11SDP-0048

Understanding Industrial Energy Use Through Lean Energy Analysis

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ABSTRACT

This paper describes a simple statistical method to statistically disaggregate industrial energy use into production-dependent, weather-dependent and independent components. This simple statistical disaggregation has many uses, including improving model calibration, quantifying non-productive energy use and identifying energy efficiency opportunities. The process is called Lean Energy Analysis (LEA) because of its relationship to Lean Manufacturing, which seeks to reduce non-productive activity. This paper describes the statistical models, discusses the application of the LEA approach to over 40 industrial facilities, and provides case study examples of the benefits.

INTRODUCTION

Effective energy management programs virtually always include the following three steps: developing an energy use baseline, taking action, and measuring energy efficiency progress. Developing an energy use baseline virtually always includes the following three steps: understanding how the cost of energy and fuel is calculated, determining where energy is used within the plant, and understanding external drivers of energy use. This paper describes our approach to understanding the external drivers of energy use and how to interpret the results. This approach has been developed and modified while performing over 100 industrial energy assessments. The method is able to derive a significant quantity of actionable information from simple utility bills and readily available weather and production data.

The method develops regression models of utility billing data against weather and production data. The first widely used method of regressing energy use data versus weather data was the PRInceton Scorekeeping Method, PRISM. PRISM regressed energy use versus variable-base degree-days [Fels, 1986a], and was mainly applied to residential and commercial buildings in which weather was the most important driver of energy use. The method described here uses temperature change-point models instead of degree-day models. The temperature change-point models were described by Kissock et al. [1998] and Kissock et al., [2003]. These models are widely used, having been incorporated into the ASHRAE Inverse Modeling Toolkit [Kissock et al. 2001] and are recommended by the International Performance Measure & Verification Protocol Committee (IPMVPC) (NREL 2002). The temperature change-point models were later extended to include additional independent variables [Kissock et al., 2003; Haberl et al., 2003]. This paper applies these multivariable, temperature change-point regression models to industrial energy use, and seeks to interpret the results. Previous efforts to interpret regression coefficients in industrial energy use models include Kissock and Seryak [2004a; 2004b] and Patil et al. [2005].

This paper first describes the regression models. Next, it discusses statistical results of the application of the LEA approach to over 40 industrial facilities. Finally, it demonstrates their use on case-study examples that show how to use the models to identify energy saving opportunities.

OVERVIEW OF THE METHOD

DESCRIPTION OF DATA AND SOFTWARE TOOLS

The method uses readily available utility billing data, weather data and production data. Utility bills accurately report the quantity of fuel and electricity consumed by industrial facilities. Average daily temperatures for 157 U.S. and 167 international cities from January 1, 1995 to present are available free-of-charge from the University of Dayton Average Daily Temperature Archive [Kissock 1999a]. Production data is available from facility management or accounting departments. Typical production data can be derived from historical averages, budgeted values, or projected production. The case studies illustrating the method use historical averages for typical production.

The algorithms used to generate multi-variable change point models are described in the previous references. These methods have been incorporated into two software applications that were used for this analysis: Energy Explorer [Kissock 2005] and ETrackerC [Kissock, 2006].

DEVELOPING ENERGY SIGNATURE MODELS

The first step of the method is to create statistical models of each facility's electricity and fuel use as functions of weather and production using utility billing data, actual weather data, and actual production data.

In many 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 building balance temperature. For example, consider the common situation where electricity is used for both air conditioning and production-related tasks such as lighting and air compression. During cold weather, no air conditioning is necessary, but electricity is still used for production 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 for space conditioning and production-related tasks, fuel use can be modeled by a three-parameter heating (3PH) change point model (Figure 1b).

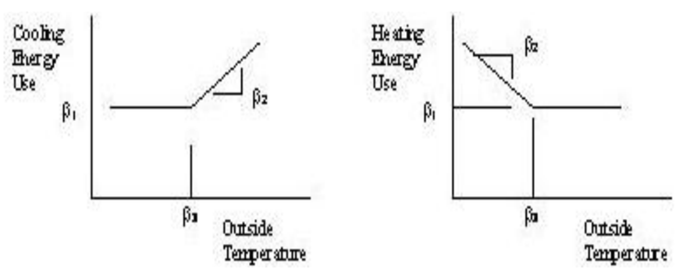

Figure 1 – (a) 3PC (cooling) and (b) 3PH (heating) regression models

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

$$E_C = \beta_1 + \beta_2\ T - \beta_3\ ^{+} + \beta_4 \cdot P \quad (1)$$

$$E_H = \beta_1 - \beta_2\ \beta_3 - T\ ^{+} + \beta_4 \cdot P \quad (2)$$

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. T is outdoor air temperature and P is the quantity of production. The superscript $^{+}$ notation indicates the parenthetic term evaluates to zero when the value of the enclosed term is negative.

