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

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ABSTRACT

A common distinguishing feature between parametric/statistical models and engineering economics models is that engineering models explicitly represent "best practice" technologies while the parametric/statistical models are typically based on "average practice." The ability to represent best practice is a very desirable modeling feature, but the data requirements for engineering economics models tend to make them difficult to maintain inappropriate for some types of analysis, or simply not readily available. Incorporating a representation of best practice in parametric/statistical models would improve upon the methods commonly used in these types of models and provide a wider range of options for policy modeling. This paper presents two parametric/statistical approaches that can be used to measure best practice and average practice thereby providing a measure of the difference, or "efficiency gap." To assist in choosing an appropriate method, the paper illustrates how these two approaches have their own tradeoffs in terms of data requirements and modeling detail. The first approach is based on aggregate published data and the parametric representation of energy intensity change used by the Long-term Industrial Energy Forecasting (LIEF) model version 2.0. This approach is best described as a parametric calibration. The second approach requires plant level data and applies a stochastic frontier regression analysis to energy intensity used by the ENERGY STAR Industrial Energy Performance Indicator (EPI). Stochastic frontier regression analysis separates the energy intensity into three components, systematic effects, inefficiency, and statistical (random) error. The paper outlines both methods, provides the results for 12 manufacturing sectors in LIEF, and gives examples of the EPI analysis for breweries and motor vehicle manufacturing. Using the aggregate LIEF model approach, the gap in various industries based on 1998 prices is estimated to range from as high as 40% to none (zero). In the EPI developed with the stochastic frontier regression for the auto industry the gap was around 30%.

Introduction

The adjectives "top-down" and "bottom-up" are commonly used to stereotype the general features and approaches used in two "schools" of energy models applied to environmental policy, in particular for greenhouse gas policy analysis. To avoid the debate

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regarding the various assumptions used in these models representing decision making behavior, equilibrium, discount rates, etc., the terms *parametric/statistical* and *engineering economic* are used here. This paper focuses on a specific distinguishing feature between parametric/statistical models and engineering/economic models; that engineering/economic models explicitly represent "best practice" technologies while the parametric/statistical models are typically based on "average practice". The notion of "Best practice" rests on the simultaneous existence and use of multiple "technologies" for a specific application or circumstance that have different levels of performance. When this variety or variation in performance for a specific application or circumstance is not explicit, but represented by a single aggregate, that is called "average practice." Intuitively the differences between average and best practice might be observed in the range of performance of specific appliances in existing homes (e.g. refrigerators) or the plant level performance differences between various facilities in an industry. The definition of best and average practice always rests on the level of investigation. For example, best practice may be identified for a motor, a motor system, or an entire production facility

Since the ability to represent best practice is a very desirable modeling feature, incorporating a representation of best practice in parametric/statistical models would improve upon the methods commonly used in these types of models and provide a wider range of options for policy modeling. Parametric/statistical models measure the variation between observed practices which can exist for a number of reasons, including those based on economic decisions, e.g. energy prices, and those that are structural, e.g. different production processes or energy service requirements. The differences due to economic or structural reasons are not considered the differences between "best" and "average" practice. The differences between "best" and "average" practice are defined for a specific application or circumstance and so observable economic and structural differences must be accounted for in measuring differences between "best" and "average" practice. Unfortunately, the parametric/statistical approach is commonly based on aggregate data, so cross-sectional industry differences or time-series price differences are included in a model but there is no explicit treatment of any remaining difference between "best" and "average" practice.

This paper presents two parametric/statistical approaches that can be used to measure best practice and average practice, thereby providing a measure of the difference, or "efficiency gap." One approach uses the aggregate data and assumes there is an implicit adjustment process between average and best practice. The other approach uses an advanced statistical approach and requires more detailed plant level data.

The first approach is based on aggregate published data and the parametric representation of energy intensity change used by the Long-term Industrial Energy Forecasting (LIEF) model version 2.0. This approach is best described as a parametric calibration, since aggregate data and some assumptions regarding economic adjustments are used. This method is based on the assumption of a partial stock adjustment process, i.e. that the industry moves toward the best practice level of performance. Partial adjustment models are not new in parametric/statistical models. The Koyck lag or the Balestra-Nerlove (BN) partial adjustment models (Balestra and Nerlove 1966) have been widely used in energy demand studies to explain the differences between long and short run demand elasticities. The NEMS industrial model (Energy Information Administration 1994) can be viewed as a variation of the BN partial adjustment model. The LIEF model also uses a partial adjustment framework, but the adjustment can vary over time since it is explicitly interpreted as the penetration of energy efficient technologies.

The second approach requires plant level data and applies a stochastic frontier regression analysis to energy intensity used by the ENERGY STAR Industrial Energy Performance Indicator (EPI). Stochastic frontier regression analysis separates the energy intensity into three components, systematic effects, inefficiency, and statistical (random) error (Aigner, Lovell et al. 1977). This approach is derived from the production efficiency literature, which examines inefficiency in production and can be traced back to (Farrell 1957). (Huntington 1995) provides a review of the production efficiency approach in the context of energy. (Green 1993) reviews the statistical methods applied to estimating parametric frontier models, including the stochastic frontier.

The paper outlines both approaches, presents an empirical example, summarizes the data used and discusses the results. The benefits of each of the two approaches, with a focus on the tradeoffs, are presented in the conclusion.

Long-term Industrial Energy Forecasting (LIEF) model

This section describes the aggregate industry model approach used to estimate the gap between of average and best practice energy intensity. Results are given for 12 industry sectors using the LIEF model.

