33.1
4	17	2003	7.4	13.0	20.4	22	50.9
5	19	2003	6.5	6.5	13.0	17	59.1
6	18	2003	7.4	0.0	7.4	33	62.1
7	21	2003	6.2	0.0	6.2	16	72.0
8	18	2004	8.1	0.0	8.1	-99	68.3
9	20	2004	6.9	0.0	6.9	25	69.5
10	19	2004	12.1	0.0	12.1	28	56.5
11	17	2004	19.9	0.0	19.9	18	50.1
12	16	2004	31.3	0.0	31.3	26	41.0
1	19	2005	37.6	0.0	37.6	23	30.2
2	16	2005	40.3	0.0	40.3	24	29.0
3	18	2005	37.4	0.0	37.4	22	31.1
4	19	2005	18.5	0.0	18.5	27	50.0
5	18	2005	14.1	0.0	14.1	22	53.0
6	17	2005	7.7	0.0	7.7	32	67.4
7	19	2005	5.7	0.0	5.7	25	74.0

Unadjusted savings are calculated as the difference between pre- and post-retrofit energy use. The time-trends of monthly fuel use from the pre- and post-retrofit periods are shown in Figure 2. The mean fuel consumption during the pre-retrofit period was 24.19 mmBtu per day, and is indicated by the top horizontal line. The mean fuel consumption during the post-retrofit period was 19.97 mmBtu per day, and is indicated by the lower horizontal line. Using the mean energy use from the pre-retrofit period as a baseline model, the unadjusted fuel savings are calculated from Equation 1 to be about 4.2 mmBtu per day with an uncertainty of ±11.3 mmBtu per day. Annual unadjusted savings are 1,533 mmBtu per year with an uncertainty of ± 4,125 mmBtu per year.