The use of a single regression coefficient, β_4, and a single metric of production, P, is arbitrary; additional terms can be added to account for multiple products. The number of production variables needed to characterize plant energy use depends on the plant and process. In many plants, such as auto assembly plants or foundries, the relationship between energy use and production is accurately characterized by a single variable. In other plants with a heterogeneous product mix, multiple variables for the most energy-intensive products may be needed. In this paper, the method is demonstrated using one production variable; however, the methodology is unchanged with additional production variables.

INTERPRETING REGRESSION COEFFICIENTS AND PARAMETERS

In Equations 1 and 2, the β_1 term represents energy use that is independent of both weather and production, such as lighting energy use in plants with limited daylighting. The $\beta_2 \bullet (T - \beta_3)+$ or $-\beta_2(\beta_3 - T)^+$ term represents outdoor air temperature-dependent energy use. Because several studies have shown that outdoor air temperature is the single most important weather variable for influencing energy use in most buildings, this is referred to as weather-dependent energy use [Fels 1986b; Kissock et al. 1998]. In cases for which the weather dependent term represents space-conditioning energy use, the coefficient, β_2, represents the overall building load coefficient, UA, divided by the efficiency of the space conditioning equipment, η. In the case of 3PC or 3PC-MVR models, this coefficient is referred to as the cooling slope (CS). Similarly, in the case of 3PH or 3PH-MVR models, this coefficient is referred to as the heating slope (HS). The coefficient, β_3, represents the building balance temperature, which is the outdoor air temperature below which heating energy is used or above which cooling energy is used. The $\beta_4 \bullet P$ term represents production-dependent energy use. Using these terms, these simple regression equations can statistically disaggregate whole-plant energy use into independent, weather-dependent and production-dependent components. The interpretation and use of this technique is called Lean Energy Analysis [Kissock and Seryak, 2004a; Kissock and Seryak, 2004b and Patil et al. 2005, Kissock and Eger, 2006; Eger and Kissock, 2007] and is useful for identifying energy saving opportunities, measuring energy effects of productivity changes, developing energy budgets, and measuring energy savings.

ESTIMATING THE UNCERTAINTY OF WEATHER ADJUSTMENT

For a simple linear regression model of energy use (E) with temperature (T) as the independent variable, the uncertainty associated with predicting energy use using the baseline model ε_{pd} is [Neter et al., 1989]:

$$\varepsilon_{pd} = t_{1-\alpha/2,n-2}\; RMSE \left[1 + \frac{1}{n} + \frac{(T_d - T)^2}{\sum_{d=1}^{n}(T_d - T)^2}\right]^{1/2} \qquad (3)$$

where:

$$RMSE = Root\ Mean\ Square\ Error = \sqrt{\frac{\sum_{d=1}^{n}(E_d - E)^2}{n-2}} \qquad (4)$$

The t-statistic, $t(1-\alpha/2, n-p)$, is a function of the level of significance (α), the number of data points in the baseline period (n), and the number of parameters in the model (p). The level of significance (α) indicates the fraction of predictions that are likely to fall outside of the prediction uncertainty bands. In practice, the value of the t-statistic is close to 1.96 for a reasonable number of pre-retrofit data points and a 5% significance (95% confidence) level. In addition, the value of the parenthetic term is usually very close to unity. Thus, ε_{pd} can be approximated as [Neter et al., 1989]:

$$\varepsilon_{pd} = 1.96 \cdot RMSE \cdot \left(1 + \frac{2}{n}\right)^{1/2} \qquad (5)$$

SUMMARY OF LEA STATISTICS

When interpreting regression coefficients it is helpful to have historical data with which to compare. Both electrical and natural gas lean energy analyses were performed for 40 and 32 mid-sized industrial facilities respectively. These plants ranged in both production-type and building demands. Tables 1 and 2 display the minimum observed data point, the first quartile, second quartile (the median), third quartile, and maximum observed data point for several helpful 3PH-MVR and 3PC-MVR statistical indicators, respectively. This information is summarized graphically in Figures 2 through 6.

