Benchmarking Approaches: An Alternate Method to Determine Best Practice by Examining Plant-Wide Energy Signatures

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ABSTRACT

Baselining and benchmarking plant-wide energy use facilitates industrial energy-efficiency by establishing reference points for comparisons of plant energy consumption. In this paper, baselining refers to establishing reference energy trends in a single facility over a defined period of time. Baselining is useful for tracking the effectiveness of energy-efficiency measures and programs over time. Benchmarking refers to establishing reference energy trends across a group of similar facilities. Benchmarking is useful for identifying "best practice" facilities across an industrial sector to establish realistic and achievable energy efficiency goals.

Unfortunately, using simple historical energy use data for baselines and benchmarks introduces uncertainty because of the strong dependence of industrial energy use on production levels and local weather conditions, which vary significantly over time and from plant to plant. Hence, both baselining and benchmarking efforts benefit from creating models of plant-wide energy use as functions of weather and production. These models can then be adjusted to different weather conditions and levels of production to facilitate accurate comparisons.

This paper describes a simple but accurate method for developing multivariable models of electricity and natural gas use as functions of outdoor air temperature and production data, which we call Lean Energy Analysis (LEA). The method incorporates statistical regression models to disaggregate energy use into facility, weather-dependent and production dependent components. Graphical analysis of the models reveals that each industrial sector has its own unique signature of electricity or gas use. These energy signatures can be compared within an industrial sector to determine best-practice facilities. This paper will discuss the overall approach associated with this method and present case-study energy signatures for several types of industrial plants.

Existing Industrial Benchmarking Efforts

Existing industrial benchmarking efforts include the Long-term Industrial Energy Forecasting model (LIEF) and the EPA Energy Star Industrial Energy Performance Indicator (EPI). LIEF evaluates sector-level energy data versus energy prices. Thus, LIEF facilitates a market solution to obtaining best-practice industrial energy use, as opposed to a technical solution. EPI uses plant-level data to facilitate a technical solution to achieving best-practice industrial energy use. The LEA energy signature method does not dispute the LIEF and EPI approach, but instead presents an alternate method that yields greater detail into plant energy use. We will review the LIEF and EPI methods.

LIEF uses published aggregated industrial sector data to statistically determine "best practice" and average energy use. LIEF assumes that energy intensity is a function of energy prices (Ross, Thimmapuran et al. 1993), and that best-practice energy use will occur when energy prices are high. Boyd (2003) applied LIEF to several major industrial sectors. Energy intensity difference between best practice and average plant use for electricity and fossil fuels were calculated for 1990 and 1998 for these industrial sectors. Energy use data was obtained from Annual Survey of Manufacturing (ASM) and the Manufacturing Energy Consumption Survey (MECS), while economic factors were obtained from the Bureau of Labor Statistics (BLS). Unlike EPI and other methods, LIEF benchmarks energy use with data from entire industrial sectors, as opposed to plant-level data. LIEF benchmarking facilitates an economic solution to obtaining best-practice industrial energy use.

EPI uses annual plant level data to create a stochastic frontier regression curve of energy use per unit of economic output. The average plant's energy intensity is equivalent to the 50^{th} percentile value of the regression, while a best-practice plant's energy intensity is equivalent to the 75^{th} percentile value of the regression. Boyd applied this method to breweries and motor vehicle assembly plants (Boyd, 2003). Source data was compiled from the confidential Longitudinal Research Database (LRD) maintained by the Center for Economic Studies (CES), US Bureau of the Census. Boyd also used plant data provided by automobile manufacturers. EPI assumes the difference between an average and best practice industrial facility is technical, while LIEF assumes the difference is based on energy prices.

EPI's industrial energy intensity indicators are calculated as simply annual plant-wide energy use divided by annual production. As such, this method does not disaggregate types of plant energy use. Non-production facility energy use and space-conditioning energy use are confounded with production energy use. Thus, there is some uncertainty whether an EPI best-practice facility is exhibiting best-practice production, facility or space-conditioning energy use. The LEA energy signature method disaggregates plant energy use into these components.

The EPA has conducted other benchmarking studies that pre-dated the development of the EPI method, but was similar if not the predecessor to the EPI method. Hicks and Dutrow (2001) used this method to quantify average and best-practice for the milk and malt beverage industries, using data from the Major Industrial Plant Database (MIPD).

The methods described above rely on data from the MECS, MIPD and ASM. The Department of Energy (DOE) Energy Information Administration (EIA) conducts the MECS every three years. The EIA mails questionnaires to a sample of industrial facilities throughout the United States. The MECS is available to the public. The 2002 MECS surveyed 15,500 industrial plants (DOE 2002). A private company compiles the MIPD database, and charges a fee for access to the MIPD database. Data is collected via telephone interviews. The database information includes SIC code, annual electricity and natural gas consumption. The ASM is compiled by the US Census Bureau and lists valued economic output per SIC code.