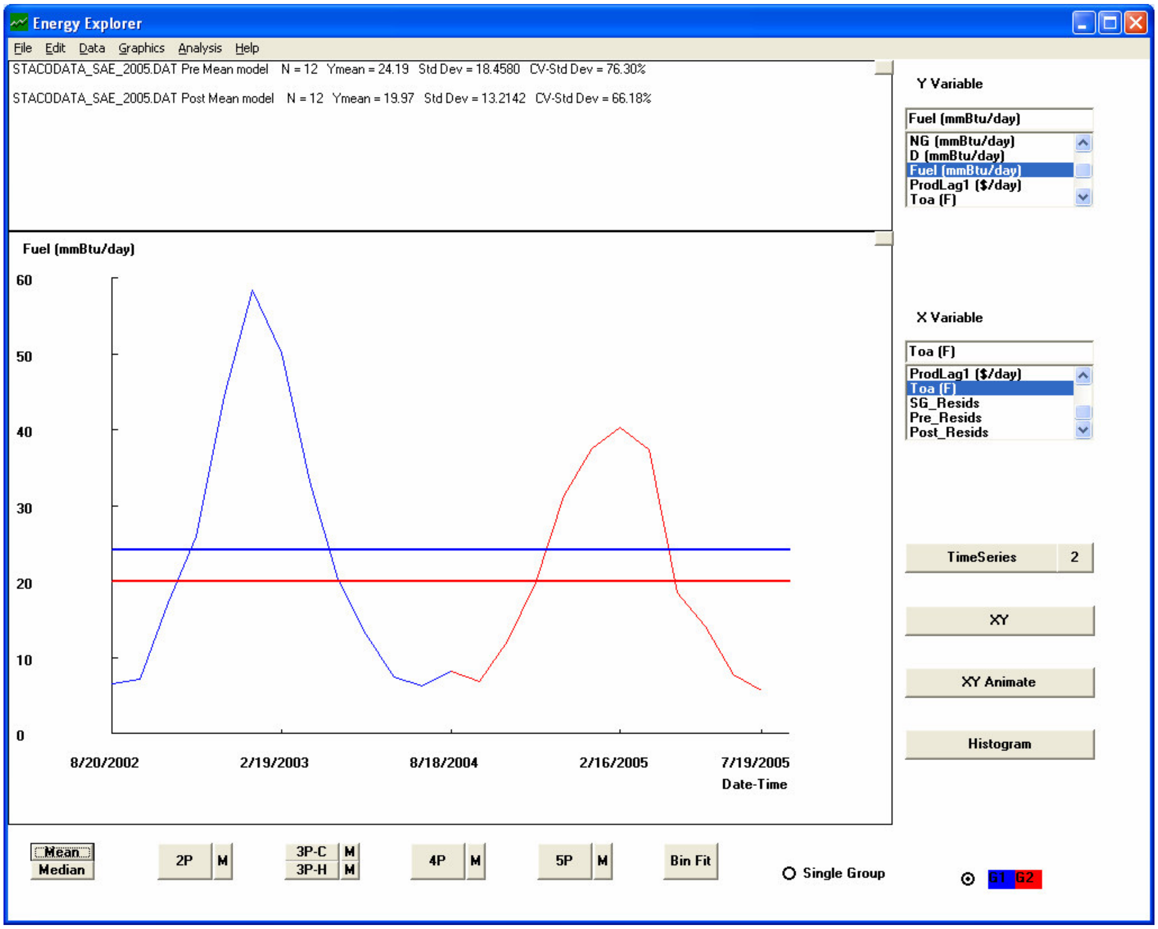

Figure 2. Pre- and Post-retrofit time trends and mean energy use

Weather-Adjusted Savings

A quick inspection of Figure 2 shows that fuel use peaks in the winter months, which indicates the strong weather dependence of fuel use. Thus, the effect of changing weather must be accounted for to accurately measure savings. To do so, a weather-dependent model of pre-retrofit fuel use is developed.

Figure 3 shows three-parameter heating (3PH) models of fuel use as functions of outdoor air temperature. The top (blue) model shows pre-retrofit fuel use and the bottom (red) model shows post-retrofit fuel use. Both models show that space heating fuel use increases linearly as outdoor air temperature decreases. The outdoor air temperature at which space heating begins is 64 F in the pre-retrofit period and 62 F in the post-retrofit period. Both models have good fits to the data; the R^2 and CV-RMSE of the pre-retrofit model are 0.93 and 21.3%, and the R^2 and CV-RMSE of the post-retrofit model are 0.99 and 7.2%.