Table 1 - 3PH-MVR lean energy breakdown fractions and statistical indicators

	R^2	Fraction of Production Dependent NG Usage	Fraction of Independent NG Usage	Fraction of Weather Dependent NG Usage	Heating Balance Temperature (F)	Weather Dependent NG Usage (mmBtu/yr-ft^2)	Percent of Prediction Uncertainty
1st quartile	0.70	0.04	0.28	0.14	58.01	29.34	0.01
Minimum	0.34	0.00	0.03	0.05	35.30	8.49	0.00
Median	0.91	0.215	0.425	0.275	63.22	47.3	0.02
Maximum	0.99	0.81	0.78	0.96	76.65	205.79	0.09
3rd quartile	0.98	0.44	0.56	0.44	66.43	117.91	0.03

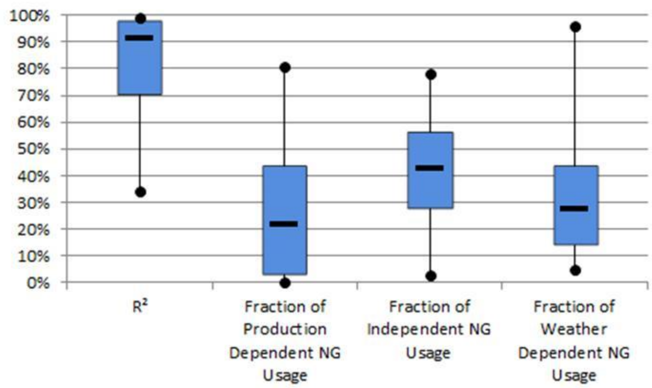

Figure 2 – Summary of 3PH-MVR breakdown fractions and statistical indicators

Table 2 -3PC-MVR lean energy breakdown fractions and statistical indicators

	R^2	Fraction of Production Dependent Electricity Usage	Fraction of Independent Electricity Usage	Fraction of Weather Dependent Electricity Usage	Cooling Balance Temperature (F)	Weather Dependent Electricity Usage (kWh/yr-ft2)	Percent of Prediction Uncertainty
1st quartile	0.33	0.09	0.43	0.02	34.93	613.792	0.01
Minimum	0.06	0.02	0.09	0.00	23.30	38.5006	0.00
Median	0.60	0.28	0.67	0.05	49.65	1662.82	0.01
Maximum	0.99	0.81	0.96	0.55	72.80	14241.7	0.04
3rd quartile	0.83	0.47	0.86	0.09	66.48	6514.56	0.02

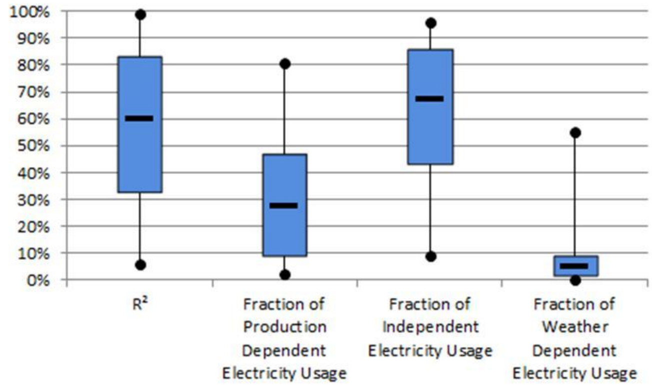

Figure 3 – Summary of 3PC-MVR breakdown fractions and statistical indicators

The first indicator is the R^2 value, or how much better the model describes the variation than a mean fit. Next, the fractions of production dependent, independent, and weather dependent energy use are displayed. In order to guide investigations into facility energy use, it can be useful to compare median breakdown fractions to observed breakdown fractions before visiting the plant. This approach is detailed in several case studies below.