Industrial Baselining

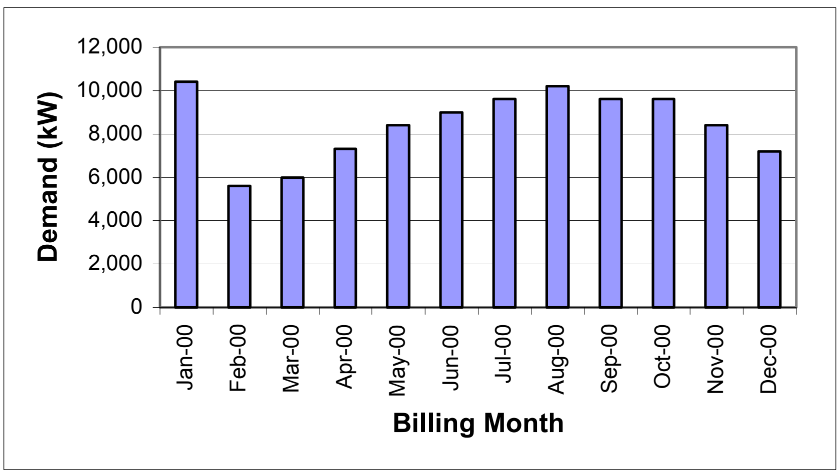
"Baselining" refers to establishing reference energy trends to track the effectiveness of energy-efficiency measures and programs over time, by comparison to actual energy use. Two simple baselining methods are predominant in industry today. The first is graphing time-dependent trends of energy use. The second is categorizing energy use by either equipment type, commonly referred to as "energy use breakdowns". We will briefly overview time-trends and energy-use and billing cost breakdowns, and then discuss a more sophisticated method of baselining called Lean Energy Analysis (LEA). LEA can be conducted quickly and simply with the aid of statistical regression analysis software packages.

Energy Time-Trends

Trending energy use is generally performed as part of any standard analysis of energy billing data. Typically electrical demand and energy are graphed, as well as natural gas use. The importance of graphing energy use data cannot be overstated. In general, our eyes are much better at identifying patterns and trends from graphical information than from tables of numbers.

For example, the anomaly in Figure 1, a profile of electricity demand in an industrial facility, was discovered only after graphing monthly electrical demand data. In this case, electrical demand spiked in the middle of the winter in a production facility located in Washington D.C. with a large air conditioning load. The cause of the demand spike was subsequently discovered to be a short scheduled shutdown of steam service, which caused electrical resistance heaters throughout the building to operate at full load. This example exhibits the usefulness of creating simple energy time-trend baselines to discover energy use anomalies.

Figure 1. Monthly Electrical Demand



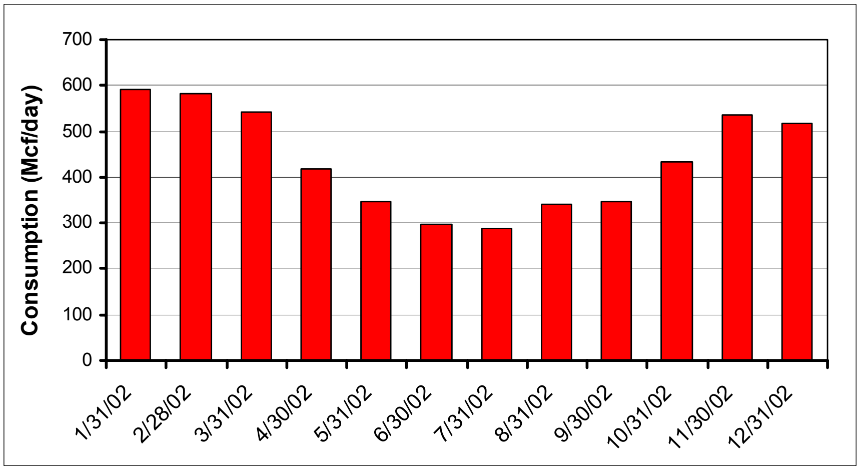
Energy Use Breakdowns

Electrical and thermal energy use can be quickly disaggregated into space conditioning and production components using graphical analysis. Then, electrical and thermal equipment energy use can be estimated and calibrated to match the graphical breakdowns. These quick breakdowns help target and screen energy saving opportunities.

Typically, electrical demand and energy can be segregated into production and air conditioning by drawing a line through winter demand/energy. Electrical demand or energy use below the line is for production and electrical demand or energy use above the line is for air conditioning.

