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Development of a Performance-based Industrial Energy Efficiency Indicator for Automobile Assembly Plants

Decision and Information Sciences Division
Argonne National Laboratory

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Development of a Performance-based Industrial Energy Efficiency Indicator for Motor Vehicle Manufacturing

Gale A. Boyd

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 (EPIs) to encourage a variety of U.S. industries to use energy more efficiently. This report describes work with the automobile manufacturing industry to provide a plant-level indicator of energy efficiency for assembly plants that produce passenger cars, light-duty trucks, sport utility vehicles, and vans in the United States. 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 in 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. The report describes the data and statistical methods used to construct the EPI for automobile assembly plants. The individual equations are presented, as well as instructions for using those equations as implemented in an associated Excel spreadsheet.

1 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;
- Conduct of audits to determine areas for improvement;
- Setting of 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
- Provision of rewards for 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 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 could 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. This report describes 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 automobile industry, the final results of this analysis, and ongoing efforts by EPA to improve the energy efficiency of this industry and others.

2 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 these data along with other available sources for the industry, and establish the benchmark on the comparison of those best practices, or best-performing plants, to the industry. The primary data sources were determined to be the Census of Manufacturing, Annual Survey of Manufacturing, and Manufacturing Energy Consumption Survey collected by the Census Bureau and supplemented by data provided by trade associations and individual companies on a case-by-case basis.

2.1 Scope of an Indicator — Experience with the Automobile 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, but they expressed concern that using the word "benchmark" would be 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 is a plant-level indicator, not process-specific, and it relates plant inputs in terms of all types of energy use to plant outputs as expressed in a unit of production. EPA relied upon a Lawrence Berkeley National Laboratory (LBNL) study of the automobile assembly industry (Galitsky and Worrell 2003) to define the energy focus of the model. The LBNL report provides a summary of the primary operations within automobile manufacturing plants, namely machining/casting, stamping, body weld, assembly, and painting. Of the nearly 60 plants operating in the United States, the majority were those containing body weld, assembly, and painting functions. 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 automobile assembly EPI applies only to automobile assembly plants that housed the painting operation (a major use of energy in automobile manufacturing), vehicle assembly, and body weld. This set of plants was substantial in number, an important factor for ensuring that no data confidentiality issues would arise.

The model was designed to account for major, measurable impacts that affect a plant's energy use. The starting point for EPI development was census data for industrial plants. For the automobile industry, these 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 annually 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., passenger cars, light-duty trucks, sport utility vehicles, 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 and CDD, respectively) data were used in the model as well.

2.2 Data Sources

Since the number of vehicles produced was not routinely collected in the Census of Manufacturing, data were provided by five companies who volunteered to participate in the study. These companies were the American affiliates of GM, Ford, Honda, Toyota, and Subaru.[1] Only plants located in the United States producing passenger cars, sport utility vehicles, light-duty trucks, and vans were used in the study. *Assembly plants* were defined to include body weld, paint, and assembly. Since some plants may include other operations, e.g., plastics, engines, or stamping, there were two options. If the energy data for those sub-sector operations could be isolated, then those data were used; otherwise, those plants were excluded. Companies provided energy data for fossil fuel and electricity use separately. Finally, companies provided the plant capacity (defined below) and the wheelbase of the vehicles produced at the plant.[2] Climate data in the form of HDD and CDD were linked by ANL to the plant locations based on the first three digits of the plant zip code for each year of the data. The HDD/CDD data are the same as those used by ENERGY STAR for the national performance rating system for buildings.

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1 The automobile manufacturing industry data are proprietary business information and was voluntarily provided to ANL under a nondisclosure agreement with the respective companies.

2 Some of the wheelbase data were compiled from public sources as well.

Three years of data were used, 1998–2000, for 35 plants. The final dataset includes 104 observations, since there was an unusable observation for one plant for one of the years. Table 1 provides the sample mean, median, standard deviation, and highest and lowest 10th percentile for all the raw variables in the dataset. Also of interest are several derived measures from the raw data, which are shown in Table 2. Capacity utilization is defined as the ratio of production to capacity. Capacity is defined as operating 2 shifts, and since some plants operate 3 shifts, utilization rates above 100% are not uncommon. Total site energy (TSE) is the variable used to aggregate energy; that is, kilowatt hours (kWh) are converted to British thermal units (Btu) using 3,412 Btu/kWh. The study focuses on the energy use per vehicle, so these data are of particular interest, and histograms of the kWh and Btu used per vehicle are shown in Figures 1 and 2, respectively.

Table 1 Summary Statistics from the Plant Data Included in the Study

Metric	kWh (10^3)	Btu (10^6)	Vehicles (10^3)	Capacity (10^3)	CDD	HDD	Wheel-base (in.)
Mean	147,689	1,160,362	225	214	1,472	4,286	121.4
Median	149,405	1,049,614	225	213	1,303	4,186	113.8
Standard Dev.	47,397	484,404	65	46	682	1,291	20.0
10th Percentile	77,645	600,972	150	165	766	2,387	103.1
90th Percentile	209,912	1,822,433	307	253	2,229	5,745	157.5

Table 2 Summary Statistics of Derived Measures

Metric	Capacity Utilization (%)	TSE (10^6 Btu)	kWh per Vehicle	10^6 Btu per Vehicle	TSE per Vehicle (10^6 Btu)
Mean	106	1,664,277	698	5.52	7.90
Median	105	1,573,313	608	4.69	6.82
Standard Dev.	25	613,859	321	2.89	3.84
10th Percentile	69	943,032	436	2.92	4.69
90th Percentile	138	2,532,417	1,104	9.83	13.56