Approach

The first approach is based on aggregate data derived from published sources and the parametric representation of energy intensity change used by the Long-term Industrial Energy Forecasting (LIEF) model (Ross, Thimmapuran et al. 1993). This approach is best described as a parametric calibration. Using 1990 as a base year in LIEF, the trends in aggregate energy intensity of 12 industry sectors from 1990 to 1998 are examined. An estimate of the gap between average and best practice energy intensity in 1990 can be made which rationalizes the actual 1998 intensity within the LIEF model framework. The LIEF model assumes that the ideal energy intensity is an industry specific function of prices; therefore the gap between average and best practice also varies with prices.

The basic form of the LIEF model is represented by two relationships. The first is a parametric conservation supply curve (CSC) with an exogenous trend that represents the idealized energy intensity in year t, e_t^* (eq. 1). The parameters _ and _ represent the slope of the CSC and the exogenous rate of change, respectively. The best practice energy intensity is computed by the CSC for electricity and fossil fuels based on the market prices and the capital recovery factor.[2]

$$e_t^* = e_0^* \left(\frac{P_{i,t} / CRF_t}{P_{i,0} / CRF_0} \right)^{\square\square} e^{\square t} \qquad (1)$$

[2] The subscript i in the price term denotes the energy type, either fossil fuel or electric. The subscript is suppressed on the realized and idealized energy intensity variables.

The second is the partial adjustment process that represents the movement of the industry average energy intensity, e_t , to approach the best practice energy intensity (eq. 2).

$$e_t = (1 - \alpha) e_{t-1} e^{\lambda} + \alpha e_t^* \qquad (2)$$

The ratio of the average energy intensity e_t to the best practice energy intensity, e_t^*in the base year, for each industry and energy type, is represented by the *Gap* parameter, since e_0^* (the idealized energy intensity in the base year) is not observable.

$$e_0^* = e_0 \left(1 - Gap\right) \qquad (3)$$

In order to update the base year of the LIEF model from version 1.0 to a new base year in version 2.0 it is necessary to reexamine the *Gap* parameter.

Version 2.0 of LIEF uses the same parameters as in LIEF 1.0 to determine what value of *Gap* in 1990 would be consistent with observed energy intensities in 1998. In other words, given a level of penetration of new energy technology and the historical energy price path, what would the *Gap* have to have been in 1990 to be consistent with the observed energy intensities in 1998? Initially the CSC slope and exogenous trend parameters remained the same as in LIEF 1.0, but as is explained below the exogenous trend parameters for electricity had to be adjusted to be more consistent with the trends that become apparent in the eighties and nineties.

The process for benchmarking the *Gap* parameter in LIEF 2.0 is conceptually simple. A penetration rate of 3% was assumed to apply for the period 1990-1998. This rate is similar to the level of capital turnover and has been used for other studies as a typical rate of penetration. Historical energy prices from 1990 to 1998 were used for the CSC, holding the slope of the curve constant. Given the exogenous trends in LIEF a set of *Gap* parameters were computed that were consistent with either the actual change from 1990-1998 or the regression growth rate. Since nearly all of the LIEF sectors had exogenous trends toward *increased* electricity use, the *Gap* parameter that would rationalize a decline in intensity was often unreasonably large. This led to a re-examination of those trends.

Historically, there was an aggregate trend toward increased electricity used from the mid-fifties to the mid-seventies (see figure 1). Even after prices had stopped rising and began to fall in the mid-eighties, aggregate electricity use per $ of GDP was flat. While the shift that occurred in the seventies may be seen as a price response, the asymmetry of the response may be attributed to electric savings technology that has become incorporated into "business as usual." Similar patterns can be seen in individual sectors, so a simplifying assumption that there is no exogenous trend in electric intensity was made.