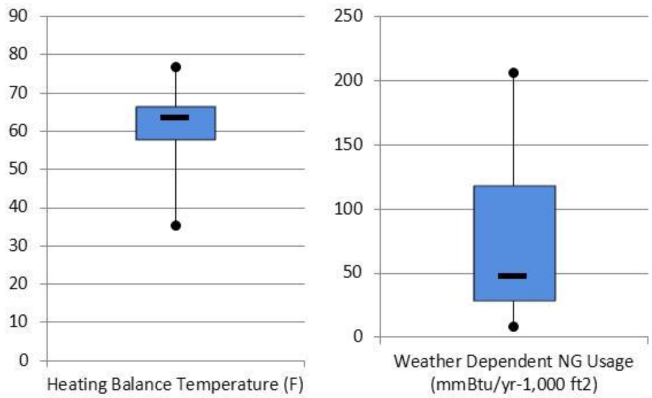

Figure 4 – 3PH model weather dependent indicators

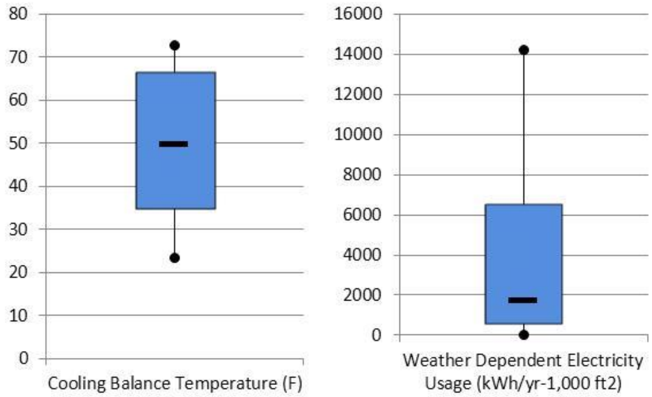

Figure 5 – 3PC model weather dependent indicators

Figure 6 displays the percent of prediction uncertainty for both natural gas and electrical 3 parameter models. As shown, the median prediction uncertainty is less than 5% for both types of regression models, giving a high confidence when predicting future energy consumption.

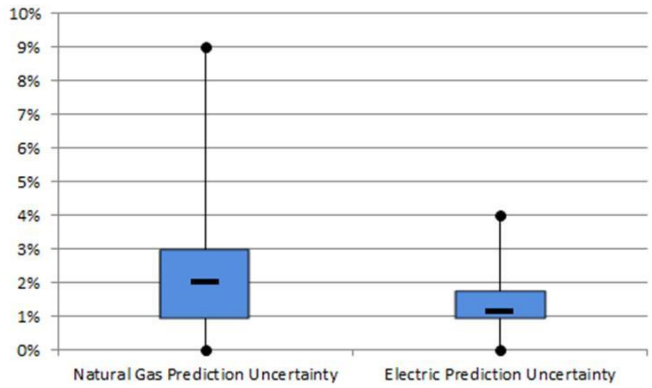

Figure 6 – Prediction Uncertainty for 3P-MVR models

APPLICATION

CASE STUDY 1: DISAGGREGATION OF ENERGY USE FOR MODEL CALIBRATION

The first case study illustrates the ability of the method to properly disaggregate independent, weather dependent, and production dependent energy use. This data is useful in calibrating energy models of both building HVAC systems and manufacturing equipment. Figure 7 shows a three-parameter heating (3PH) model of natural gas energy use as a function of outdoor air temperature. Table 3 shows the model's coefficients and statistical indicators. The very low R^2 and large CV-RMSE (coefficient of variation) statistics indicates outdoor air temperature alone is a poor predictor of natural gas energy use.

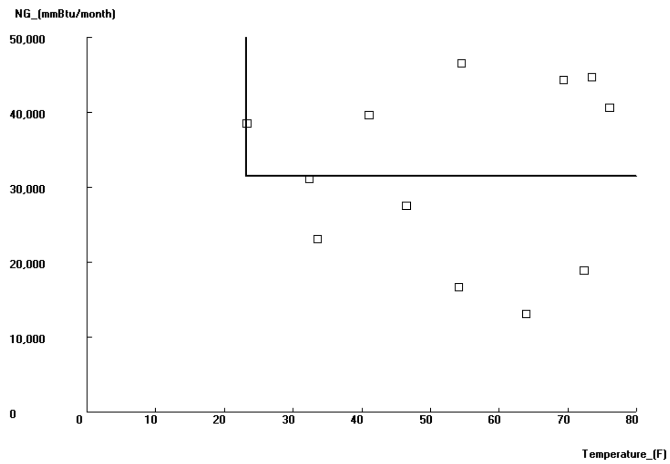

Figure 7 – 3PH model of natural gas energy use as a function of weather

Table 3 - 3PH model coefficients and statistical indicators

Coefficient	Description	Value
R^2		0.03
CV-RMSE		38.4%
β_1	Independent Fuel-use	31,508.55 mmBtu/period
β_2	Weather Dependence	665,844.77 mmBtu/period-F
β_3	Balance-Point Temperature	23.3 F

Figure 8 shows a two-parameter (2P) model of natural gas use as a function of production, where production data is scaled to increase the resolution of the model coefficients. The model indicates a significant increase in natural gas use as production increases. Table 4 shows the model coefficients and statistical indicators. The high R^2 statistic indicates production alone is a better predictor of natural gas energy use than outdoor air temperature.