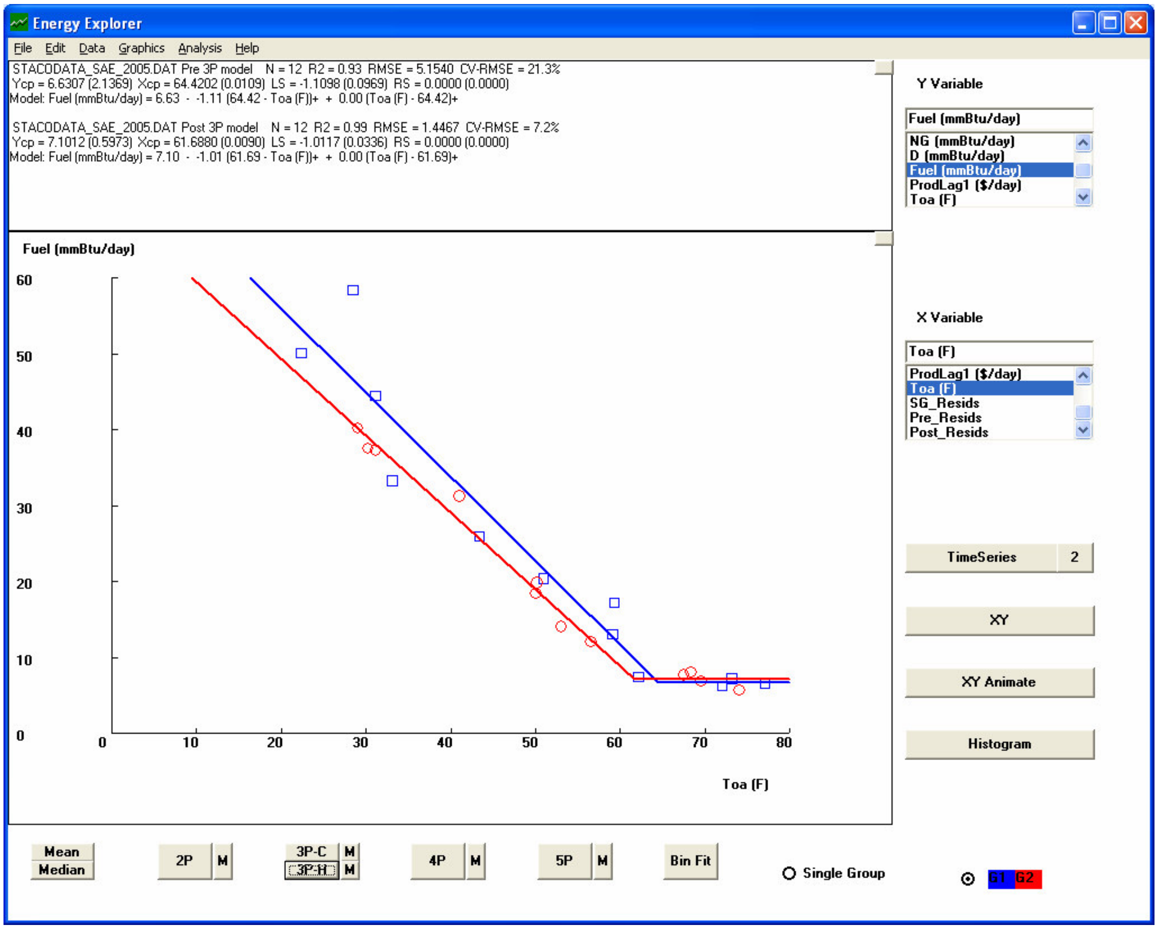

Figure 3. Pre- and post-retrofit fuel use data with 3PH models through each data set.

From Figure 3, the weather-adjusted 3PH model (Equation 10) and coefficients for pre- and post-retrofit fuel use (Table 3) are:

$$\text{Fuel (mmBtu/day)} = \beta_1 \text{ (mmBtu /day)} - \beta_2 \text{ (mmBtu /day-F)} \times [\beta_3 \text{ (F)} - T_{oa} \text{ (F)}]^+ \quad (10)$$

Table 3. Regression coefficients for 3PH models of pre- and post retrofit fuel use.

Coefficient	Pre-retrofit	Post-retrofit
β_1	6.632	7.100
β_2	-1.109	-1.012
β_3	64.43	61.65

The fuel use savings are the sum of the differences between the actual energy use in post-retrofit period and the energy use predicted by the pre-retrofit period for the same weather conditions. Fuel use savings can be visualized as the difference between the model lines in Figure 3. Fuel use savings can also be visualized by projecting the weather-adjusted baseline model onto the post-retrofit period (Figure 4). The weather-adjusted baseline model shows the energy use that would have occurred if the retrofits had not taken place given the actual weather conditions in the post-retrofit period. The savings are calculated using Equation 1 to be about 2.8 mmBtu per day with an uncertainty of ± 3.1 mmBtu per day. Annual weather-adjusted savings are 1,022 mmBtu per year with an uncertainty of ± 1,132 mmBtu per year.