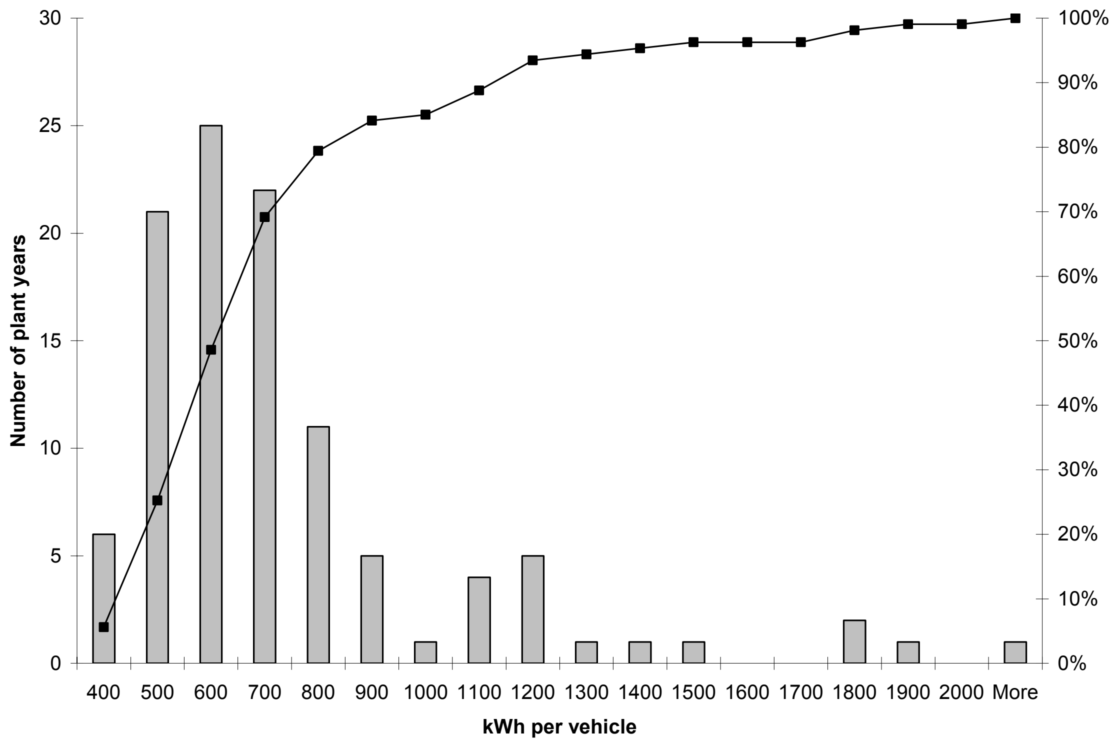

Figure 1 Distribution of Electricity Use per Vehicle (kWh)

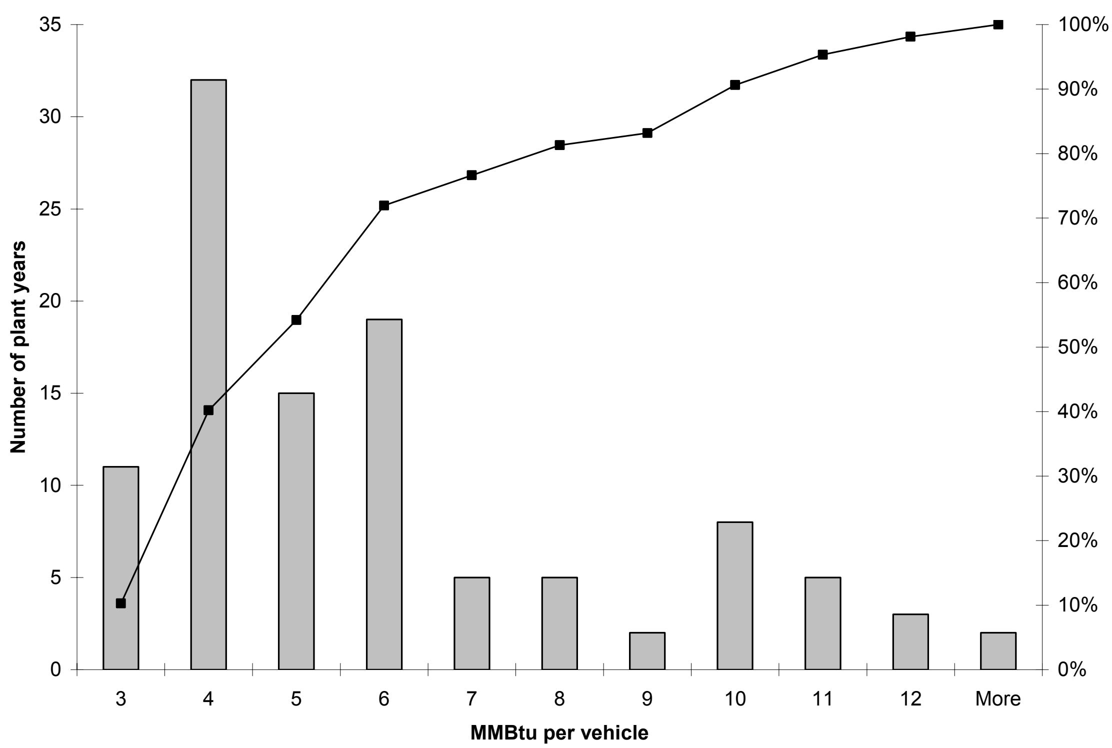

Figure 2 Distribution of Fossil Fuel Use per Vehicle (10^6 Btu)

3 Statistical Approach

The goal of this study was 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." This section provides the background on the stochastic frontier, a discussion on the review process and evolution of the model's equations, and the final model estimates.

