Motivating Industrial Energy Efficiency Through Performance-Based Indicators

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ABSTRACT

Organizations that implement strategic energy management programs undertake a set of activities that, if carried out properly, have the potential to deliver sustained energy savings. One key management opportunity is determining an appropriate level of energy performance for a plant through comparison with similar plants in its industry. Performance-based indicators are one way to enable companies to set energy efficiency targets for manufacturing facilities.

The U.S. Environmental Protection Agency (EPA), through its ENERGY STAR® program, is developing plant energy performance indicators to encourage a variety of U.S. industries to use energy more efficiently. This paper reports on work with the automobile manufacturing industry to provide a plant-level indicator of energy efficiency. Consideration is given to the role that performance-based indicators play in motivating change, the steps necessary for indicator development, from interacting with an industry to securing adequate data for the indicator, and actual application and use of an indicator when complete. How indicators are employed in EPA's efforts to encourage industries to voluntarily improve their use of energy is discussed as well.

Introduction

ENERGY STAR was introduced by EPA in 1992 as a voluntary, market-based partnership to reduce air pollution through increased energy efficiency. This government program enables industrial and commercial businesses as well as consumers to make informed decisions that save energy, reduce costs and protect the environment.

A key step in improving corporate energy efficiency is to institutionalize strategic energy management. Modeled on the International Organization for Standardization (ISO) quality and environmental standards, the ENERGY STAR Guidelines for Energy Management identify the components of successful energy management (EPA 2003). These include:

- Commitment from a senior corporate executive to manage energy across all businesses and facilities operated by the company,
- Appointment of a corporate energy director to coordinate and direct the energy program and multi-disciplinary energy team,
- Establishment and promotion of an energy policy,
- Development of a system for assessing performance of the energy management efforts including tracking energy use as well as benchmarking energy in facilities, operations and subunits therein,
- Conducting audits to determine areas for improvement,
- Setting goals at the corporate, facility and subunit levels,

- Establishment of an action plan across all operations and facilities, as well as monitoring successful implementation and promoting the value to all employees, and,
- Rewarding the success of the program.

Of the major steps in energy management program development, benchmarking energy use by comparing current energy performance to that of a similar entity is a critical. In manufacturing, it may take the form of detailed comparisons of specific production lines or pieces of equipment; or, it may be performed at a higher organizational level by gauging the performance of a single manufacturing plant to its industry. Regardless of the application, benchmarking enables companies to determine whether better energy performance should be expected. It empowers them to set goals and evaluate their reasonableness.

Boyd (2003) describes early experiences in developing a statistically-based plant energy performance indicator for the purpose of benchmarking manufacturing energy use in the automobile industry. Here the basic concept of benchmarking and the statistical approach employed, more recent experience gained with the automobile industry in developing performance-based energy indicators, the evolution of the analysis done for the auto industry, the final results of this analysis and ongoing efforts by EPA with this industry and others is described.

Benchmarking the Energy Efficiency of Industrial Plants

Among U.S. manufacturers, few industries participate in industry-wide plant benchmarking. The petroleum and petrochemical industries each support plant-wide surveys conducted by a private company and are provided with benchmarks that address energy use and other operational parameters related to their facilities. Otherwise, most industries have not benchmarked energy use across their plants. As a result, some energy managers find it difficult to determine how well their plants might perform.

In 2000, EPA and Argonne National Laboratory (ANL) discussed a method for developing benchmarks of energy performance for plant-level energy use within a manufacturing industry. Discussions yielded a plan to use a source of data that would nationally represent manufacturing plants within a particular industry, create a statistical model of energy performance for the industry's plants based on this data along with other available sources for the industry, and establish the benchmark on the comparison of those best practice, or best-performing plants to the industry. The primary data sources would be the Census of Manufacturing, Annual Survey of Manufacturing, and Manufacturing Energy Consumption Survey collected by the Census Bureau.