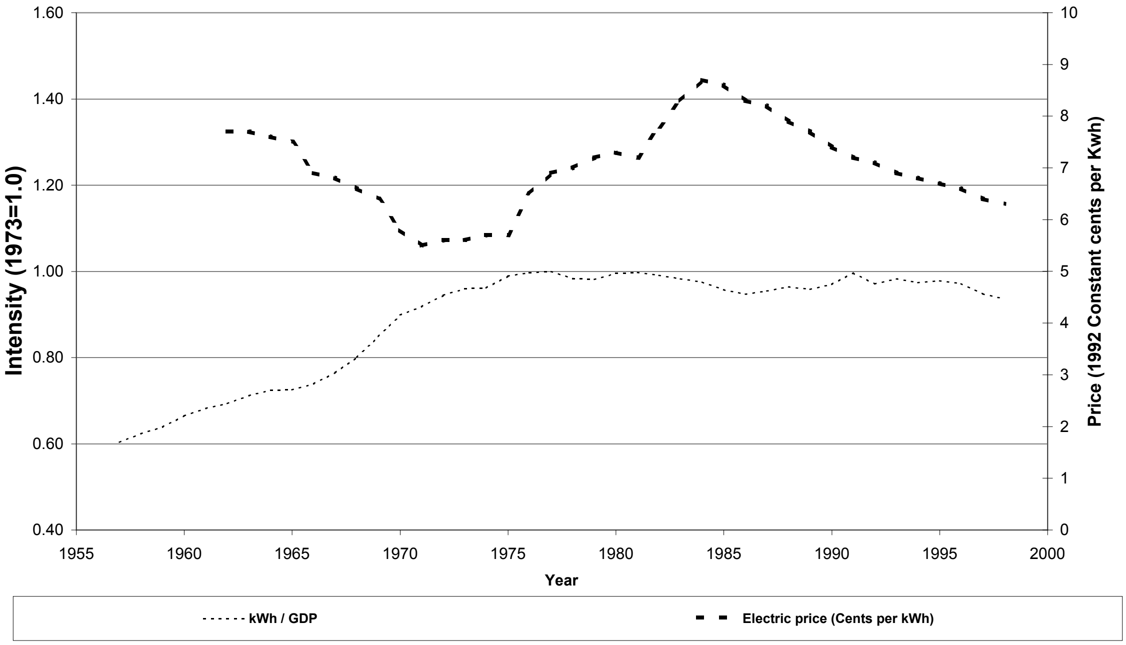
Data

Data for the manufacturing sectors in LIEF (12 of the 18 total sectors) was updated to the year 1998[3]. Table 1 provides the stylized facts of the changes in energy intensity between 1990 and 1998. The data for energy use is based primarily on the Annual survey of Manufacturing (ASM) with supplemental data from the Manufacturing Energy Consumption Survey. The denominator for energy intensity is value added from the Bureau of Labor Statistics (BLS) input output tables. The choice between economic measures of output, e.g.

[3] The dataset is available from the author on request.

value added, and physical measures, e.g. tons of steel, have been a important issue in industrial modeling. The choice of value added as the data in LIEF was made for the sake of consistency and expediency. The issue of physical output measures is reexamined in the next section on the second method for measuring the efficiency gap. The first two rows are the annual average change from the year 1990 to 1998. Although it is the base year of Version 1.0 of LIEF and therefore the base year of the update, 1990 may not be a good benchmark year. In 1990 there was significant economic slowdown. Historically, years with low levels of capacity utilization have higher energy intensity, particularly for energy intensive sectors. To the extent that the year 1990 lies above the long term trend for energy intensity, using the two endpoint years may overstate the change in intensity for that sector. The second two rows give the annual average change based on a simple trend regression from 1986 to 1998[4]. In 1986, energy prices dropped significantly, so this period represents a new period for energy markets, relative to the previous years. For many sectors the regression line provides a more conservative estimate of the changes in energy intensity. What is of particular note is that both the 1990-1998 and the trend line growth rates for electricity all are lower than the historical trends incorporated in LIEF 1.0. In many cases, the sign has reversed from positive to a negative, indicating a reversal in the growth in electric intensity (i.e. electrification) toward energy savings.

Figure 1. Trends in Aggregate Manufacturing Electricity Intensity and Price



Results

Given no exogenous trends in electric intensity in LIEF, the *Ga0* parameter was again computed as described above. This resulted in *Gap* estimates of much more reasonable magnitude. These estimates, which are denoted as *Gap1990* are given in table 2. Many of these estimates are similar in magnitude with those from LIEF version 1.0. The three largest

[4] For a few sectors, a ten year trend was used, due to concerns about the quality of the aggregate time series.

are for electricity in Fast-Growing Manufacturing, and electricity in Petroleum Refining, and Fossil fuel use in Glass. The magnitude of the gap in glass fossil fuel use appears quite high, but may be consistent with the rapid introduction of oxy-fuel furnaces. This sector results bear closer examination. The Petroleum Refining result for electricity is also quite high, but Petroleum Refining is not electric intensive per se. These results may reflect substantial opportunities in the area of motors and pumps. The results for electricity use in Fast-Growing Manufacturing may also reflect these opportunities. Rising trends in energy intensity imply that the *Gap1990* was zero in four sectors; Cement electricity use, Stone and Clay fossil use, Primary Aluminum electricity use, and Non-ferrous fossil fuel use. Computing energy weighted *Gap1990* for the entire manufacturing sector yields 29% for electricity and 13% for fossil fuel use.

Table 1. Trends in Energy Intensity by LIEF Sectors (Annual Average % Change)

	General	Fast-Growing	Pulp & Paper	Organic & Inorganic	Petroleum Refining	Glass	Cement	Stone and Clay	Iron and Steel	Prim. Alum.	Non-ferrous
					1990-1998						
Electric	-0.50	-4.04	0.70	-0.56	-5.95	-1.79	0.19	0.25	-1.06	0.47	0.00
Fossil	-1.49	-2.68	-1.37	3.03	-3.11	-5.54	0.22	-3.02	-0.40	16.42	3.42
					Regression Trend 1986-1998 except as noted						
Electric	0.70	-1.40	-0.45	-1.62	-1.92*	-0.88	0.76	0.16	-0.31	0.59	0.21
Fossil	-0.25	0.11	-0.31	-0.88	-0.27	-2.95*	-0.66	0.12	0.38	-0.05	0.30
					Historically Estimated Exogenous Growth in LIEF						
Electric	2.10	2.70	1.14	1.08	1.44	1.50	1.92	1.56	1.14	0.00	1.08
Fossil	-0.24	-0.42	0.00	-0.36	-0.36	-0.72	-0.18	-0.42	-0.30	0.00	-0.36

* Trend based on 1989-1998 due to data issues.