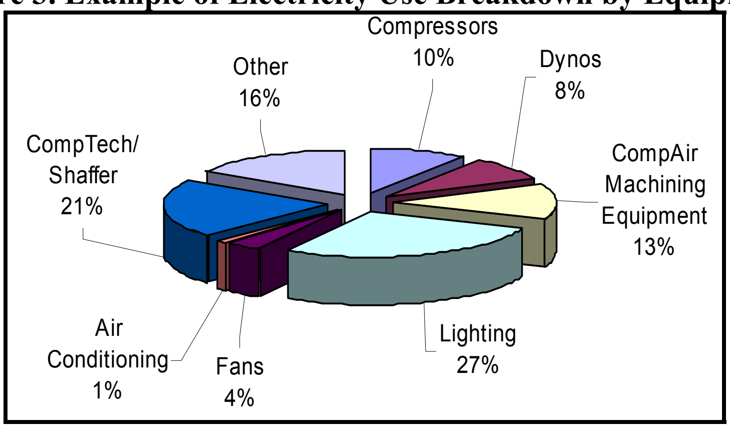
Thermal energy use can also be segregated into production and space heating components by drawing a line through summer gas use. Gas use below the line is for production and gas use above the line is for space heating. Figure 2 shows a generic plant's gas use, where summer use is about 310 Mcf/day and the annual average gas use is about 430 Mcf/day, indicating that about 72% of gas use is for production and about 28% is for space heating.

Figure 2. Typical Monthly Gas Use Pattern



Finally, energy use by equipment can be estimated based on rated power, fraction loaded, and hours of operation. Initial estimates of electricity and gas use by equipment should be calibrated to match the breakdowns of electricity and gas use into production and space conditioning components. Figure 3 shows such a breakdown from a generic plant.

Figure 3. Example of Electricity Use Breakdown by Equipment



Base-lining equipment energy use with energy-use breakdowns can prioritize savings opportunities by identifying space-conditioning, process and equipment loads. Energy-use breakdowns can also identify equipment loads that are greater than expected.

Lean Energy Analysis (LEA)

Alternately, statistical regression can be used to create a more sophisticated baseline of industrial energy use. We call the approach of using statistical regression models to baseline energy use "Lean Energy Analysis" (LEA). Energy in industrial facilities is used for direct production of goods, for space conditioning, and for general facility support such as lighting. LEA statistically analyzes plant energy in terms of these major end uses. LEA uses as few as 60 data points that are relatively easy for most plants to obtain. Multivariable change-point models of electricity and natural gas use as functions of outdoor air temperature and production data are then developed.

LEA has many useful functions including: Characterizing industrial energy use into facility/production/space-conditioning components, identifying energy savings opportunities, budgeting and costing models, baselines for measuring and tracking savings, and quantifying savings from productivity.

Statistical regression models. Statistical models can be developed specifically to describe energy use as a function of outdoor air temperature and other influential variables (Kissock et al., 1998a; Kissock et al., 2003). The statistical models can be represented by mathematical equations. Each independent variable has at least one accompanying coefficient. If change-points exist, some independent variables may have more than one coefficient. Change-points represent a change in energy use associated with a specific physical difference in how energy is used. Typical regression independent variables include Toa (F/unit-time), the average outdoor temperature during a given period of time, and P (units/time), the production quantity during a given period of time.

Inverse modeling. Inverse modeling is the derivation of plant, building or equipment energy characteristics from statistical regression models of historical or logged energy data. For example, change-points in temperature-dependent regression models represent heating or cooling balance-points of the building. The coefficient of the production parameter represents energy-intensity of the manufacturing process, while the slope coefficients of the temperature parameters represent cumulative insulating value (R-value) of the building. Following are regression parameters, units and inverse modeling interpretation:

- Yint (energy/unit-time) = the y-intercept = the "facility" component of energy use
- Xcp (F) = the x change-point = the building heating/cooling balance-point in a 3P/4P model.
- Xcp1 (F) = the first x change-point = the building heating balance-point in a 5P model
- Xcp2 (F) = the second x change-point = the building cooling balance-point in a 5P model
- Ycp (energy/unit-time) = the y change-point = the "facility" component of energy use in a 3P or 5P model and the energy use at the Xcp in a 4P model
- LS (energy/independent variable) = left slope = the energy use per decreasing temperature/production unit
- RS (energy/independent variable) = right slope = the energy use per increasing temperature/production unit
- X2 (energy/production) = typically in a multi-variable regression, the energy use per unit production

Other papers (Haberl et al., 2003; Kissock and Seryak, 2004) address the interpretation of statistical parameters in more detail.

Energy signatures. Different industrial plants' energy use are associated with different statistical regression models. However, plants within an industrial sector should all have the same basic shape of statistical regression. We call these shapes "energy signatures". Energy signatures represent baseline energy use. Equations can be derived from the parameter coefficients and model change-points to predict baseline energy use based on the values of the independent variables.

Data for constructing energy signatures can be readily obtained by most industrial facilities. The manufacturing company typically records monthly electricity and natural gas use, as well as monthly production numbers. Average outdoor temperatures can be obtained from a variety of sources, notably the UD/EPA Average Daily Temperature Archive. Software programs can quickly merge energy consumption and temperature data, and regress the energy signatures.

Energy signatures can serves as baselines to measure energy savings or budget costs. Average temperature and production numbers for the given time period are used to calculate expected energy use, which can be compared with actual energy use.