3.1 Stochastic Frontier

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 on the evolution of the statistical approaches for estimating efficiency can be found in Greene (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

$$E_i = \alpha + \beta y_i \tag{1}$$

where

E = energy use of plant i and
y = production of plant i.

Given data on energy use and production, the parameters α and β 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 Eq. 1 are "random." This implies that the actual relationship, represented by Eq. 2, includes a random error term ε that follows a normal (bell-shaped) distribution with a mean of 0 and variance of σ^2. In other words, about half of the actual values of energy use are less than what Eq. 1 would predict and half are greater:

$$\begin{gathered} E_i = \alpha + \beta y_i + \varepsilon_i \\ \varepsilon \sim N(0,\sigma^2) \end{gathered} \tag{2}$$

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 Eq. 1 that gives the "best" (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 v_i in the analysis but also add a second random component u_i to reflect energy inefficiency.[3] Unlike the statistical noise term, which may be positive or negative, this second error term will follow a one-sided distribution. If we expand the simple example of energy use and production to include a range of potential effects, we can write a version of the stochastic frontier model as energy use per unit of production as a general function of systematic economic decision variables and external factors,

$$E_i/Y_i = h(X_i, Z_i;\ \beta) + \varepsilon_i \tag{3}$$
$$\varepsilon_i = u_\mathrm{i} - v_\mathrm{i} \qquad\qquad v \sim N\,[0,\sigma_\mathrm{v}^2]\ ,$$

where

E = energy use, either electricity, non-electric energy, or TSE (i.e., total site energy or the total measure of fuel and electricity);
Y = production, measured by physical production;
X = systematic economic decision variables (i.e., labor-hours worked, materials processed, plant capacity, or utilization rates);
Z = systematic external factors (i.e., heating and cooling loads); and
β = all the parameters to be estimated.

We assume that energy (in)efficiency u is distributed according to one of several possible one-sided statistical distributions,[4] for example gamma, exponential, truncated normal, etc. It is then possible to estimate the parameters of Eq. 3, along with the distribution parameters of u.

[3] By random we mean that this effect is not directly measurable by the analyst, but that it can be represented by a probability distribution.
[4] 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 3), but the frontier regression (the dotted line in Figure 3) 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 Eq. 3 to compute the difference between the actual energy use and the predicted frontier energy use:

$$E_i - Y_i \bullet \left[h\left(X_i, Z_i; \beta\right) + v_{\mathrm{i}}\right] = u_{\mathrm{i}} \tag{4}$$

Since we have estimated the probability distribution of *u*, Eq. 5 represents the probability that the plant inefficiency is greater than this computed difference:

$$\begin{aligned}\text{Probability}&\left[\textit{energy inefficiency} \geq E_i - Y_i \bullet \left(h\left(X_i, Z_i; \beta\right) + v_{\mathrm{i}}\right)\right] = \\ &1 - F\left({E_i}/{Y_i} - h\left(X_i, Z_i; \beta\right) + v_{\mathrm{i}}\right)\end{aligned} \tag{5}$$

F( ) is the cumulative probability density function of the appropriate one-sided density function, i.e., gamma, exponential, truncated normal, etc. The value 1 - *F( )* in Eq. 5

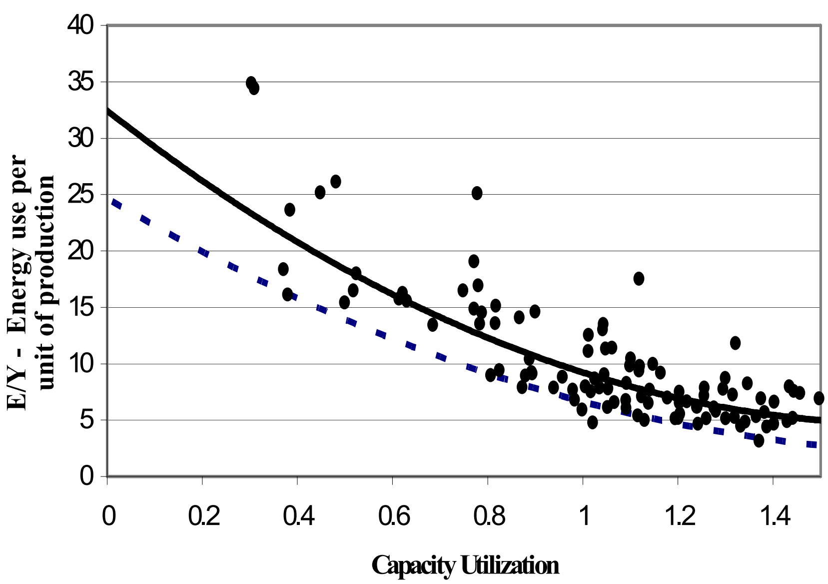

Figure 3 COLS and Frontier Regression of Energy Use per Unit of Production against Capacity Utilization

defines the EPI score and may be interpreted as a *percentile ranking of the energy efficiency* of the plant. In practice we only can measure $E_i/Y_i - h(X_{t,i}, Z_{t,i}\,;\,\beta) = u_i - v_i$, so this implies that the EPI score $1 - F\left(E_i/Y_i - h(X_{t,i}, Z_{t,i}\,;\,\beta) \right) = 1 - F\left(u_i - v_i\right)$ is affected by the random component of v_i; that is, the score will reflect the random influences that are not accounted for by the function *h(*).* 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?"

3.2 Evolution of the Model

The model evolved over a period of time, based on comments from industry reviewers and subsequent analyses. Industry participants 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 resulting comments improved the EPI.