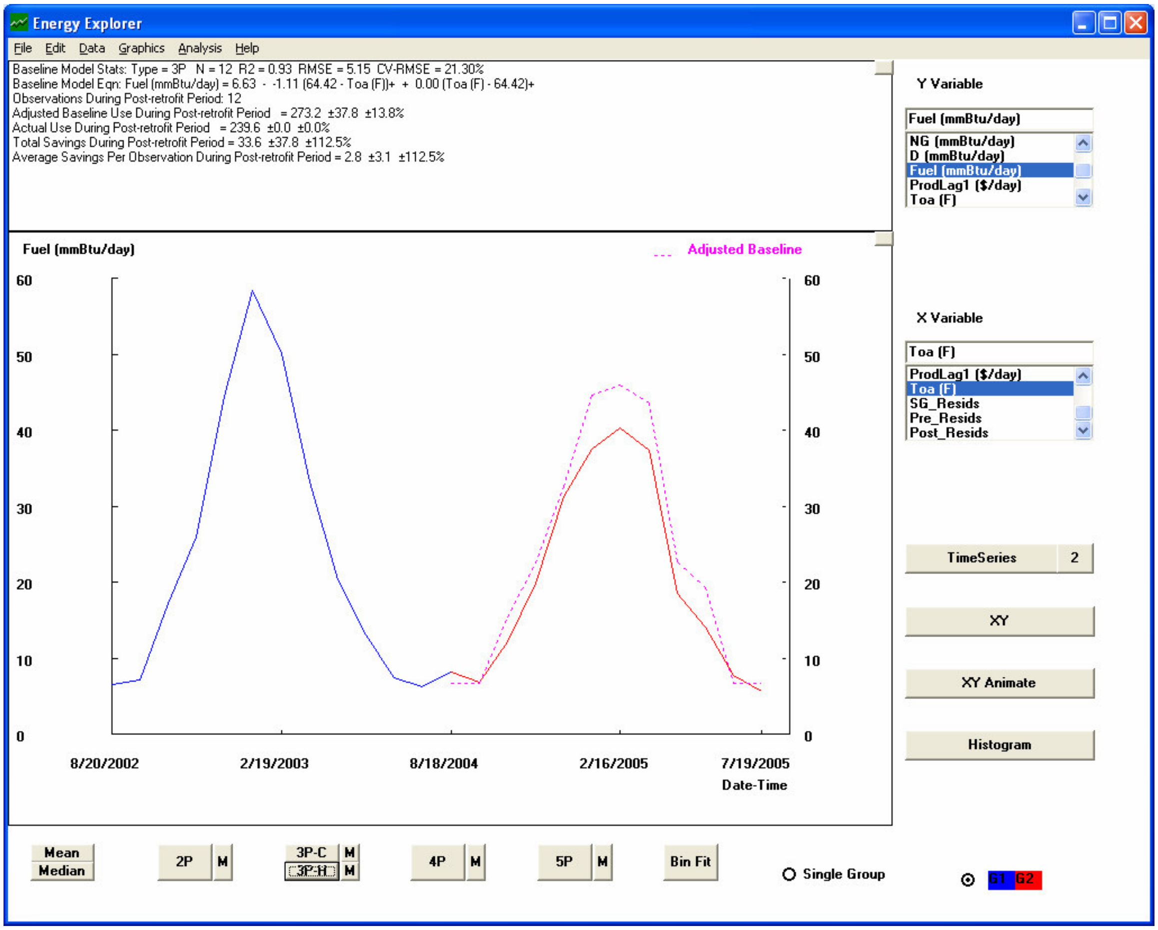

Figure 4. Time trends of pre- and post-retrofit energy use, with a projection of the weather-adjusted baseline model. Savings are the difference between the adjusted baseline and actual post retrofit energy use.