Energy signatures can then be used to create benchmarks for plant-wide energy use. In addition, energy signatures provide benchmarks for facility, production, space-conditioning use and heating and cooling balance-points.

In the following case studies, energy signatures will be presented graphically. Light-gray boxes indicate actual data and a solid line represents the predicted energy use from the statistical regression. Dark-gray boxes represent energy use from a multi-variable regression, and are typically slightly offset from the light-gray boxes.

Energy Signature Case Studies

Note that each energy signature presented below is associated with a separate industrial facility. Multiple facilities with 4PH energy signatures are compared in the 4PH section of this paper. The R^2 and CV-RSME are presented for each regression. R^2 values range from 0 to 1, higher R^2 values indicating greater influence of the independent variable. The CV-RSME ranges from 0% to 100%, low values indicating a tighter fit of the regression model to the data. In general, the high R^2 and low CV-RMSE values suggest that LEA energy signatures are accurate models of plant energy use based on production and outdoor temperature.

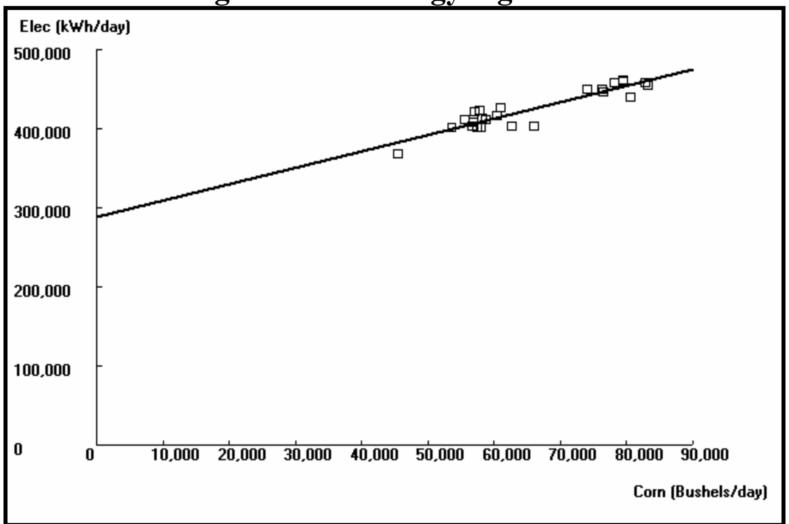
2P: production and facility energy use. Two-parameter (2P) energy signatures are dependent on facility and production energy use, and are typical of industrial facilities with no temperature-dependent energy use. Equation 1 presents a generic form of the 2P equation, while Equation 2 presents the equation specific to the energy signature shown in Figure 4.

$$\text{Eng/day} = \text{Yint (eng/day)} + \text{RS (eng/unit)} \times \text{P (unit/day)} \tag{1}$$
$$\text{kWh/day} = 288{,}673\ \text{(kWh/day)} + 2.07\ \text{(kWh/unit)} \times \text{P (unit/day)} \tag{2}$$

3PC-MVR: production, facility and air conditioning. Three-parameter cooling (3PC) energy signatures are dependent on facility and space conditioning energy use, with no production or production affects. Figure 5 shows a 3PC energy signature. In industrial plants, energy use should always vary with production. Thus, 3PC industrial facilities with production-dependent energy use should be modeled with a multi-variable regression (3PC-MVR). Figure 6 shows the same plant in Figure 5, but modeled as a 3PC-MVR instead of a 3PC. Note the greatly improved R^2 and CV-RMSE values in Figure 6, when production is accounted for. Equation 3 presents a generic form of the 3PC-MVR equation, while Equation 4 presents the equation specific to the energy signature shown in Figure 6.

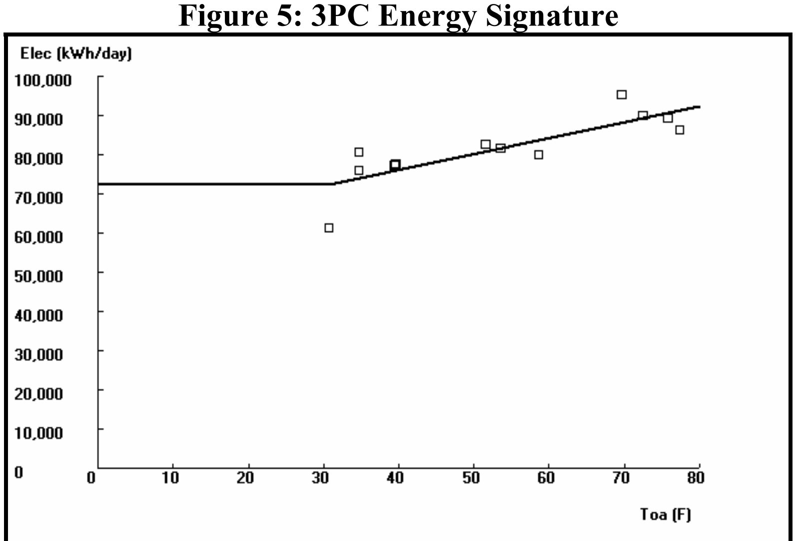
$$\text{Eng/day} = \text{Ycp (eng/day)} + \text{RS (eng/F)} \times (\text{Toa} - \text{Xcp})^{+}\ \text{(F)} + \text{X2 (eng/unit)} \times \text{P (units)} \tag{3}$$
$$\text{kWh/day} = 41{,}589\ \text{(kWh/day)} + 361\ \text{(kWh/F)} \times (\text{Toa} - 30.7)\ \text{(F)} + 2.5\ \text{(kWh/unit)} \times \text{P (units)} \tag{4}$$