Scope of an Indicator – Experience with the Auto Manufacturers

EPA and ANL initiated discussions about developing a plant-level benchmark with the automobile manufacturers. Companies with manufacturing plants located within the United States were invited to participate in discussions. Initial reaction from most companies was supportive yet skeptical about whether a useful benchmark could be developed. Nevertheless, they agreed to "walk the path" to create one.

At the outset, the term "plant benchmark" was discussed. Industry engineers routinely develop benchmarks at many levels of plant operation. They felt using the word "benchmark" was confusing and could imply a particular process or tool. For this reason, it was decided that a more descriptive term would be clearer; thus, ENERGY STAR plant energy performance indicator (EPI) was adopted.

EPA and ANL defined the scope for the EPI. It would be a plant-level indicator, not process-specific and would relate plant inputs in terms of all types of energy use to plant outputs as expressed in a unit of production. EPA relied upon the Lawrence Berkeley National Laboratory report "Energy Efficiency Improvement and Cost Saving Opportunities for the Vehicle Assembly Industry: An ENERGY STAR® Guide for Energy and Plant Managers" to define the energy focus of the model (Galitsky & Worrell 2000). This energy guide provides a summary of the primary operations within automobile manufacturing plants. These include machining/casting, stamping, body weld, assembly and painting. Of the nearly 60 plants operating in the U.S., the majority were those with body weld, assembly and painting functions contained therein. A few machining and casting plants were operated separately from assembly operations by some manufacturers but these were insignificant in number, and most assembly plants did not contain casting. Thus, it was decided that the EPI would apply only to auto assembly plants which housed the painting operation (a major use of energy in auto manufacturing), vehicle assembly, and body weld. This set of plants also was substantial in number, an important factor for ensuring that no data confidentiality issues would arise.

The model would be designed to account for major, measurable impacts that affect a plant's energy use. The starting point for EPI development would be the Census data for industrial plants. For the auto industry, this included information on energy use, the fraction of costs representing stampings and engines (to control for assembly plants that included other upstream production activities), and the total value of product shipments for a plant. Upon discussion with the industry, it was decided that instead of the value of product shipments, the number of vehicles produced over the course of a year would be needed. Industry pricing and markups vary widely depending on the model, options, and market conditions, making the total value of product shipments an unreliable measure of production. Production was instead measured as the total number of vehicles produced at a single plant. The type of vehicle produced, i.e. autos, trucks and vans, would also be included in the model. Capacity utilization of the plant was included to account for the fixed and variable components of plant operation. Finally the heating and cooling loads of the plants would differ depending on their local climate/weather, so heating and cooling degree day (HDD/CDD) data would need to be accounted for in the model as well.

Statistical Approach

The goal is to develop an estimate of the distribution of energy efficiency across the industry. Efficiency is the difference between the actual energy use and "best practice," i.e. the lowest energy use achievable. What is achievable is influenced by operating conditions that vary between plants, so the measure of best practice must take these conditions into account. Statistical models are well-suited for accounting for these types of observable conditions, but typically are focused on average practice, not best practice. However, stochastic frontier regression analysis is a tool that can be used to identify "best practice."

The concept of the stochastic frontier analysis that supports the EPI can be easily described in terms of the standard linear regression model, which is reviewed in this section. A more detailed discussion of the evolution of the statistical approaches for estimating efficiency can be found in the literature (Green 1993). Consider at first, the simple example of a production process that has a fixed energy component and a variable energy component. A simple linear equation for this can be written as,

$$E_{t,i} = \alpha + \beta_y \, y_{t,i} \qquad (1)$$

where
t is the smallest time period of interest,
i is the ith plant, and
y is production.