One example of an adjustment made based on industry comment is production capacity. ANL suggested that a common definition of production capacity was needed. Automobile industry representatives decided to define production capacity as 2 standard shifts per day with 7 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 an Excel spreadsheet. The spreadsheet allowed them to input their own plant data and view the results. The first version of the model was based on TSE, i.e., the total Btu of fuel and electricity (converted at 3,412 Btu/kWh). The industry response was initially quite positive, and participants requested that 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 provide a control for this effect, so that plants with "air tempering" do not set an unrealistic frontier.

A subsequent version of the model 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, which generated a suggestion from industry that the size of vehicle should influence energy use. The model only distinguished between passenger cars and "large vehicles," including light-duty trucks, sport utility vehicles, 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 were 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 led to the identification of some erroneous plant data, which were excluded from the analysis, and further modeling. Careful attention was given to how the air-tempering variable was implemented; specifically, the adjustment was no longer treated as linear but rather declined when the cooling load dropped.

Throughout the process the estimation 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 to have insufficient levels of statistical confidence to remain in the model.

3.3 Model Estimates

For simplicity, we assume that the function *h( )* is linear in the parameters, but allow for non-linear transformations of the variables. In particular, we found that non-linear (quadratic) terms in some of the variables were appropriate. Several alternatives for the distribution of the inefficiency term u were tried. For both models, the gamma distribution was used. The gamma distribution and density function are

$$f(u) = \left[\theta^{P} / \Gamma(P)\right] e^{-\theta u} u^{P-1},\ u, P, \theta > 0$$
$$\text{and} \qquad (6)$$
$$F(x) = \int_0^x f(u)du,$$

respectively. This distribution provides a more flexible parameterization of the distribution than either exponential or half normal.

The example in Figure 4 (from Greene 2000) illustrates a case in which the exponential and gamma variates both have mean of 1, and the shape parameter of the gamma density is P = 1.5. In the exponential model, θ = 1, while in the gamma model, θ = 1.5. When the value of P is larger than 1, the mass of the distribution moves away from u = 0, i.e., no inefficiency, while values of P less than 1 produce densities that resemble the exponential distribution. As can be seen, the prior assumption of a value of P (e.g., 1) amounts to a substantive assumption about the distribution of inefficiencies in the population. A commercially available statistical package, LIMDEP, provides a method of simulated maximum likelihood to estimate the parameters of the normal-gamma stochastic frontier (Greene 1995) as well as the other variants that were tested.

The final version of the equation for electricity is

$$\begin{aligned} E_i / Y_i = {} & A + \beta_1 WBASE_i + \beta_2 HDD_i + \beta_3 HDD_i^2 \\ & + \beta_4 Util_i + \beta_5 CDD_i + \beta_6 CDD_i^2 + u_i - v_i \end{aligned} \qquad (7)$$

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; and
β	=	vector of parameters to be estimated.

The variable v is distributed as $N(0, \sigma_v^2)$.

The estimated parameters of the model are shown in Table 3. All parameters with an asterisk (except σ_v) are statistically significant at the 10% level or greater in a two-tailed test. All other estimates shown are significant at the 99% level in a two-tailed test. The small size of σ_v suggests that the model has very little error attributable to random noise and that most departures are attributable to inefficiency.

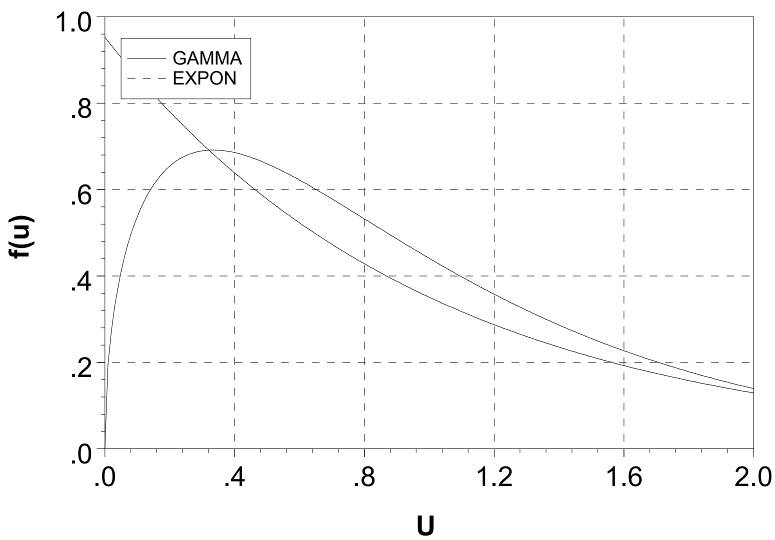

Figure 4 Illustrative Densities for the Gamma and Exponential Distributions (Source: Greene 1995)

Table 3 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)	41.91	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

The final version of the equation for fossil fuel is

$$F/Y_i = A + \beta_1 WBASE + \beta_2 Util + \beta_3 Util^2 + \beta_4 HDD + \beta_5 HDD^2 + u_i - v_i \tag{8}$$

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; and
β = vector of parameters to be estimated.

The variable v is distributed as $N(0, \sigma_v^2)$.

The parameters of the final version of the model are shown in Table 4. All parameters except σ_v are statistically significant at the 99% level in a two-tailed test. The small size of σ_v suggests that the fuel model also has very little error attributable to random noise and that most departures are attributable to inefficiency.

Table 4 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

4 Judging Automobile Assembly Plant Energy Efficiency

4.1 How the EPI Works

The automobile assembly EPI scores the energy efficiency of an automobile 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;
- Line speed, the number of vehicles produced per hour, which is used to compute annual plant capacity;
- Wheelbase of largest vehicle produced at the plant;
- Whether or not the air in the plant is cooled, or tempered; and
- 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 for that year.