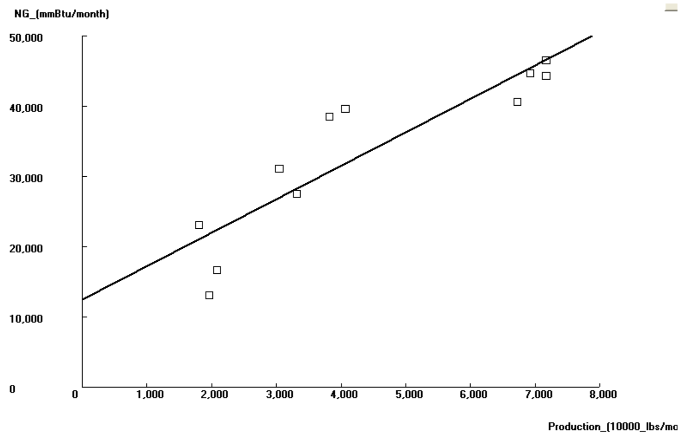

Figure 8 – 2P model of natural gas energy use as a function of production

Table 4 – 2P model coefficients and statistical indicators

Coefficient	Description	Value
R^2		0.80
CV-RMSE		16.5%
β_1	Independent Fuel-use	12,467.35 mmBtu/period
β_4	Production-Dependent	1,447.14 mmBtu/10,000 lbs

Figure 9 shows the 3PH-MVR model, which accounts for both outdoor air temperature and production. Light squares indicate the actual natural gas energy use and dark squares indicate the natural gas energy use predicted by the model, this is typical for all MVR models presented below. Model coefficients and goodness-of-fit statistics are shown in Table 5. An R^2 of 0.97 and a CV-RMSE of 6.3% indicate that the 3PH-MVR model is able to account for almost all of the variation in fuel use.

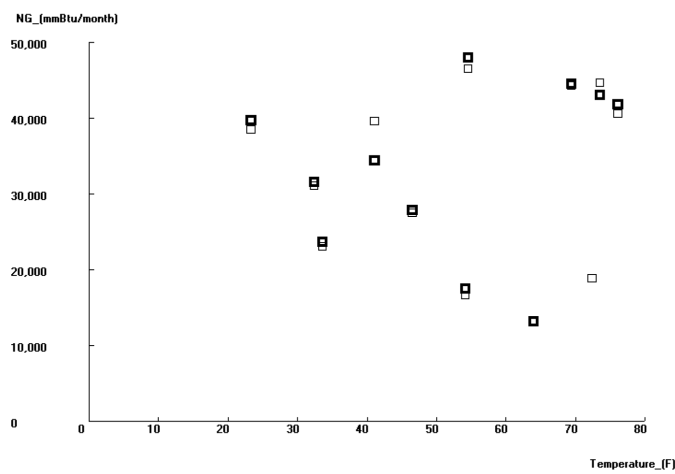

Figure 9 – 3PH-MVR model of fuel use as a function of weather and production

Table 5 - 3PH-MVR model coefficients and statistical indicators

Coefficient	Description	Value
R^2		0.97
CV-RMSE		6.3%
β_1	Independent	1,302.12 mmBtu/period
β_2	Weather Dependent	383.59 mmBtu/period-F
β_3	Balance-Point Temperature	63.61 F
β_4	Production Dependent	6.04 mmBtu/10,000 lbs

This case study illustrates the importance and power of using both weather and production data as regression variables in a 3PH-MVR model. Using only weather or production data resulted in the ability to describe 3.0% and 80.0% of the variation of natural gas use respectively. However, taking into account both the effect of weather and production, yields a model which can describe 97.0% of the variation of natural gas use. This results in a much stronger and accurate model.

From the 3PH-MVR model, natural gas energy use can be disaggregated into constituent components according to the model coefficients. Figure 10 shows this disaggregated breakdown. Independent natural gas use accounts for about 3.9% of the total. Weather-dependent natural gas use accounts for about 16.7% of the total. Production-dependent natural gas use accounts for about 79.4% of the total. This data was used to calibrate natural gas use of space heating equipment as well as production related equipment such as furnaces and boilers. The ability to precisely calibrate the models both increased accuracy and confidence in the magnitude of energy savings recommendations.