Given data on energy use and production, the parameters α and β_y can be fit via a linear regression model. Since the actual data may not be perfectly measured and this simple relationship between energy and production may only be an approximation of the "true" relationship, linear regression estimates of the parameters rely on the proposition that any departures in the plant data from equation (1) are "random." This implies that the actual relationship, represented by equation (2) includes a random error term, ε, that follows a normal (bell-shaped) distribution with a mean of zero and variance, σ^2. In other words, about half of the actual values of energy use are less than what equation (1) would predict and half are greater.

$$\begin{gathered} E_{t,i} = \alpha + \beta_y \, y_{t,i} + \varepsilon_{t,i} \\ \varepsilon \sim N(0, \sigma^2) \end{gathered} \qquad (2)$$

The linear regression gives the average relationship between production and energy use. If the departures from the average, particularly those that are above the average, are due to energy inefficiency, we would be interested in a version of equation (1) that gives the "best" or lowest observed energy use. For example, consider that capacity utilization can influence the energy use per unit of production, due to the fixed and variable components of plant energy use (see Figure 1). A regression model can find the line that best explains the average response of energy use per unit of production to a change in utilization rates. The relationship between the lowest energy use per unit of production relative to changes in utilization can be obtained by shifting the line downward so that all the actual data points are on or above the line. This "corrected" ordinary least squares (COLS) regression is one way to represent the frontier.

While the COLS method has its appeal in terms of simplicity, a more realistic view is that not all the differences between the actual data and the frontier are due to efficiency. Since we recognize that there may still be errors in data collection/reporting, effects that are unaccounted for in the analysis, and that a linear equation is an approximation of the complex factors that determine manufacturing energy use, we still wish to include the statistical noise, or "random error," term in the analysis, $v_{t,i}$, but also add an second random component, $u_{t,i}$, to reflect energy inefficiency[1]. If we expand the simple example of energy use and production to include a range of potential effects we can write the more general version of the stochastic frontier model as,

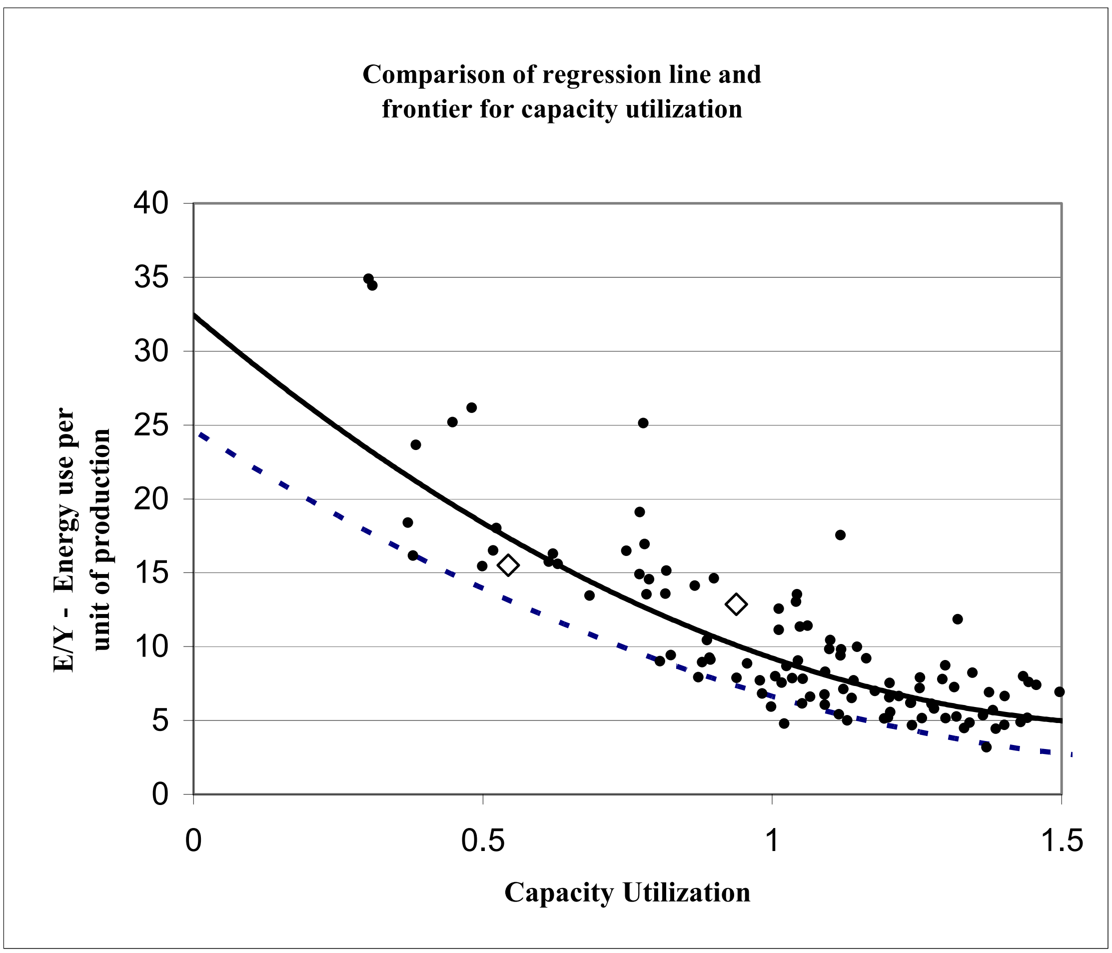
[1] By random we mean that this effect is not directly measurable by the analyst, but that it can be represented by a probability distribution.