Table 2. LIEF Version 2.0 *Gap1990* and *Gap1998* Estimates

LIEF Sector Name	LIEF Sector number	Gap1990 Electric	Gap1990 Fossil	Gap1998 Electric	Gap1998 Fossil
General Manufacturing	1	0.250	0.100	0.11	0.05
Fast-Growing Manufacturing	2	0.600	0.030	0.43	-0.09
Pulp and Paper	3	0.225	0.200	0.14	0.12
Organics & Inorganics	5	0.250	0.250	0.17	0.18
Petroleum Refining	6	0.500	0.100	0.41	0.07
Glass	7	0.300	0.800	0.21	0.75
Cement	8	0.000	0.225	-0.04	0.16
Stone and Clay	9	0.050	0.000	0.00	-0.03
Iron and Steel	10	0.300	0.050	0.20	0.03
Primary Aluminum	11	0.000	0.100	-0.02	0.06
Nonferrous	12	0.450	0.000	0.36	-0.03

Since the *Gap* parameter reflect the difference between actual and "best practice" energy intensity in any given year, based on current energy prices, it is natural to ask what the *Gap1998* parameters are. Average industrial energy prices had fallen substantially between 1990 and 1998. The *Gap1998* fall also. In those sectors where *Gap1990* was zero, *Gap1998* is negative. Computing energy weighted *Gap1998* for the entire manufacturing sector yields 18% for electricity and 8% for fossil fuel use. These are based on 1998 energy prices. EIA forecasts fossil fuel prices to quickly return to 1990 levels, but electricity prices are expected to remain low. In a general sense, this price outlook suggests that a typical gap in manufacturing in the next ten years will be in the "mid-teens." However, individual sectors may vary substantially from that average.

Energy Performance Indicator (EPI)

This section describes the plant-level, frontier regression model approach used to estimate the distribution of energy efficiency. Examples are given from the ENERGY STAR energy performance indicator for breweries and motor vehicle assembly.

Approach

The second approach requires plant level data and applies a stochastic frontier regression analysis to energy intensity. Stochastic frontier regression analysis separates the energy intensity into three components, systematic effects, inefficiency, and statistical (random) error. Standard linear regression analysis only includes systematic effects and random error. As in standard regression, the stochastic frontier regression requires that a linear model of systematic effects on energy intensity is specified. Variables in the model could include economic decision variables like energy prices and capital costs, or structural variables like plant size, location, utilization, technology, etc. The stochastic frontier regression analysis assumes there are two types of error terms. The first is the random "noise" error term. The second error term has a one sided distribution and represents inefficiency, i.e. the degree of departure from best practice energy intensity. Various assumptions can be made regarding the distribution of this inefficiency component. It can be distributed as an exponential, truncated normal, or Gamma distribution. The flexibility of the Gamma distribution makes this approach highly desirable, but difficult to estimate. A method of moments (Greene 1995) and a recently developed method of simulated maximum likelihood (SML) makes this approach feasible (Greene September 30, 2000).

The parameters in the stochastic frontier model are typically estimated directly via maximum likelihood techniques.

$$E/Y_i = f(X_i, Z_i; \square) + \square_i$$

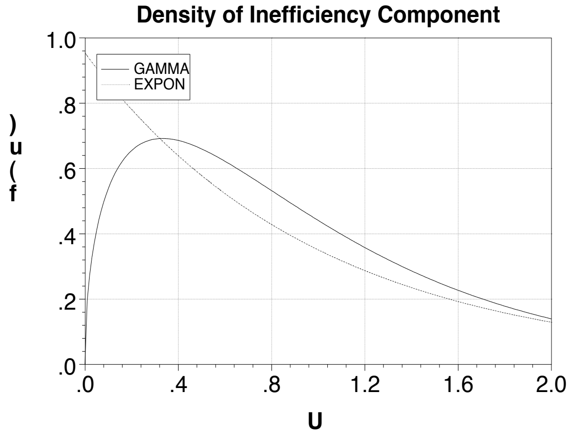
$$\square_i = u_i - v_i$$

Where
E is energy use, either electricity, non-electric energy, or total primary energy,
Y is output, measured by either physical production or as total value of output
(i.e. value of shipments corrected for inventory changes),
X is the vector of systematic economic variables,
Z is the vector of systematic external factors,
_ is the vector of parameters to be estimated,
v is a typical random error term, $v \; \square \; \boxed{\quad}$,
u is distributed according to some one-sided error distribution,
for example gamma, half normal, truncated normal, etc.,
and $\square_{u,v} = 0$.

The flexibility of the Gamma distribution makes this approach highly desirable, but difficult to estimate. The Gamma distribution can generate the exponential distribution as a special case, as well as a more ‘general’ one-sided distributions (see figure 1). There are no maximum likelihood techniques when u is distributed following a gamma distribution, but a consistent moments estimator exists. Conceptually, the regression is shifted so that (nearly) all the residuals are positive and the parameters of the normal error and gamma efficiency distributions are computed from those residuals. The method of moments computes the parameters of the gamma distribution *f(u)* and provides is a consistent adjustment to the linear regression intercept, a, based on the residuals, e_i.

$$
\begin{aligned}
f(u) &= [\theta^P / \Gamma(P)] e^{-\theta u} u^{P-1}, \; u, P, \theta > 0 \\
\hat{\theta} &= -3m_3 / (m_4 - 3m_2^2) \\
\hat{P} &= \hat{\theta}^3 m_3 / 2 \\
\hat{\sigma}_v^2 &= m_2 - \hat{P} / \hat{\theta}^2 \\
\hat{\alpha} &= a + \hat{P} / \hat{\theta} \\
m_r &= (1/N) \sum_i e_i^r
\end{aligned}
$$

Figure 2. Example of Gamma Density



A recently developed method of SML makes substantial improvement on the method of moments, since the parameters of the gamma distribution are simultaneously estimated with the systematic effects, _. We used both the moments estimator and SML[5]. We report examples of both approaches below.