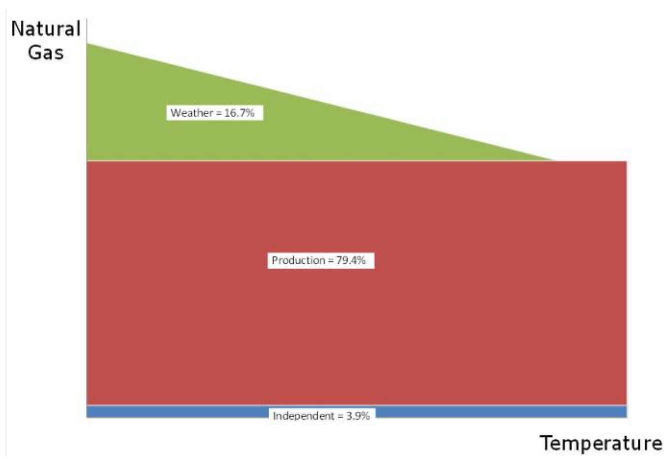

Figure 10 – Disaggregated Natural Gas Breakdown

CASE STUDY 2: IDENTIFYING CAUSES OF LOW INDEPENDENT ELECTRICITY USE

This case study details an industrial facility that flattened, cut, and shaped metal, then machined and welded together the formed parts to create the finished product. The product is then painted, and shipped to customers. Because the size of products range from small to very large, labor-hours of production was chosen as the production metric. The multivariate three-parameter cooling change-point (3PC-MVR) model is shown in Table 6 and Figure 11.

Table 6 - 3PC-MVR model coefficients and statistical indicators

Coefficient	Description	Value
R^2		0.82
CV-RMSE		6.8%
β_1	Independent	6,200.16 kWh/period

β_2	Weather Dependent	285.94 kWh/period-F
β_3	Balance-Point Temperature	48.79 F
β_4	Production-Dependent	4.56 kWh/hours

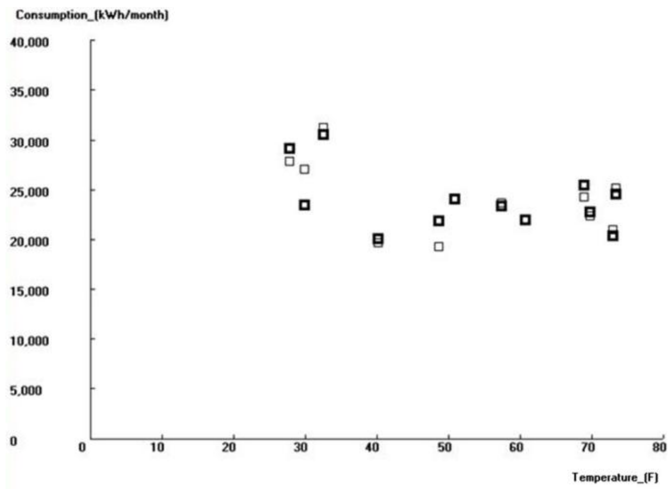

Figure 11 – 3PC-MVR Predicted and Actual Electrical Consumption

According to the model, the average independent electricity usage for this facility was 26%, as shown in Figure 12. As shown in the *Summary of LEA Results* section, the median independent electricity use for the 40 industrial facilities considered was roughly 67%.

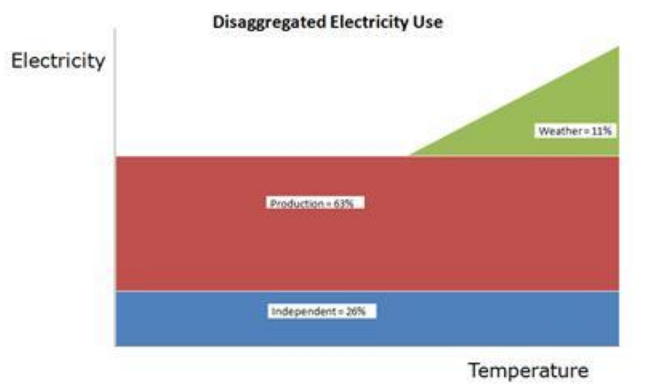

Figure 12 – Lean Energy Breakdown

The question one must ask is: why does a comparatively small amount of electrical consumption vary with neither weather nor production? From a list of large electrical equipment and confirmed during the visit to the plant it was estimated that around 75% of the electrical use could be attributed to press brakes and punches and air compressors. The large press brakes and punches were used to slowly bend or cut the metal. Because an employee would punch and bend the piece required before welding, the equipment was only in operation when an operator ran the machine. Because this press varied directly with production hours worked, all energy use from these machines could be contributed to production dependent.

One of the other largest energy consumers was the plant's compressed air system. The plant was served by two reciprocating air compressors. Reciprocating compressors operate by alternating periods of operation and idling to maintain a set pressure band. When the system's pressure drops to the bottom set-point the compressor fires until the top set-point pressure is reached, at which point the compressor idles. Therefore, as plant demand increases the compressor fires more often. Unlike screw type compressors that can draw anywhere from 20% to 70% of full load power while unloaded, reciprocating compressors draw negligible power while idling. Because the compressor only consumes power while producing compressed air, reciprocating compressor power draw follows load very well.