$$E_{t,i} = f(Y_{t,i}, X_{t,i}, Z_{t,i}\,;\,\beta) + \varepsilon_i \qquad (3)$$
$$\varepsilon_i = u_i - v_i \qquad v \sim N\,[0,\sigma_v^2]\,,$$

where,
E is energy use, either electricity, non-electric energy, or total primary energy,
Y is production, measured by either physical production or total value,
X includes systematic economic decision variables (i.e. non-energy production inputs like the amount of labor hours worked or materials processed),
Z includes systematic external factors (i.e. heating and cooling loads), and,
β includes all the parameters to be estimated.

We assume that energy (in)efficiency, u, is distributed according to some one-sided statistical distribution[2], for example gamma, exponential, truncated normal, etc. It is then possible to estimate the parameters of equation (3), along with the distribution parameters of u.

Figure 1. Average and Corrected Linear Regression of Production and Energy



[2] We also assume that the two types of errors are uncorrelated, $\sigma_{u,v} = 0$.

One advantage of the approach is that the parameters used to normalize for systematic effects and describe the distribution of efficiency are jointly estimated. The standard regression model captures the behavior of the average (see solid line in Figure 1), but the frontier regression (the dotted line in Figure 1) captures the behavior of the best performers. For example, if the best performing plants were less sensitive to capacity utilization because they use better shutdown procedures, then the estimated slope of the frontier capacity utilization curve would not be as steep as the slope for the average plants.

Given data for any plant, we can use equation (4) to compute the difference between the actual energy use and the predicted frontier energy use

$$E_{t,i} - f(Y_{t,i}, X_{t,i}, Z_{t,i}; \beta) + v_{\mathrm{i}} = u_{\mathrm{i}} \qquad (4)$$

Since we have estimated the probability distribution of *u*, equation (5) represents the probability that the plant inefficiency is no greater than this computed difference

$$\Pr(\textit{inefficiency} \le E_{t,i} - f(Y_{t,i}, X_{t,i}, Z_{t,i}; \beta) + v_{\mathrm{i}}) \qquad (5)$$

This is the EPI score and is the same as a *percentile ranking of the energy efficiency* of the plant. In practice we only can measure $E_{t,i} - f(Y_{t,i}, X_{t,i}, Z_{t,i}; \beta) = u_{\mathrm{i}} - v_{\mathrm{i}}$, so this implies that the EPI score is affected by the random component of v_i, i.e. the score will reflect the random influences that are not accounted for by the function *f(*)*. Since this ranking is based on the distribution of inefficiency for the entire industry, but normalized to the specific systematic factors of the given plant, this statistical model allows the user to answer the hypothetical but very practical question, "How does my plant compare to everyone else's in my industry, *if all other plants* were similar to mine?"