Figure 4: 2P Energy Signature



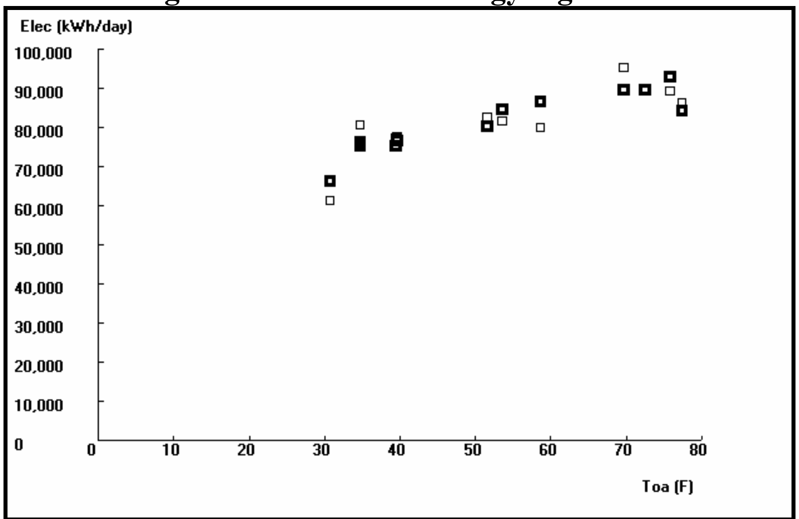
$R^2 = 0.85$	CV-RMSE = 2.4%

Figure 5: 3PC Energy Signature



$R^2 = 0.67$	CV-RMSE = 6.4%

Figure 6: 3PC-MVR Energy Signature

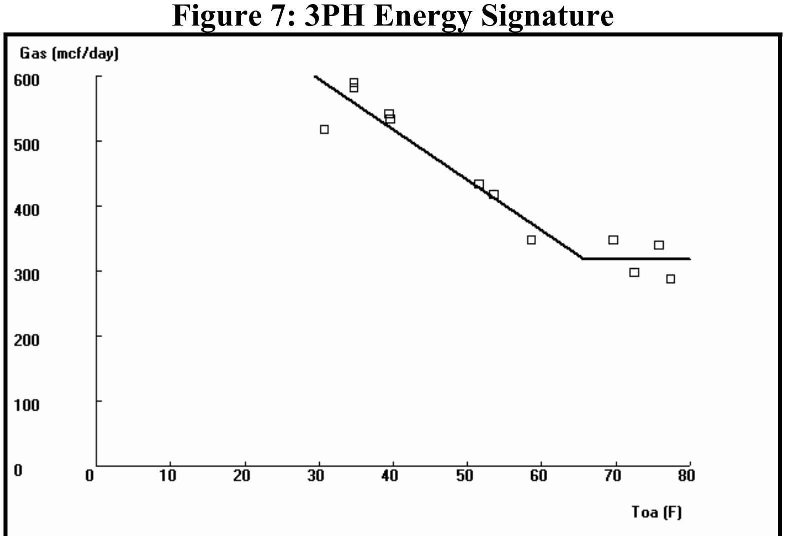


$R^2 = 0.82$	CV-RMSE = 5.1%

3PH-MVR: production, facility and space heating. Three-parameter heating (3PH) energy signatures are dependent on facility and space heating energy use, with no production or production affects. Figure 7 shows a 3PH energy signature. In industrial plants, energy use should always vary with production. Thus, industrial facilities with production-dependent energy use and temperature-dependent energy use would be modeled with a multi-variable regression (3PH-MVR). Figure 8 shows the same plant in Figure 7, but modeled as a 3PH-MVR instead of a 3PH. Note the greatly improved R^2 and CV-RMSE values in Figure 8, when production is accounted for. Equation 5 presents a generic form of the 3PH-MVR equation, while Equation 6 presents the equation specific to the energy signature shown in Figure 8.