Data

This analysis uses confidential plant level data from two sources; Longitudinal Research Database (LRD) maintained by the Center for Economic Studies (CES), U.S. Bureau of the Census and data provided to Argonne National Laboratory by companies participating in the U.S. Environmental Protection Agency (EPA) ENERGY STAR automobile manufacturing industry focus[6]. The LRD includes the non-public, plant-level data which is the basis of the government published statistics on manufacturing. CES has constructed a panel of plant-level data from the Annual Survey of Manufactures (ASM) and the Census of Manufacturers (CM). The LRD includes economic activity, e.g. labor, energy, plant and equipment, and materials costs and total shipment value of output, for a sample of plants during the survey years and complete coverage during the years of the economic census.[7]

[5] The simulated maximum likelihood has only recently be made operational in the LIMDEP statistical package, so this paper only presents the SML for the auto industry data.
[6] The auto manufacturing industry data is proprietary business information and was provided to ANL under a non-disclosure agreement with the respective companies.
[7] Those are the years ending in ‘2’ or ‘7’, e.g. 1982 or 1997.

Under Title 13 of the U.S. Code this data is confidential, however CES allows academic and government researchers with "Specially Sworn Status" to access these confidential micro-data under its research associate program. The confidentiality restrictions prevent the disclosure of any information that would allow for the identification of a specific plant or firm's activities. Aggregate figures or statistical coefficients that do not reveal the identity of individual establishments or firms can be released publicly. The ability to use plant level data, rather than aggregate data, significantly enhances the information that can be obtained about economic performance, particularly when examining the issue of energy efficiency.

In the examples presented below, the results for breweries, *NAICS code 312120* are based on the Census LRD data and the results for motor vehicle assembly are from *NAICS code 33611, 336112, and 336120,* based on the Census LRD data (see table 3) and also on data provided directly from four manufacturing companies with operations in the United States (see table 4).

Table 3. Sample Means for Brewery EPI
($ and physical units in thousands)

Variable		Sample mean
Number of plants		42
total value of shipments	$	365,689
Production (thousand barrels)		4,408
Fuel costs	$	2,374
Fuel mMBTU (thousand)		618,394
electricity costs	$	3,353
KWH (thousand)		63,576

Table 4. Sample Means for Motor Vehicle Assembly EPI

Variable	Sample mean
Kwh (thousands)	156,641
Fuel use (mMBTU)	1,273,120
Total site energy (mMBTU)	1,783,842
Production (thousands vehicles)	227,615
Capacity (thousands vehicles)	285,751
Heating degree days	4,970
Number of plant years	139

The choice of the variables in the X vector include energy prices, plant scale (measured by output), and other input/output ratios, e.g. capital, materials, labor etc. Since energy consumption may be influenced by climate, as well as production activity, state level data on heating and cooling degree days are included in the energy intensity regressions in the Z vector. This data is matched to the plant location. Plants that manufacture certain energy intensive inputs, rather than purchase them will have a different pattern of efficient energy use. The level of upstream integration in motor vehicle assembly was initially measured by the fraction of material costs for stampings and engines. For breweries, those than manufacture malt from grain were similarly identified by the share of costs.

The data from the four automotive manufacturing companies was provided after a review of the initial results (described below). This data was more limited in scope, but included numbers of vehicle produced, plant capacity, electricity and non-electric energy consumption. Plants with upstream parts operations, e.g. stamping and engines, had the energy use for those parts of the plant subtracted from the plant total. In principle, this allows a more direct comparison of energy use in assembly plants[8].

Results

Initial model results for energy intensity equations for both sectors and two forms of energy, electricity and non-electric energy, principally purchased fossil fuels, were cleared by Census for public review. The functional form was a generalized quadratic linear model. Cross-product and squared terms were evaluated, but were rarely significant.

To assist the review a spreadsheet was constructed to display the gamma density and distribution functions for the parameters that were estimated, evaluated at user selected values of the X and Z vectors. This aided in comparing the magnitude of the systematic effects (changes in X and Z) with the gamma efficiency distribution by graphically displaying the results. The spreadsheet was provided to energy managers from companies in the brewery and auto assembly sectors. Examples of the spreadsheets are shown in figures 3 and 4 for the brewery and auto assembly sectors, respectively, with data based on the sample means. The energy managers were allowed to input data for their own plants and then provide comments.

During the review process the point was made shipment value of production might not be an appropriate measure of output. This question of whether to use physical units (tons, barrels, etc) instead of economic units (total value of production, value added, etc.) has been well studied in analysis of energy intensive industries (Freeman, Niefer et al. 1997). In particular the use of physical units are useful of international comparisons (Battles 1996) because of difficulties over exchange rates or purchasing power parity. In the case of breweries and motor vehicles the issue is that product pricing in these industries reflect a number of market characteristics, including oligopoly-pricing, rebates, cross-subsidization etc. such that value of production might not be a good indicator of energy intensity. For breweries we constructed a physical measure of production, gallons of malt beverages, using detailed Census product code data which reports shipments identified by packaging type (cans, bottles, etc) and size. We compared this estimate (5.7 billion gallons) to the total industry gallons of production published by the Bureau of Alcohol, Tobacco, and Firearms (6.2 billion) and determined that it was consistent[9]. For automobile manufacture, the participating companies provided plant level production and energy data.

The re-estimated models illustrate the difference that this price variation makes in the estimates of the efficiency distribution. Figure 5 shows a near exponential distribution for the electricity output ratio when production is measured in barrels. A similar figure 6 shows a near exponential distribution for the total site energy per vehicle. The results from the auto assembly analysis are discussed in more detail.

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[8] For the purposes of this paper "assembly" encompasses painting, body weld, and the final assembly process.

[9] We include only large breweries in our analysis. Small breweries produced 9% of the total value of output in 1997, which is consistent with the differences in physical volume that we estimated.