Evolution of the Model

The model evolved over a period of time, based on comments from industry reviewers and subsequent analyses. Industry tested each version of the model. Companies were asked to input actual data for all of their plants and then to determine whether the results were consistent with any energy efficiency assessments that may have been made for these plants. The industry's comments improved the EPI.

One example of an adjustment made based on industry comment is production capacity. ANL suggested a common definition of production capacity was needed. Auto industry representatives decided to define production capacity as two standard shifts per day with seven hours per shift and 244 days worked for the year multiplied by the number of vehicles produced per hour.

The model equations were provided to reviewers in the form of a spreadsheet. The spreadsheet allowed them to input their own plant data and view the results.

The first version of the model was based on total site energy, i.e. the total Btu's of fuels and electricity. The industry response was initially quite positive, and participants requested the model provide separate scores for electricity and fuel use. Since some plants cool, or "temper," the outside air and others do not, it was suggested that ANL control for this effect, so that plants with "air-tempering" do not set an unrealistic frontier.

A subsequent version of the model was prepared that included a control for the air-tempering effect for the electricity, with a separate model without this effect for fuel use. This model underwent further review and generated a suggestion from industry that the size of vehicle should influence energy use. The model only distinguished between autos, and "large vehicles" including trucks, sport utility vehicles (SUVs) and vans. Industry reviewers suggested that wheelbase size would better reflect the differences, so data on the wheelbase of the vehicles produced in each plant was compiled and the model was updated again.

The resulting model was better at adjusting for vehicle size, but additional industry comments identified some unrealistic adjustments for capacity utilization and for air-tempering. This lead to the identification of some erroneous plant data which was excluded from the analysis and additional modeling. Careful attention was given to how the air-tempering variable was implemented; specifically, the adjustment was no longer treated as linear, but declined when the cooling load dropped.

Throughout the process the approach provided statistical tests to determine the confidence level of the adjustment factors that would, or would not be included. Adjustments for plant size were tested, but found not to have sufficient levels of statistical confidence to remain in the model. The final version of the equations for electricity and fuels are

$$E/Y_i = A + \beta_1 WBASE + \beta_2 HDD + \beta_3 HDD^2 + \beta_4 Util + \beta_5 CDD + \beta_6 CDD^2 + u_i - v_i$$

Where

E	= total site electricity use in kWh
Y	= number of vehicles produced
UTIL	= plant utilization rate, defined as output/capacity
HDD	= heating degree days for the plant location and year
HDD^2	= HDD squared
CDD	= cooling degree days for the plant location and year if the plant is air tempered and zero otherwise
CDD^2	= CDD squared
WBASE	= wheelbase of the largest vehicle produced

β is the vector of parameters to be estimated, $v \sim N(0, \sigma_v^2)$, and $u \sim \Gamma(\theta, P)$.

and

$$F/Y_i = A + \beta_1 WBASE + \beta_2 Util + \beta_3 Util^2 + \beta_4 HDD + \beta_5 HDD^2 + u_i - v_i$$

Where

F	= total site fossil fuel use in 10^6 Btu
Y	= number of vehicles produced
WBASE	= wheelbase of the largest vehicle produced
UTIL	= plant utilization rate, defined as output/capacity
$UTIL^2$	= UTIL squared
HDD	= heating degree days for the plant location and year
HDD^2	= HDD squared

β is the vector of parameters to be estimated, $v \sim N(0, \sigma_v^2)$, and $u \sim \Gamma(\theta, P)$.

The parameters of the final version of the model are shown in Tables 1 and 2.