Based on these data inputs, the automobile assembly 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 0–100. Plants that score 75 or better are classified as efficient. (ENERGY STAR defines the 75^{th} percentile as efficient.) A score of 75 means a particular plant is performing better than 75% of the plants in the industry.

The model also reports on the average plant in the industry (defined as the 50^{th} percentile). Aside from scoring, an industrial user can determine the energy output ratio (million Btu/vehicle) and an annual energy cost in dollars per year for a plant, 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 contain or reveal any confidential information.

4.2 Spreadsheet Tool

To facilitate the review of and use by automobile industry energy managers, a spreadsheet was constructed to display the results of the EPI for an arbitrary[5] set of plant-level inputs. The spreadsheet accepts the raw plant-level inputs described above, computes the values for *h( ),* and then displays the results from the gamma distribution functions for the electricity and fuel models presented in Eqs. 7 and 8. The results are based on user-input values of the basic model input described above. This aids in

[5] In other words, for plant data that may not have originally been in the data set used to estimate the model equations.

comparing the magnitude of the systematic effects attributable to changes in those inputs on the gamma efficiency distribution by graphically displaying the results. The energy managers were encouraged to input data for their own plants and then provide comments. A version of this spreadsheet, dated 5/25/2005, which corresponds to the results described in this report, is available from the EPA ENERGY STAR web site.[6]

An example of the input section of the spreadsheet is shown in Figure 5. The results section for TSE use is shown in Figure 6. The spreadsheet has additional tabs that display the fossil fuel and electricity results separately. The results for the electricity and fuels models are based directly on the parameter estimates in Tables 3 and 4 and the formulae in Eqs. 5–8. To obtain a distribution function for TSE, it was assumed that the distributions for electricity and fuels were independent[7] and a piecewise approximation of the distribution function was constructed by adding the fossil and electric energy (converted to million Btu) per vehicle at each percentile from 1 to 100.

4.3 Summary Results

Although the automobile assembly EPI is intended to produce plant-specific analysis of energy efficiency, some broad inferences about efficiency in automobile assembly can be made based on the models and the underlying data. The dataset includes 35 plants for 3 years each (1998–2000). The average energy consumed per vehicle manufactured was 8.1 million Btu and the median 6.9 million Btu per vehicle. The difference between the average and the median is due to the nature of the one-tailed distribution that characterizes energy efficiency. If we compute the EPI model's "best practice" estimates, i.e., the predicted values for the function *h( )* for every plant in the dataset, and aggregate the electricity and fossil fuels to TSE, we obtain the results shown in Table 5. The average "best practice" consumption per vehicle would be 4.8 million Btu and the median "best practice" would be 4.6 million Btu. The full distributions for predicted "best practice" values for fossil fuel, electric, and TSE aggregate energy use per vehicle are shown in Figures 7, 8, and 9, respectively.

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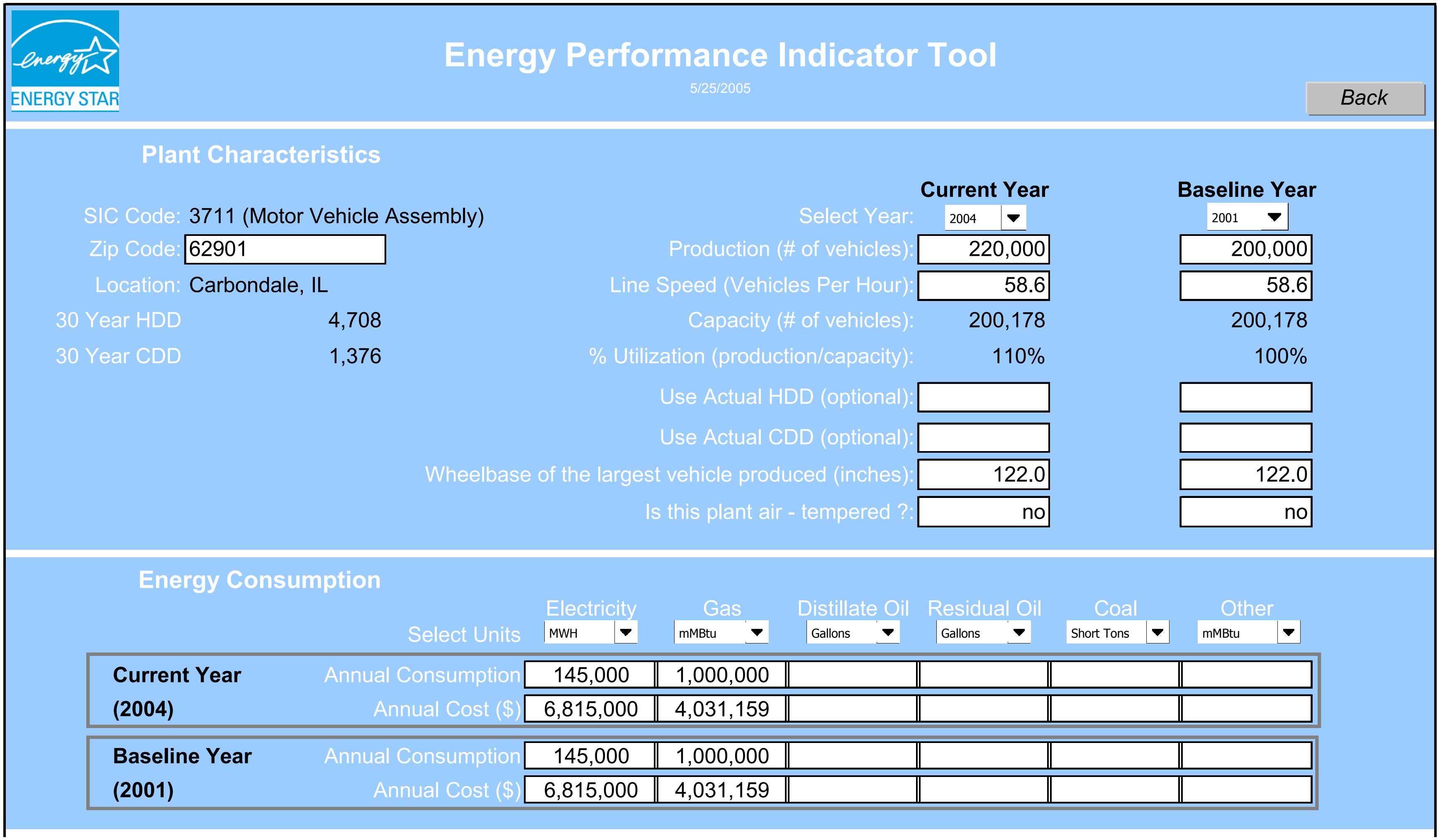
[6] http://www.energystar.gov/index.cfm?c=industry.bus_industry