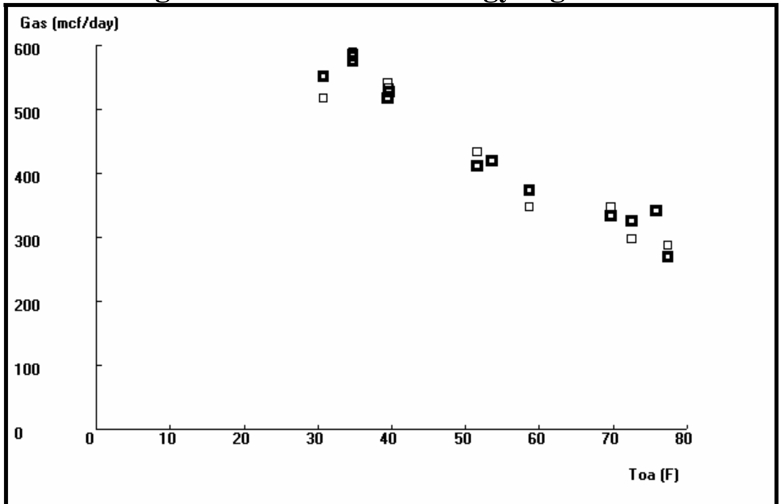
$$\text{Eng/day} = \text{Ycp (eng/day)} + \text{LS (eng/F)} \times (\text{Xcp-Toa})^{+} \text{(F)} + \text{X2 (eng/unit)} \times \text{P (units)} \quad (5)$$
$$\text{Mcf/day} = 59.6 \text{ (Mcf/day)} + 9.4 \text{ (Mcf/F)} \times (62.1\text{-Toa}) \text{ (F)} + 0.02 \text{ (Mcf/unit)} \times \text{P (units)} \quad (6)$$

Figure 7: 3PH Energy Signature



$R^2 = 0.92$	CV-RMSE = 7.5%

Figure 8: 3PH-MVR Energy Signature



$R^2 = 0.97$	CV-RMSE = 5.1%

4PH-MVR: temperature dependent production and space heating. Four-parameter heating (4PH) energy signatures reflect temperature-dependent facility and temperature-dependent production use. Figure 9 shows two different 4PH energy signatures.

In industrial plants, energy use should always vary with production. Thus, industrial facilities with production-dependent energy use and temperature-dependent energy use would be modeled with a multi-variable regression (4PH-MVR). Equations 7 and 8 presents a generic form of the 4PH-MVR equation. For conceptualization purposes, we are only presenting 4PH energy signatures here. 4PH-MVR energy signatures are typical of industrial plants with space heating and temperature-dependent production. For example, a heat-treating plant's gas use is temperature-dependent even during the non-heating season, as combustion gas will vary with combustion air temperature.

Figure 9 shows 4PH energy signatures of two different metal plating operations. Unfortunately, monthly production numbers were not available for these plants. However, the usefulness of LEA energy signatures for benchmarking is still apparent. In these figures, we see that the heating balance-point for the two facilities is very different, about 40 F for the left plant and about 55 F for the right plant. The ability to inverse-model plant characteristics such as building balance-points and energy per unit production or degree F adds incredibly useful details to benchmarking efforts.

If Toa > Xcp

$$\text{Eng/day} = \text{Ycp (eng/day)} - \text{RS (eng/F)} \times (\text{Toa} - \text{Xcp})^{+} \text{ (F)} + \text{X2 (eng/unit)} \times \text{P (units)} \qquad (7)$$

If Toa < Xcp

$$\text{Eng/day} = \text{Ycp (end/day)} + \text{LS (eng/F)} \times (\text{Xcp} - \text{Toa})^{+} \text{ (F)} + \text{X2 (eng/unit)} \times \text{P (units)} \qquad (8)$$

4PC-MVR: temperature dependent production and air conditioning. Four-parameter cooling (4PC) energy signatures are dependent on temperature-dependent facility and temperature-dependent production use. 4PC energy signatures are like mirror images of 4PH energy signatures. In industrial plants, energy use should always vary with production. Thus, industrial facilities with production-dependent energy use and temperature-dependent energy use would be modeled with a multi-variable regression (4PC-MVR). Equations 9 and 10 present a generic form of the 4PC-MVR equation. For conceptualization purposes, we are only presenting a 4PC energy signature here in Figure 10. 4PC-MVR energy signatures are typical of industrial plants with air-conditioning and temperature-dependent production. For example, an ice-cream plant's electricity use is temperature-dependent even during the non-cooling season, as compressor energy will vary with outdoor air temperature.