Figure 3. Breweries Model Spreadsheet

Plant Energy Performance Indicator

05/15/2002

Plant Characteristics

SIC Code: 2082 (Malt Beverages)

5-digit Zip Code: 10101

General Location: New York, NY

Cooling Degree Days	Heating Degree Days
1096	4805

Operating Characteristics

			Material Cost Share
Total Value of Plant Output ($):	$370,000,000	A	
Total Annual Material Cost ($):	$150,000,000	B	
Malt Annual Material Cost ($):	$18,000,000	C	12.00%
Non-malted Grain Annual Material Cost ($):	$1,500,000	D	1.00%

Annual Energy Consumption

		Electricity	Gas	Distillate Oil	Residual Oil	Coal
	Select Units	kWH	mMBtu	mMBtu	Gallons	Short Tons
E	Annual Consumption	63,000,000	600,000			
F	Annual Cost	3,000,000	2,500,000			
	Unit Cost ($/unit)	0.048	4.17			

Results

	Average Plant	Efficient Plant	Your Plant	
Energy Performance Indicator (Electricity)	50	75	54	(1 to 100)
Energy Performance Indicator (non-Elec Fuels)	50	75	48	(1 to 100)
Annual Energy Cost ($/year)	$5,519,083	$4,445,252	$5,500,000	
Electric Output Ratio (kWh/$ product)	0.1766	0.1476	0.1727	(see Table-1)
Fossil Fuel Output Ratio (mMBtu/$1000 product)	1.6120	1.2370	1.6446	(see Table-2)
Total Site Energy (mMBtu/year)	807,957	635,051	814,956	
CO_2 Emissions Equivalent (Lbs/year)	164,363,898	132,384,139	163,795,596	

Table-1 (Electricity)

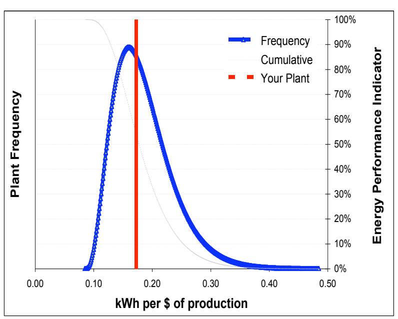


Table-2 (non-Electric Fuels)

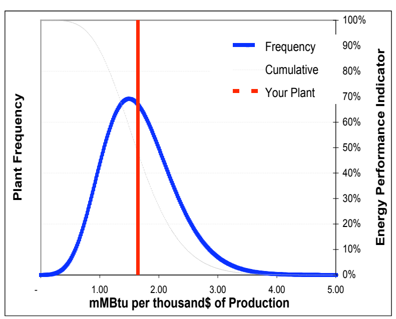


Figure 4 Motor Vehicle Assembly Model Spreadsheet

Plant Energy Performance Indicator

05/20/2002

Plant Characteristics

SIC Code: 3711 (MOTOR VEHICLE ASSEMBLY)

5-digit Zip Code: 10101

General Location: New York, NY

Cooling Degree Days	Heating Degree Days
1096	4805

Operating Characteristics

			Material Cost Share
Total Value of Plant Output ($):	$3,000,000,000	A	
Total Annual Material Cost ($):	$2,000,000,000	B	
Automotive Stamping Annual Material Cost ($):	$180,000,000	C	9.00%
Gas Engines & Parts Annual Material Cost ($):	$300,000,000	D	15.00%
Painting Annual Material Cost ($):	$20,000,000	E	1.00%
Drive Train & Parts Annual Material Cost ($):	$250,000,000	F	12.50%

Annual Energy Consumption

		Electricity	Gas	Distillate Oil	Residual Oil	Coal
	Select Units	kWH	mMBtu	Gallons	Gallons	Short Tons
G	Annual Consumption	162,715,141	1,028,690			
H	Annual Cost	8,034,483	4,047,090			
	Unit Cost	0.0494	3.93			

Results

	Average Plant	Efficient Plant	Your Plant	
Energy Performance Indicator (Electricity)	50	75	66	(1 to 100)
Energy Performance Indicator (non-Elec Fuels)	50	75	74	(1 to 100)
Annual Energy Cost ($/year)	$14,210,225	$11,087,757	$12,081,573	
Electric Output Ratio (kWh/$ product)	0.065	0.049	0.055	(see Table-1)
Fossil Fuel Output Ratio (mMBtu/ $1,000 product)	0.41	0.34	0.35	(see Table-2)
Total Site Energy, All Fuels (mMBtu/year)	1,406,638	1,159,645	1,028,690	
Estimated CO_2 Emissions (Tons/year)	213,558	166,632	181,568	

Table-1 (Electricity)

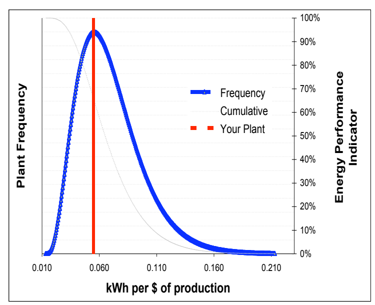


Table-2 (Fossil Fuels)