Weather and Production-Adjusted Savings

To adjust the baseline model for possible changes in production, as well as weather, an additional regression coefficient is added to the pre-retrofit model (Equation 3). In this case, lagged sales data were the best indicator of production available. Figure 5 shows an XY plot of pre- and post-retrofit fuel use versus outside air temperature with the multivariate three-parameter heating (3PH-MVR) models of each data set. Actual pre-retrofit fuel use is shown as the light blue squares, and predicted pre-retrofit fuel use is shown as the dark blue squares. Similarly, actual post-retrofit fuel use is shown as the light red circles, and the predicted post-retrofit fuel use is shown as the dark red circles. The goodness-of-fit of the models is visually indicated by the proximity of the dark and light data markers at each outdoor air temperature.

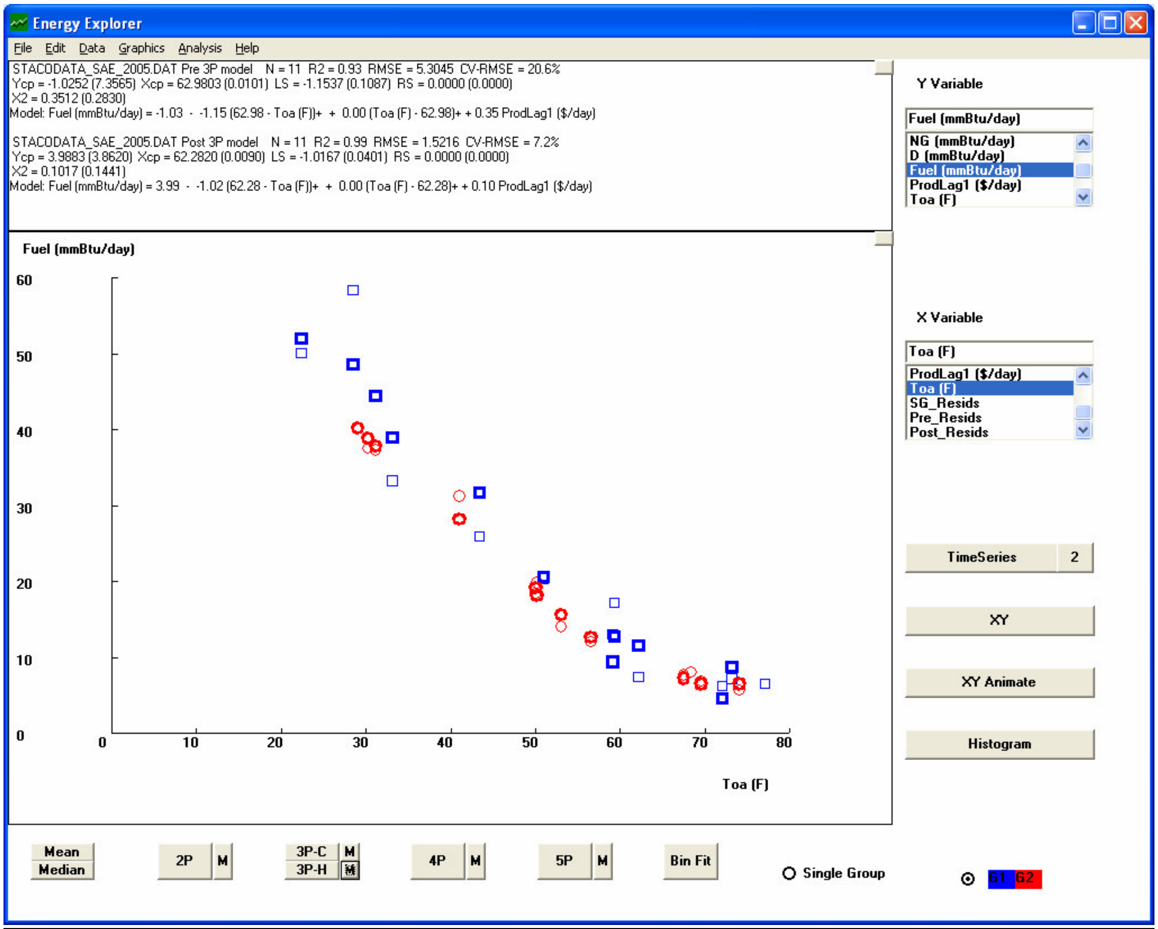

Figure 5. Pre- and post-retrofit fuel use data with 3PH plus production models through each data set.