The likelihood and priority of energy savings opportunities can be efficiently determined prior to the assessment by performing a Lean Energy Breakdown, and by quickly checking conclusions during the site visit.

CASE STUDY 3: IDENTIFYING CAUSES OF HIGH INDEPENDENT ELECTRICITY USE

This case study illustrates the ability of the method to identify significant electrical energy saving opportunities. This case study details a plant in which powdered metal was compressed to shape, then held under vacuum at high temperatures to blend and forge the part. The forged part is then machined to form the finished product. The production metric was measured in labor-hours of production. The multivariate three-parameter cooling change-point (3PC-MVR) model is shown in Table 7 and Figure 13.

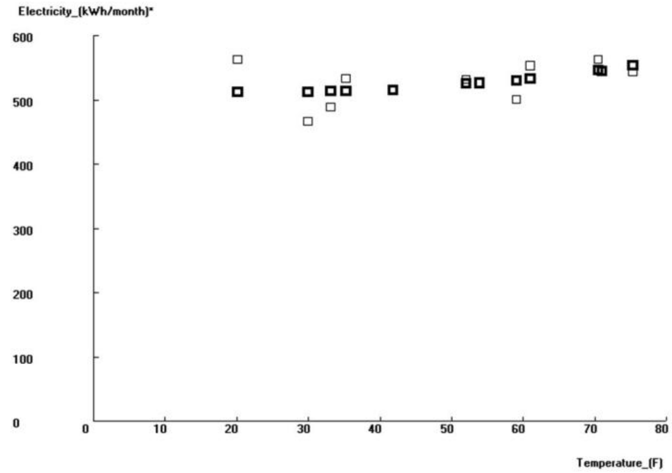

Figure 13 – 3PC-MVR Predicted and Actual Electrical Consumption

Table 7 - 3PC-MVR model coefficients and statistical indicators

Coefficient	Description	Value
R^2		0.25
CV-RMSE		5.4%
β_1	Independent	504 kWh/period
β_2	Weather Dependent	1.39 kWh/period-F
β_3	Balance-Point Temperature	47.00 F
β_4	Production-Dependent	1.69 kWh/hrs

According to the model, the average independent electricity usage for this facility was 96%, as shown in Figure 14. This is much higher than the median independent electricity use of 67% found for the 40 industrial facilities considered.

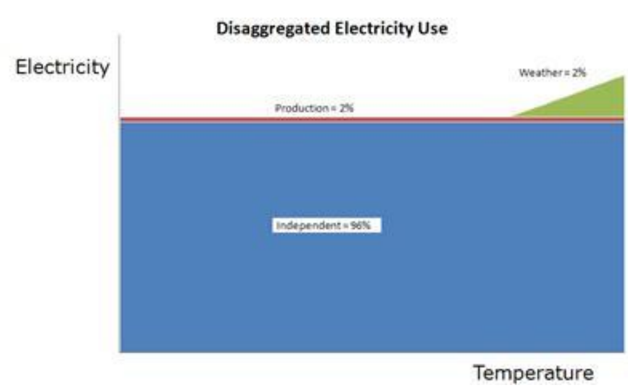

Figure 14 – Lean Energy Breakdown

To estimate why a comparatively large amount of electrical consumption varied with neither weather nor production, a list of large electrical equipment received before the audit was reviewed. According to the list of equipment, it was estimated that a large portion of electrical consumption might be contributed to several electrical furnaces and ovens, space conditioning, plant lighting, and a compressed air system.

High independent energy use dominated by process heating can usually be caused by one of two ways. First, assuming a constant plant temperature, while a furnace temperature is maintained, heat loss through the envelope varies neither with production nor weather. If this heat loss is comparatively large it can cause changes to overall plant energy dependence. Second, while a temperature is maintained it is sometimes required to cool certain elements of the system, such as conveyors, to avoid overheating. Upon visiting the plant, it was determined that the envelopes of most of the furnaces were adequate insulators, but that a few large older units were being held at process temperatures (roughly 1,500 C) to avoid heat cycle fatigue. These units were rejecting a significant amount of heat to the plant through the walls of the furnace every hour of the year. To meet process tolerance requirements, the plant was also air conditioned and humidity controlled by several large rooftop units. Because many of these rooftop units did not have functioning economizers, the refrigeration compressors were required to run throughout the year, regardless of outdoor air temperature. Thus, the plant was simultaneously heating and cooling, not only in cooling elements of the furnace, but also of the production area itself.