[7] This is a very strong assumption, but we are not aware of any method that would allow the joint estimation of the fossil and electric efficiency simultaneously.



Energy Performance Indicator Tool

5/25/2005

Back

Plant Characteristics

SIC Code: 3711 (Motor Vehicle Assembly)

Zip Code: 62901

Location: Carbondale, IL

30 Year HDD 4,708

30 Year CDD 1,376

	Current Year	Baseline Year
Select Year:	2004	2001
Production (# of vehicles):	220,000	200,000
Line Speed (Vehicles Per Hour):	58.6	58.6
Capacity (# of vehicles):	200,178	200,178
% Utilization (production/capacity):	110%	100%
Use Actual HDD (optional):		
Use Actual CDD (optional):		
Wheelbase of the largest vehicle produced (inches):	122.0	122.0
Is this plant air - tempered ?:	no	no

Energy Consumption

		Electricity	Gas	Distillate Oil	Residual Oil	Coal	Other
	Select Units	MWH	mMBtu	Gallons	Gallons	Short Tons	mMBtu
Current Year (2004)	Annual Consumption	145,000	1,000,000				
	Annual Cost ($)	6,815,000	4,031,159				
Baseline Year (2001)	Annual Consumption	145,000	1,000,000				
	Annual Cost ($)	6,815,000	4,031,159				

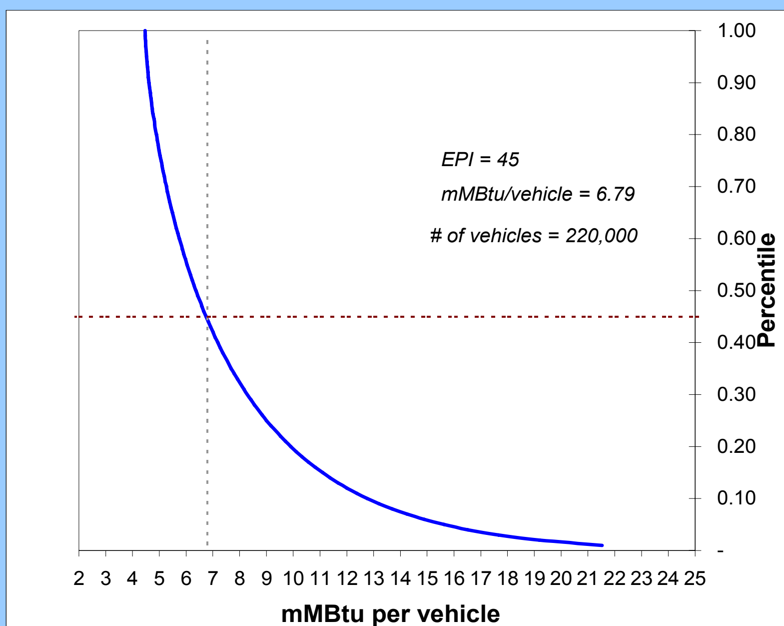
Figure 5 Input Section of the EPI Spreadsheet Tool

Total Site Energy Results

Electric | **Fuels**

	Your Plant Current (2004)	Your Plant Baseline (2001)	Average Plant (2004)	Efficient Plant (2004)
EPI	45	40	50	75
Annual Energy Cost ($/year)	$10,846,159	$10,846,159	$9,091,530	$7,611,187
# of Vehicles	220,000	200,000	220,000	220,000
$ Energy/vehicle	49.30	54.23	41.33	34.60
Energy Output Ratio (mMBtu/vehicle)	6.79	7.47	6.37	5.07

Current Year (2004)



Baseline Year (2001)

