

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 (IPMVP) (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).

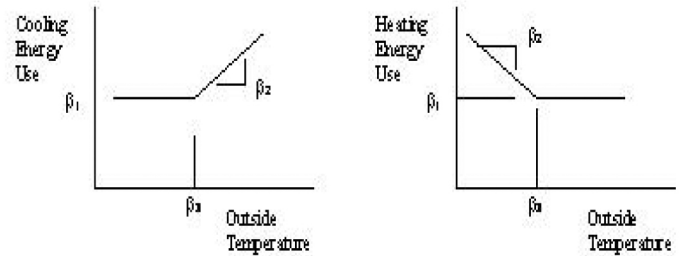


Figure 1. (a) 3PC (cooling) and (b) 3PH (heating) regression models

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 parenthetical 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 $\beta_2 \cdot (T - \beta_3)^+$ or $-\beta_2(\beta_3 - T)^+$ term represents outdoor air temperature-

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

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, p_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 $\beta_4 \cdot P$ 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]:

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

where

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

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]:

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

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, 3, 4, 5, 6.