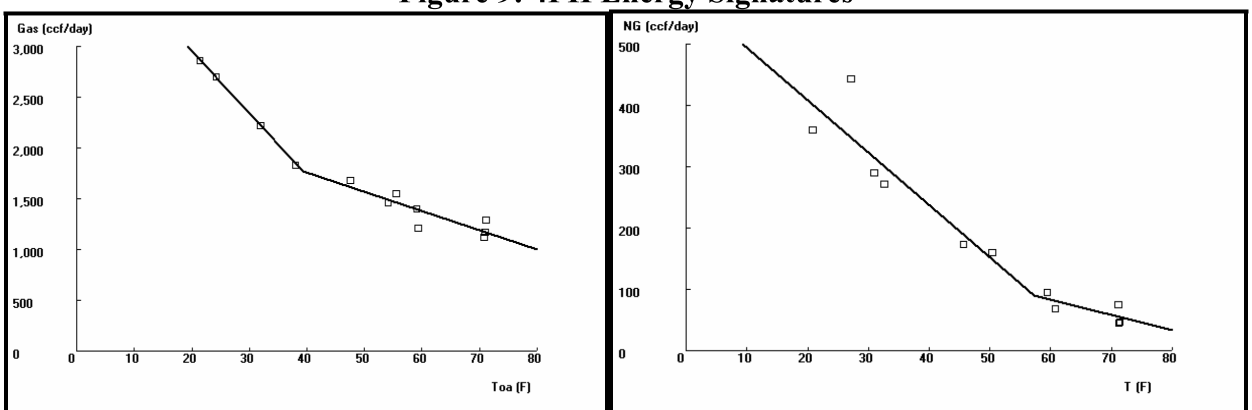
If Toa > Xcp

$$\text{Eng/day} = \text{Ycp (eng/day)} + \text{RS (eng/F)} \times (\text{Toa} - \text{Xcp})^{+} \text{ (F)} + \text{X2 (eng/unit)} \times \text{P (units)} \qquad (9)$$

If Toa < Xcp

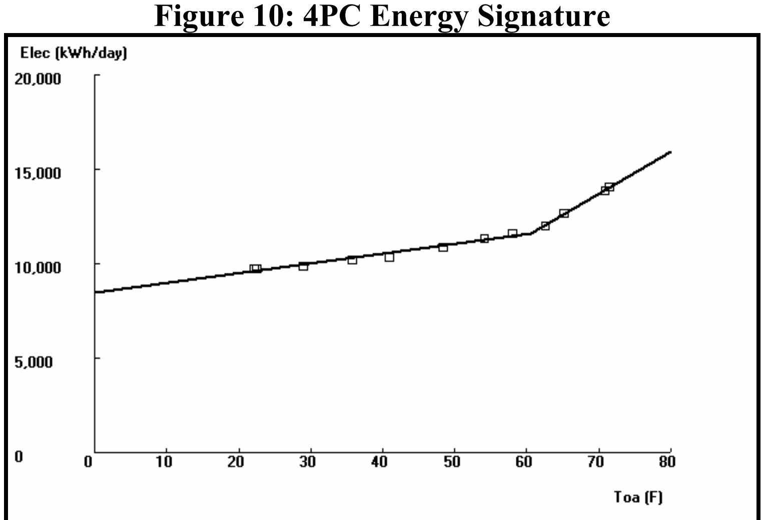
$$\text{Eng/day} = \text{Ycp (end/day)} - \text{LS (eng/F)} \times (\text{Xcp} - \text{Toa})^{+} \text{ (F)} + \text{X2 (eng/unit)} \times \text{P (units)} \qquad (10)$$

Figure 9: 4PH Energy Signatures



$R^2 = 0.98$	CV-RMSE = 4.9%	$R^2 = 0.93$	CV-RMSE = 22.1%

Figure 10: 4PC Energy Signature

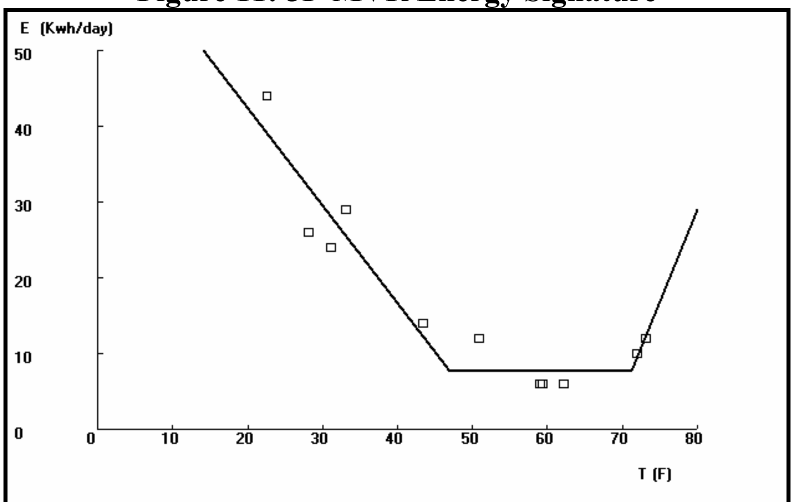


$R^2 = 0.99$	CV-RMSE = 1.1%

5P-MVR: production, air conditioning and space heating. Five-parameter (5P) energy signatures are dependent on facility, space conditioning and space heating. In industrial plants, energy use should always vary with production. Thus, industrial facilities with production-dependent energy use and temperature-dependent energy use would be modeled with a multi-variable regression (5P-MVR). Equation 11 presents a generic form of the 5P-MVR equation. For conceptualization purposes, we are only presenting a 5P energy signature here in Figure 11. 5P-MVR energy signatures are typical of industrial plants with air-conditioning and electric space-heating.