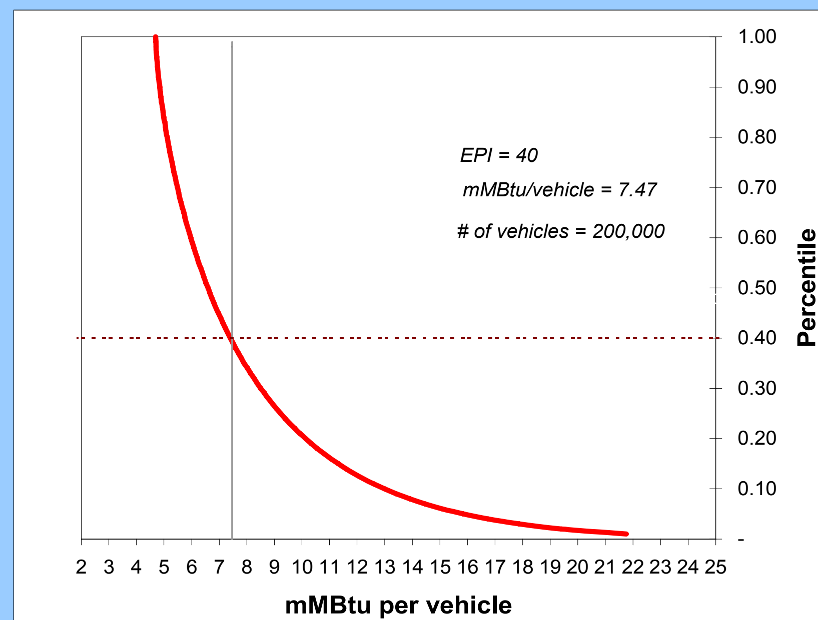


Figure 6 Output Section of the EPI Spreadsheet Tool (TSE results)