The R^2 and CV-RMSE of the weather and production-dependent pre-retrofit model are 0.93 and 20.6% and the R^2 and CV-RMSE of the post-retrofit model are 0.99 and 7.2% (Figure 5). For comparison, the R^2 and CV-RMSE of the weather dependent pre-retrofit model were 0.93 and 21.3% and the R^2 and CV-RMSE of the weather-dependent post-retrofit model were 0.99 and 7.2% (Figure 3). Thus, the addition of lagged sales data as an independent variable added almost no information to the models. Hence, for simplicity and clarity, we choose to use the weather-dependent model (Figures 3 and 4) as the basis for calculating savings.

Comparison of Expected, Unadjusted and Adjusted Savings

Total expected savings from implementing all six recommendations was 2,969 mmBtu per year (Table 1). Unadjusted savings were 1,533 mmBtu per year, and weather-adjusted savings were 1,022 mmBtu per year. Many important lessons can be learned from comparing these results.

First, the dramatic difference between expected and measured savings shows the importance of measuring savings. In this case, measured savings were only 34% of expected savings. This difference illustrates the limitations of engineering modeling to predict the long term behavior of complicated systems. Some of these limitations are functions of the assumptions and simplifications used to create workable engineering models. The limitations may also include actual errors in the engineering models. Finally, the recommendations may not be implemented in exact accordance with recommendation specifications.

Second, the importance of weather adjustment when measuring savings is also clear. Weather-adjusted savings were only 67% of unadjusted savings. The large difference between unadjusted and weather-adjusted savings may not be apparent from a casual inspection of the weather data. For example, the average annual temperatures were 51.0 F and 51.7 F during the pre- and post-retrofit periods, and average temperatures during the heating season (October through May), were 34.9 F and 38.5 F during the pre- and post-retrofit periods. Intuition may not conclude that such small temperature differences could lead to such a large change in measured savings. This suggests that the best way to account for changes in weather is to employ weather-adjusted models, rather than by simple inspection of weather data.

Disaggregating Savings Into Components

The pre and post-retrofit models also lend insight into the nature of the savings and how much energy was saved by each type of retrofit. For example, visual inspection of the pre and post-retrofit models in Figure 3 shows that:

- Weather-independent fuel use increased
- The balance-point temperature of the facility decreased
- The slope of the fuel use versus temperature line decreased.

This indicates that:

- Negative savings resulted from non-weather dependent retrofits.
- Some savings resulted from decreasing the set point temperature
- Some savings resulted from increasing the efficiency of the boiler

The quantity of savings associated with each of these types of retrofits can be quantified by noting that savings, S, are the change in fuel use, dF, and can be estimated by taking the total derivative of the equation for fuel use (Equation 10).

$$S = dF = (\delta F/\delta\beta_1)\, d\beta_1 + (\delta F/\delta\beta_2)\, d\beta_2 + (\delta F/\delta\beta_3)\, d\beta_3 \qquad (11)$$

Thus, the total savings can be disaggregated into the savings from changing:

Weather-independent fuel use = $(\delta F/\delta\beta_1)\, d\beta_1 = \beta_{1Pre} - \beta_{1post}$ (12)

Temperature set point or internal loads = $(\delta F/\delta\beta_2)\, d\beta_2 = -(\beta_{3Pre} - T)^{+} (\beta_{2Pre} - \beta_{2post})$ (13)

Heating efficiency or building loss coefficient = $(\delta F/\delta\beta_3)\, d\beta_3 = -\beta_2 (\beta_{3Pre} - \beta_{3post})$ (14)

Equations 12, 13 and 14 can be applied to this case study to disaggregate total measured savings into components. The savings expected from each type of retrofit can then be compared to the disaggregated savings to show the measured savings associated with each type of recommendation.