High electrical independent energy consumption dominated by lighting is usually the result of fixtures left on over areas of nonproduction. While visiting the plant it was confirmed that lighting fixtures in all areas of the plant were left on all operational hours, or roughly 7,200 hours per year. Therefore, lighting energy, which accounted for an estimated 12% of total plant energy consumption varied with neither total man-hours nor outdoor area temperature.

As discussed in Case Study 2, compressed air systems that draw a large fraction of full load power while unloaded do not follow load well and result in high independent energy consumption. However, upon visiting the plant it was discovered that the compress air system was comprised of two variable speed drive compressors. Variable speed drive compressors follow a similar part load efficiency curve as reciprocating compressors, typically drawing around 10% of full load power while unloaded. This is because as plant compressed air demand changes, the compressor screw motor can slow or speed up to match required plant demand. Therefore, if independent sources of compressed air consumption are negligible, such as continuous blow off or compressed air leaks, variable speed compressor power draw varies almost entirely with production.

Performing a Lean Energy Breakdown before the audit, and quickly checking conclusions during the visit to the plant, several energy savings opportunities were determined to likely to be most effective and further investigation was made into quantifying savings potential.

CASE STUDY 4: IDENETIFIYING CAUSES OF HIGH WEATHER DEPENDENT NATURAL GAS USE

The final case study illustrates the ability of the method to identify significant natural gas energy saving opportunities. A 3PH-MVR model was developed to determine the relationship between outdoor air temperature, production level and natural gas use. Natural gas use was disaggregated, into constituent components according to the 3PH-MVR model coefficients, and shown in Figure 15.

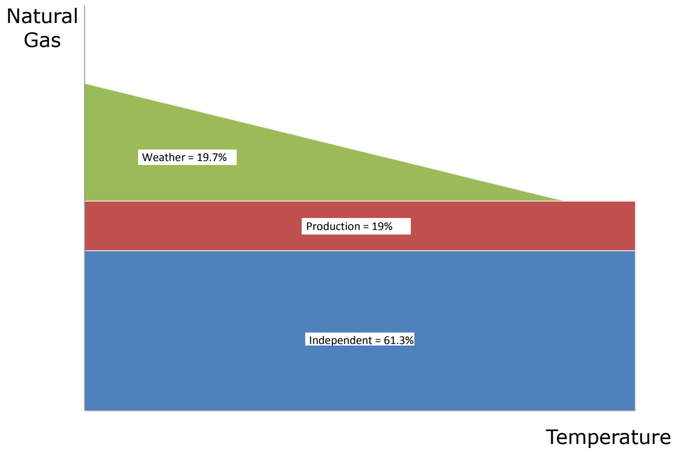

Figure 15 – Disaggregated Natural Gas Breakdown

Annual natural gas use was normalized by the floor area of the plant, resulting in a specific weather dependent natural gas use of 125.0 mmBtu/yr-1,000 ft^2. This statistic is almost three times larger when compared to the median statistic, 47.3 mmBtu/yr-1,000 ft^2, of the historical data set. The larger than expected specific weather dependent natural gas use showed the possibility of significant energy saving opportunities. Possible scenarios considered prior to the field visit were, poorly insulated and sealed building envelope and large amounts of airflows related to process heating applications.

Nine natural gas fired dryers which pull combustion and ventilation air from the outdoors were observed during the site visit. The dryers operate at an internal temperature of about 300 F and require about 30,000 ft^3/min of outdoor air. Furthermore, the facility also employs two paper trim collections systems estimated to be exhausting about 40,000 ft^3/min. These systems are operated continuously, and are only shut down for product changeovers or maintenance.

Several energy savings opportunities were recommended to reduce the airflows to the minimum possible as well as reclaiming waste heat from the process. The Lean Energy Analysis performed prior to the field visit increased the understanding of how natural gas was consumed by the plant and aided in prioritizing potential opportunities.

SUMMARY/CONCLUSIONS

This paper describes our approach to understanding the external drivers of energy use in a manufacturing facility and how to interpret the results. This approach has been developed and modified while performing over 100 industrial energy assessments. The paper begins by describing the multivariable, temperature change-point regression models used in the LEA method. Next the results of the application of the LEA approach to over 40 industrial facilities are presented and significant results discussed. Finally, the method is applied to several case studies from the industrial sector and their results are interpreted and compared to what was encountered in the field. Interpretation of the LEA results has shown to be effective at providing a significant quantity of actionable information to determine and prioritize energy saving opportunities. Future work should increase the understanding and application of the LEA method results. In addition, future work should further investigate the ability of the LEA method to accurately forecast energy use.

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ACKNOWLEDGMENTS

This work was graciously supported by the U.S. Department of Energy Industrial Technologies Program through its support of the Industrial Assessment Center program.