Energy (eng/day) = Ycp (eng/day) + LS (eng/F) x (Xcp1 – Toa) (F/day) + RS (eng/F) x (Toa-Xcp2) (F/day) (11)

Figure 11: 5P-MVR Energy Signature



R^2 = 0.92	CV-RMSE = 22.4%

Benchmarking Energy Signatures

Benchmarking industrial sector energy use with LEA energy signatures offers several advantages over the LIEF and EPI methods discussed earlier. Energy signatures provide greater detail into the energy use of industrial facilities. For example, the EPI method, as used by Boyd, simply divides plant energy use by production for comparative benchmarking purposes. This quick and simple metric is not merely indicative of production energy, but it is confounded with the affects of facility and space-conditioning energy as well. While EPI is certainly useful, it fails to capture whether an average industrial plant has average production, facility or space-conditioning use. Therefore, without this information, a plant with best-practice production energy use, but worst-practice facility and space-conditioning use, could be viewed as an "average" plant. LEA can pinpoint upfront whether a plant is best practice because of process energy use, facility energy use, space-conditioning energy use or a combination of these three.

In addition to the added detail of plant-wide energy use, LEA energy signatures offer several other benchmarking opportunities. The facility, production and space-conditioning components of industrial energy use can all be benchmarked, as well as the building heating and cooling balance points. The authors have noted that facility energy use is a quantification of control inefficiency (Seryak and Kissock, 2005). As such, benchmarking facility energy use would be extremely interesting.

The adverse aspects of using LEA energy signatures to benchmark energy use lies in data collection. Current surveys only collect annual production and energy use statistics, while a survey that would facilitate LEA benchmarking would require monthly production and energy use statistics. As this survey and subsequent database do not currently exist, conducting benchmarking studies based on LEA energy signatures would require prohibitive time allocated for data collection. However, as this data is readily available to most industrial facilities, future survey and data collection efforts by MECS, MIPD or ASM could incorporate monthly energy consumption and production values.

Conclusions

This paper presented a simple method for developing accurate multivariable regression models of energy use (LEA energy signatures) as functions of outdoor air temperature and production. LEA energy signatures for several plants were presented in detail, and discussed as more in-depth benchmarking alternatives than the LIEF or EPI methods. LEA energy signatures disaggregate plant energy use into facility, production and space-conditioning uses, while EPI confounds these components. LEA energy signatures also widen benchmarking possibilities from plant-wide energy to the facility, production and space-conditioning components, as well as building heating and cooling change-points. Future efforts to gather monthly energy and production data, as opposed to annualized data, would result in increased feasibility of using LEA energy signatures for benchmarking.

References

Boyd, G., 2003. “Two Approaches for Measuring the Efficiency Gap Between Average and Best Practice Energy Use: The LIEF Model 2.0 and the Energy Star Performance Indicator.” *ACEEE 2003 Summer Study on Energy-Efficiency in Industry*.

Haberl. J., Sreshthaputra, A., Claridge, D.E. and Kissock, J.K., 2003. “Inverse Modeling Toolkit (1050RP): Application and Testing”, ASHRAE Transactions, Vol. 109, Part 2.

Hicks, T., Dutrow, E., 2001. “Energy Performance Benchmarking for Manufacturing Plants”. *ACEEE 2001 Summer Study on Energy-Efficiency in Industry.*

Kissock, K., Reddy, A. and Claridge, D., 1998a. "Ambient-Temperature Regression Analysis for Estimating Retrofit Savings in Commercial Buildings", ASME Journal of Solar Energy Engineering, Vol. 120, No. 3, pp. 168-176.

Kissock, J.K., 2000, “Energy Explorer Data Analysis Software”, Version 1.0, Dayton, OH.

Kissock, J.K., Haberl. J. and Claridge, D.E., 2003. “Inverse Modeling Toolkit (1050RP): Numerical Algorithms”, ASHRAE Transactions, Vol. 109, Part 2.

Kissock, J.K. and Seryak, J., 2004, “Understanding Manufacturing Energy Use Through Statistical Analysis”, Proceedings of National Industrial Energy Technology Conference, Houston, TX, April 20-23, 2004.

Ross, M., P. Thimmapuran, et al., 1993. Long-Term Industrial Energy Forecasting (LIEF) Model (18-Sector Version), Argonne National Laboratory.

Seryak, J. and Kissock, J.K., 2005. “Lean Energy Analysis: Guiding Industrial Energy Reduction Efforts to the Theoretical Minimum Energy Use.”

UD/EPA Average Daily Temperature Archive. www.udayton.edu/~weather.