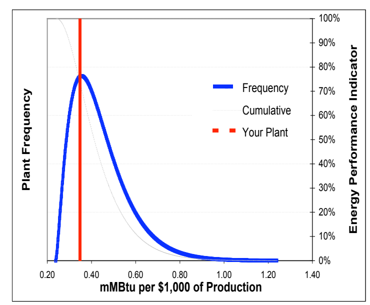


Figure 5. Efficiency Distribution for Electricity per Barrel

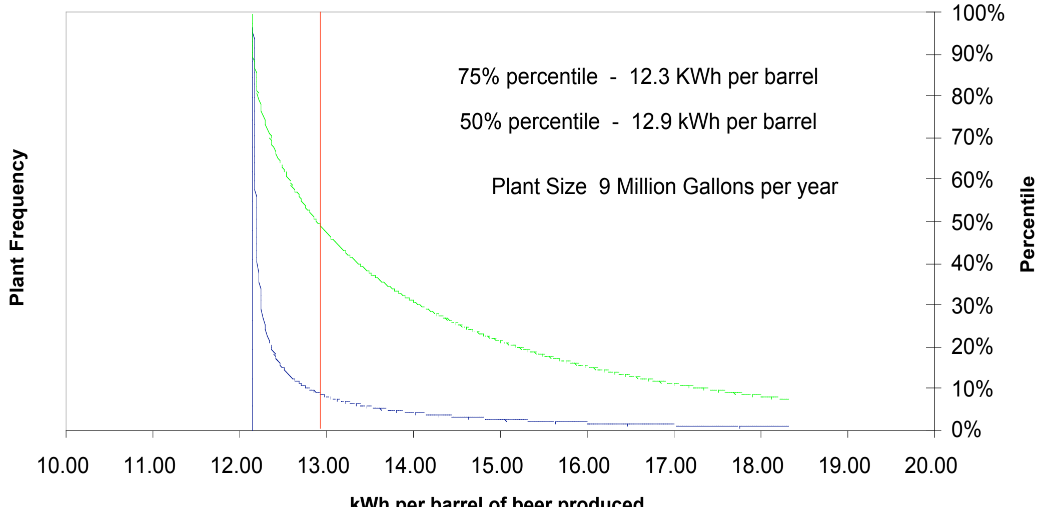
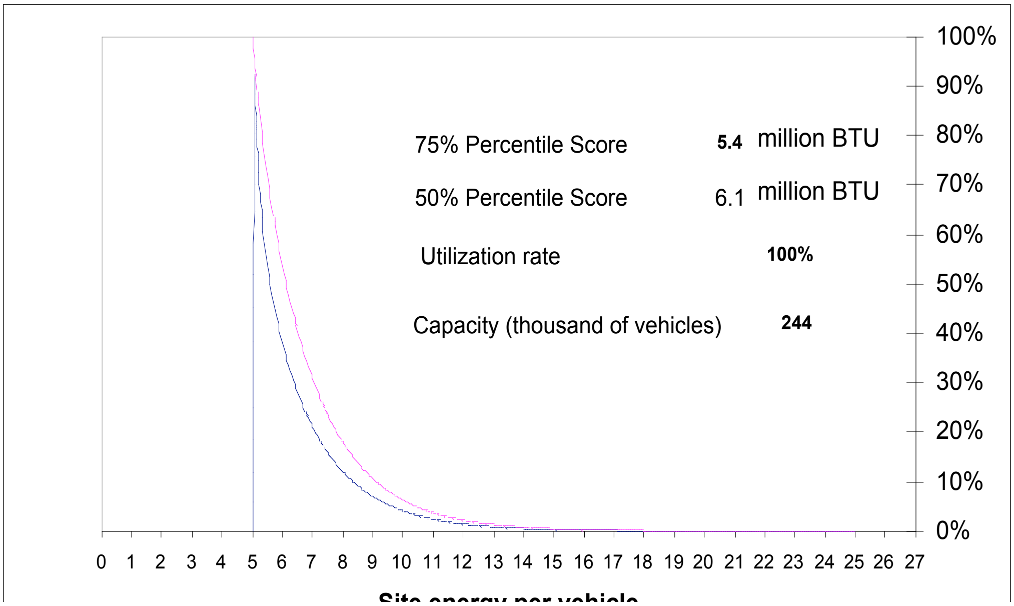


Figure 6. Efficiency Distributions for Total Site Energy per Vehicle



The final EPI model for motor vehicle assembly was based on 139 plant years of data from four motor vehicle manufacturing companies with assembly plants in the U.S. All four of the companies provided data for each of their plants in operation in the U.S. Two companies provided data for each plant for 4 years (1997-2000), while the other two companies provided data for three years (1999-2001). A more balance panel would have been desirable. The final model estimated was

$$E/Y_i = A + \beta_1 \ln cap + \beta_2 Util + \beta_3 Util^2 + \beta_4 HDD + \beta_5 TRCVAN + u_i - v_i$$

Where

E = total site energy use in mMBTU (1 kwh=3412BTU)

Y = number of vehicles produced

LNCAP = natural log of capacity
UTIL = plant utilization rate, defined as output/capacity
$UTIL^2$ = the square of utilization
HDD = heating degree days for the state and year
TRCKVAN = dummy variable that indicates if the plant primary product is a truck, SUV, or van
_ is the vector of parameters to be estimated, v ~ N(0, $\__v^2$), and u ~ _(_, P).

Capacity was included to capture plant scale effects while Plant utilization rates were included to capture the quasi-fixed relationship between energy-capital equipment and production throughput. We did not expect these effects to be linear, so we tested specification that included the natural log and a linear second order term. Using the natural log of capacity and the quadratic in utilization produced the best model fit. The final parameter estimates are presented below. All variables are significant at the 5% level or less, except those noted with *, which are significant at 10% level. The signs of all variables are as expected. The sign of the LNCAP indicated that larger plants have lower best practice energy use. The sign of HDD and TRCKVAN indicate that a plant in colder climates and those producing other than passenger cars have higher best practice energy use. The mean of the TRCKVAN variable indicates that 60% of the plant years in the dataset were for non-passenger car plants. The best practice for plants producing trucks, vans, and SUVs would be 1.5 mMBTU per vehicle higher than for passenger cars.