Table 1: Electricity Energy Model Estimates

Variable	Estimate	Standard Error	t-ratio
Constant	369.39	86.89835	4.25
WBASE	2.77	9.88E-02	28.13
HDD	-48.41	26.26136	-1.84
HDD^2	4.79	2.60086	1.84
UTILIZATION RATE	-138.61	34.31109	-4.04
CDD (if plant is air-tempered)	-59.32	5.22852	-11.34
CDD^2 (if plant is air-tempered)	41.90866	0.988851	42.38
error distribution parameters			
θ	2.78E-03	6.52E-04	4.27
P	0.542444	0.116438	4.659
σ_v	3.51E-05	4.84E-03	0.007

Table 2: Fuel Energy Model Estimates

Variable	Estimate	Standard Error	t-ratio
Constant	3.826872	0.837056	4.572
WBASE	3.22E-02	6.10E-04	52.726
UTIL	-6.78767	1.280148	-5.302
$UTIL^2$	2.398563	0.622385	3.854
HDD	-0.54486	0.121115	-4.499
HDD^2	0.109983	1.31E-02	8.385
error distribution parameters			
θ	0.267789	6.94E-02	3.861
P	0.723982	0.144349	5.016
σ_v	7.01E-03	6.98E-02	0.1

Judging Auto Assembly Plant Energy Efficiency - How the EPI Works

The auto assembly EPI scores the energy efficiency of an auto assembly plant based in the United States. To use the tool, the following information must be available for a plant:

- annual energy use for the current year and a baseline year as defined by the user,
- number of vehicles produced in the current and baseline years,
- linespeed, the number of vehicles produced per hour,
- wheelbase of largest vehicle produced at the plant,
- whether or not the air in the plant is cooled, or tempered, and,
- a five digit zip-code for the location of the plant if the default 30-year average HDD and CDD data are used, otherwise the user provides actual annual HDD and CDD.

Based on these data inputs, the EPI will report a score for the plant in the current time period that reflects the relative energy efficiency of the plant compared to that of the industry. It is a percentile score on a scale of zero to one hundred (0-100). Plants that score 75 or better are classified as efficient. (ENERGY STAR defines the 75th percentile as efficient.) A score of 75 means a particular plant is performing better than 75 percent of the plants in the industry.

The model also reports on the average plant in the industry (defined as the 50th percentile). Aside from scoring, an industrial user can determine the energy output ratio (mMBtu/vehicle) and an annual energy cost in dollars per year calculated from national cost figures for the current and baseline years as well as for the average and efficient plants. While the underlying model was developed from data for U.S.-based assembly plants, it does not reveal any confidential information.

Use of the ENERGY STAR Auto Assembly EPI

After three years of work with the auto manufacturers, the ENERGY STAR auto assembly EPI is now complete. EPA intends to use this model to motivate change in energy use in U.S.-based automobile manufacturing. Working closely with the manufacturers through an ENERGY STAR focus on energy efficiency in auto manufacturing, EPA promotes strategic energy management among the companies in this industry. Already the corporate energy managers in these companies are making plans to use the EPI to motivate change. One has expressed the plan to calculate EPI scores for each plant and perhaps provide EPI goals to the plants. While not required to report actual plant scores, companies informally have shared their success in using the EPI, and one company noted it has improved a plant score in the past year.

In the meantime, the EPI is available to the public on the ENERGY STAR website. EPA will continue to work closely with the industry to challenge improvement based on the EPI's ability to score performance. The industry has requested periodic updates of the model as the industry's energy performance improves so that the EPI will continue to be a challenge.

EPA is considering the option of offering the ENERGY STAR for industrial plants that score 75 or greater along with meeting a few yet-to-be-defined requirements. This system would be similar to that offered by EPA in the commercial and public sectors for recognizing building performance. Industry has been positive about this potential opportunity for recognition of their energy achievements. Finally, EPA is working with additional industries (including cement, corn refining, and glass) to create EPI's to help motivate greater energy efficiency and to enable them to compare plant energy performance.

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