For example, ARs 3 and 4, "Reduce Air Flow Through Dispatch and Jensen Ovens" and "Turn Off Exhaust Fans on IR Oven When Not in Use" recommend measures to reduce fuel use in production-related ovens. Fuel use in these ovens is relatively insensitive to outdoor air temperature since the ovens use indoor air for ventilation and combustion, and all parts enter the ovens at the indoor air temperature of the plant. Thus, the energy savings from ARs 3 and 4 should reduce the weather-independent energy use, as measured by $\beta 1$, in the regression models. The total expected fuel use from these recommendations was 618 mmBtu/year (Table 1). However, applying Equation 12 to the data from the post-retrofit period indicates that weather-independent fuel use actually increased by 172 mmBtu/year. Thus, no savings from these recommendations could be measured. In part, the lack of measurable savings results from the lack of production data in the model. In addition, the uncertainties with which the β_1 regression coefficients are known are greater than the result we are trying to measure. Thus, this data set does not have enough resolution to identify savings from these measures.

In comparison, the impact of AR 2, "Reduce Night Setback Temperature from 65 F to 60 F" is clearly apparent in the models, as the shift in the change-point temperature from 64.4 F to 61.7 F (Figure 3). Applying Equation 13 to the data from the post-retrofit period indicates that the measured savings from reducing the night setback temperature are 738 mmBtu/year, compared to the expected savings of 900 mmBtu/yr. Thus, this retrofit produced significant and measurable savings.

ARs 1 and 6, "Run Boiler in Modulation Mode" and "Reduce Excess Combustion Air in Boiler" recommend measures that improve the efficiency of the boiler. The impact of these recommendations is also apparent in the models, as the reduced slope of the post-retrofit model (Figure 3). The slope in these models represents the building load coefficient divided by the efficiency of the heating source. Thus, the effect of increasing the efficiency of the boilers is measurable as reduction in slopes, β_2, from -1.11 to -1.01 mmBtu/day-F (Equation 10). Applying Equation 14 to the data from the post-retrofit period indicates the measured savings from improving boiler efficiency are 521 mmBtu/year, compared to the expected savings of 1,078 mmBtu/yr. In this case, about half of the discrepancy between measured and expected savings is because of an error in the engineering model used to estimate savings. In subsequent work, the model for estimating savings by switching to modulation mode was refined, and expected savings using the refined model are about 75% of the previous estimate (Carpenter and Kissock, 2005).

In summary, the recommendations to reduce the building set point temperature at night and to improve the efficiency of the boilers produced significant and measurable savings. The effect of the recommendations to improve the efficiency of the production ovens could not be measured with the available data.

Summary and Conclusions

This paper presents a general method for measuring industrial energy savings and demonstrates the method using a case study from an actual industrial energy assessment. The method takes into account changes in weather and production, and can use sub-metered data or whole plant utility billing data. In addition to calculating overall savings, the method is also able to disaggregate savings into weather-dependent, production-dependent and independent components. This disaggregation provides additional insight into the nature and effectiveness of the individual savings measures. Although the method incorporates search techniques and multi-variable least-squares regression, it is easily implemented using data analysis software.

The case study compared expected, unadjusted and weather-adjusted savings from six recommendations to reduce fuel use. In the study, unadjusted savings overestimated weather-adjusted savings by about 50%, which demonstrates the importance of adjusting for weather variation between the pre- and post retrofit periods. The weather adjusted savings were about 33% of expected savings, which demonstrated the limitations of the engineering models used to estimate savings.

In general, we believe that the use of this method to measure savings will lead to greater industrial energy efficiency by identifying energy conservation retrofits which do not perform up to expectations, providing data to refine engineering methods, and redirecting resources to retrofits that consistently produce the greatest measured savings.

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