Table 5. Model Results for Motor Vehicle Assembly EPI

Variable	Coefficient	t-ratio	Sample mean
Constant	33.25	6.06	
LNCAP	-2.08	-2.11	5.31
UTIL	-24.88	-8.83	1.08
UTIL_2	6.86	7.69	1.31
HDD	3.13E-04	1.79*	4954
TRCKVAN	1.46	3.28	0.60
_	0.326	2.95	
P	0.945	1.71*	
$\__v$	1.347	4.32	

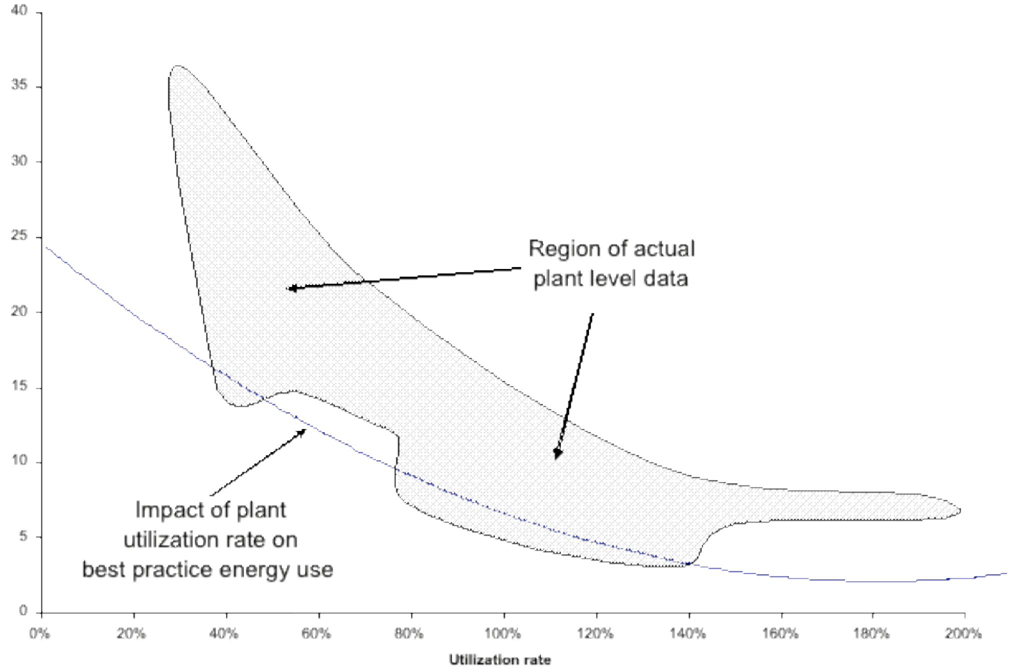
* significant at 10% level
All other variable significant at the 5% level or less

The impact of utilization rates is best illustrated graphically (see figure 7). Since capacity is defined as two shifts, greater than 100% utilization is possible. Best practice declines at a declining rate until the plant is at three shifts (150%), where the impact on the best practice energy use is negligible.

SUMMARY

This paper presents two approaches that allow the notion of best practice to be incorporated into a parametric model of sector energy demand. Although the objectives of these methods are the same, obtaining an estimate of the energy efficiency gap, the actual implementation is quite different. The choice between these two methods is dependent on the types of data available to the modeler.

Figure 7. Impact of Utilization on Best Practice Total Site Energy per Vehicle



The first method, employed by the LIEF model relies on a pre-specified adjustment process and can be applied to aggregate data. It shares common features with other stock adjustment econometric models, but is formulated to be comparable to conservation supply curves derived from engineering economic approaches. The principle strength of this approach is its relative simplicity and the ability to use aggregate time series data to derived the parameters. The model can be readily updated to newer published data. Its transparency makes it a useful tool for scenario and policy modeling. However, like some general equilibrium models which also have parameters that are obtained by calibration, rather than statistical estimation, it is not possible to place confidence intervals on the LIEF model results or to conduct standard statistical tests of significance. The principle tradeoff in using this method is ease of use versus statistical properties.

The second method, employed by the ENERGY STAR Industrial EPI, is much more general but also has much higher data requirements. This method is quite flexible. Any type of functional form for the systematic relationships and a wide range of statistical distributions for the efficiency gap can be used. In the example shown a mixture of log, linear, and quadratic terms are used for the systematic relationships. The relatively flexible gamma distribution is used to represent efficiency, but other statistical distributions are commonly used. Since this method is derived from the frontier production literature, it is a natural place to begin the investigation between productivity in general and energy efficiency specifically. However, the method is only applicable to cross section data, preferably at the plant or unit process level. The availability of confidential plant-level data at the Census Bureau and from proprietary data made available to Argonne National Laboratory under non-disclosure agreements has made this approach feasible. Obtaining access to such confidential data can be very time consuming. The process to obtain access approval to plant level data at the Census is very rigorous. Even after approval is obtained, Census data can only be accessed at a limited number of secure research data centers. For researchers who are willing to clear these hurdles, there are benefits to this approach in terms of statistical rigor and model detail.

Regardless of the data and the choice between these methods, this paper illustrates the parametric/statistical models need not be based solely concepts of average practice. Parametric/statistical models can be used to represent notions of best practice technologies and estimate the efficiency gap. As the parametric/statistical methods presented in this paper are put into more widespread use, the "Gap" between parametric/statistical and engineering economics models may narrow as well.

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