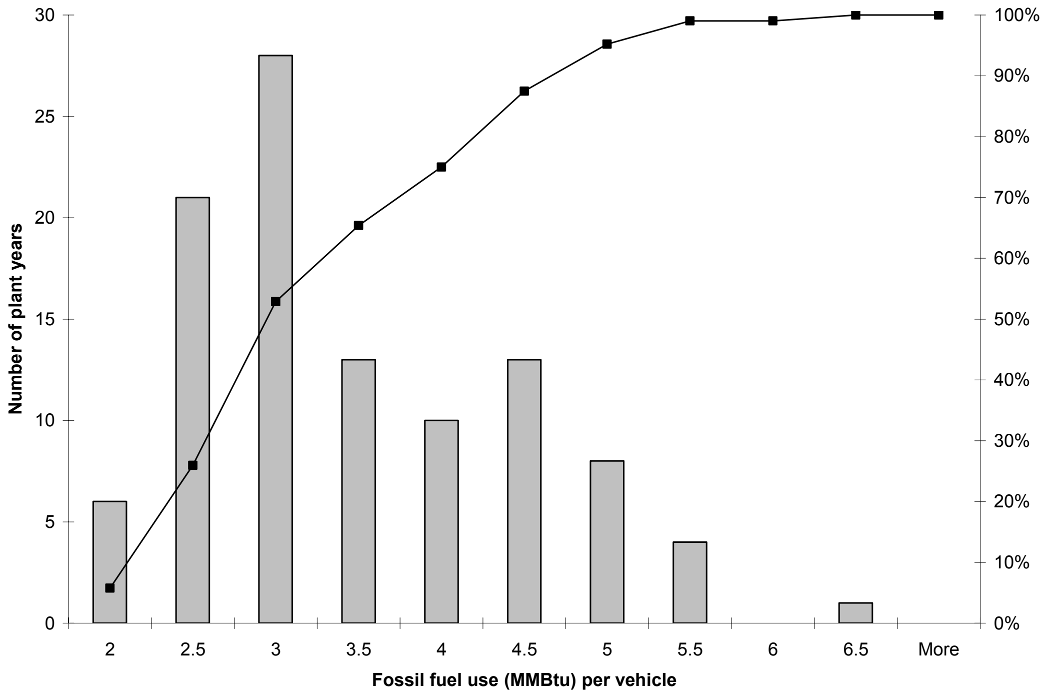


Figure 7 Distribution of Predicted "Best Practice" Fossil Fuel Use per Vehicle

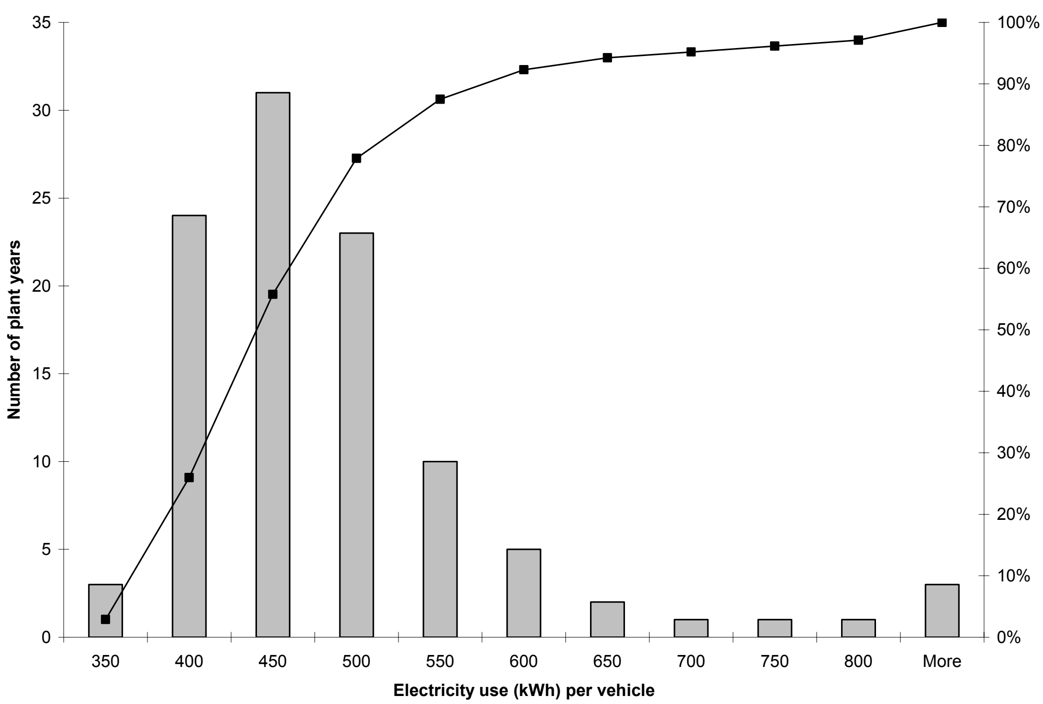


Figure 8 Distribution of Predicted "Best Practice" Electricity Use per Vehicle

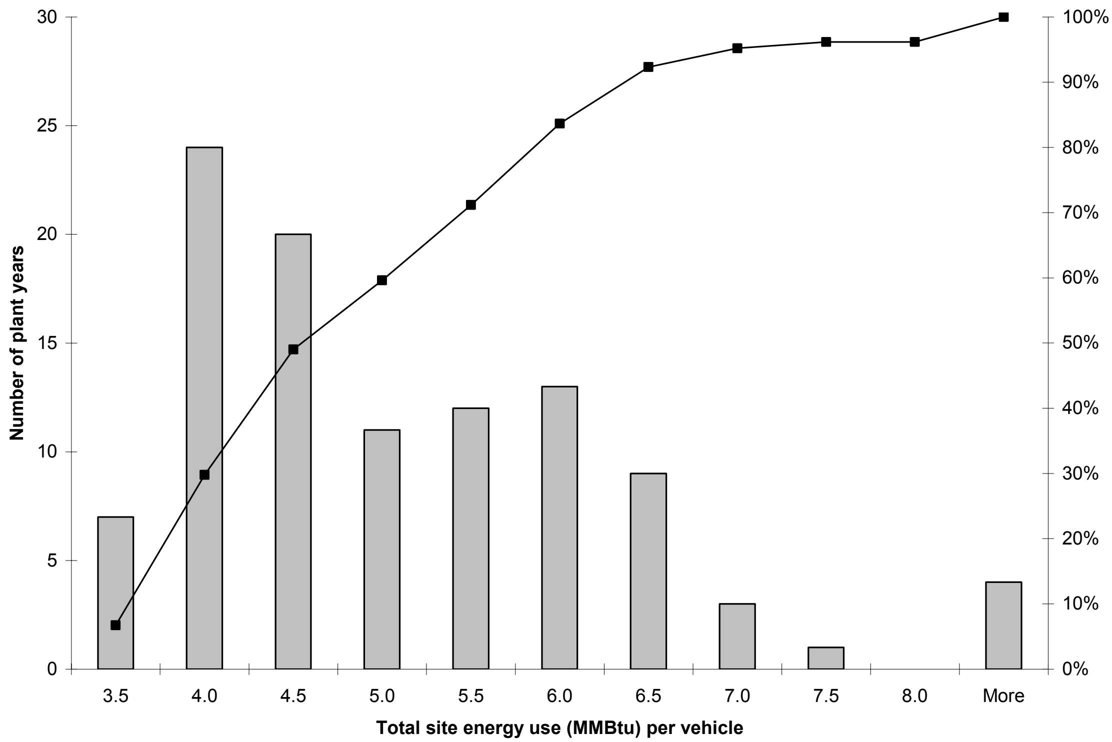


Figure 9 Distribution of Predicted "Best Practice" TSE Use per Vehicle

Table 5 Summary Statistics for the Predicted "Best Practice" Values of Fossil Fuel, Electric, and TSE Aggregate Energy Use per Vehicle

Metric	Fossil (10^6 Btu)	Electric (kWh)	TSE (10^6 Btu)
Mean	3.24	467	4.83
Median	2.96	442	4.57
Standard Deviation	0.94	118	1.19
10^{th} Percentile	2.21	369	3.67
90^{th} Percentile	4.59	569	6.33

4.4 Caveats

This model was estimated using a set of plant data for specific years and locations. The spreadsheet is intended to apply to any automobile assembly plant, not just those in the original dataset. In this sense, the model is being used to measure efficiency behavior beyond the original sample dataset. The use of plant-level information that is dramatically different from that used to develop the model may produce unreliable results. Users of the model equations presented above and implemented in the spreadsheet should consider if the plant-level data inputs are within a similar range as those use to estimate the model parameters. In particular, if plant level inputs are beyond the upper or lower deciles of the original data distribution shown in Table 6 (as derived from Tables 1 and 2), then the results should be interpreted with caution. This is especially true if several of the model inputs lie outside of this range.

Table 6 Reasonable Data Ranges Based on Plant Data Included in the Study

	Capacity Utilization (%)	Vehicles (10^3)	Capacity (10^3)	CDD	HDD	Wheel-base (in.)
10th Percentile	69	150	165	766	2,387	103.1
90th Percentile	138	307	253	2,229	5,745	157.5

4.5 Use of the ENERGY STAR Automobile Assembly EPI

After three years of work with the automobile manufacturers, the ENERGY STAR automobile assembly EPI is now complete, as is a spreadsheet tool for calculating EPI scores. EPA intends to use the EPI to motivate improvement in energy use in U.S.-based automobile manufacturing. EPA works closely with the manufacturers, through an ENERGY STAR Industrial Focus on energy efficiency in motor vehicle manufacturing, to promote strategic energy management among the companies in this industry. The automobile assembly EPI is an important tool that enables companies to determine how efficiently each of the plants in the industry is using energy and whether better energy performance could be expected.

EPA recommends that companies use the automobile assembly EPI on a regular basis. At a minimum, it is suggested that corporate energy managers benchmark each automobile assembly plant on an annual basis. A more proactive plan would provide for quarterly use for every plant in a company. EPA suggests that the EPI scoring be used to set energy efficiency improvement goals at both the plant and corporate levels.

The model described in this report is based on the performance of the industry for a specific period of time. One may expect that energy efficiency overall will change as technology and business practices change, so the model will need to be updated. EPA plans to update this model every few years, contingent on newer data being made available by the industry.

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