Modelling and analysis of energy footprint of manufacturing systems

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1. Introduction

Many operational decisions impact the energy footprints of discrete manufacturing firms. Since energy footprints are closely connected to energy costs and environmental consequences, these operational decisions can have long-lasting effects. Hence, making informed decisions with the aid of energy evaluation tools is important to manufacturing firms. Evaluating energy footprints in manufacturing is not, however, straightforward. A plant-level energy footprint requires machine-level energy analysis, and machine-level energy use has to be investigated with product-level considerations. Thus, we need to explore and improve approaches for analysing manufacturing energy use on different levels.

A broad review of manufacturing energy analysis and sustainable manufacturing is provided in Garetti and Taisch (2012). This study establishes a comprehensive framework for green manufacturing and sustainability. In Gungor and Gupta (1999), a number of environmentally conscious manufacturing studies are surveyed, and methods for connecting product design and manufacturing processes are discussed, with a focus on sustainable manufacturing.

At the product level, life cycle assessment (LCA) has been a major component of energy evaluation (Rebitzer et al. 2004; Pennington et al. 2004; Finnveden et al. 2009). Since LCA takes account of a broad range of environmental effects for each type of product or service, it can be used as a basis for product-level energy analysis. Detailed product-level data may not, however, be available at early stages of planning a new product; so, LCA techniques may be less useful to future manufacturing plants.

Various studies have been conducted on machine-level energy analysis. For instance, Gutowski et al. (2009) show that manufacturing energy is related to the types of materials and processes, and propose that machine power is a function of a material processing rate. Diaz, Redelsheimer, and Dornfeld (2011) estimate the relationships between power consumption and material removal rates (MRR) to be quadratic or linear in experiments with a milling machine. Since conventional methods provide only approximated energy requirements for processing materials (Kalpakjian and Schmid 2001), considering machine power with MRR could help to build a more accurate machine power model.

At the component or subsystem level of a machine, Dietmair and Verl (2009) perform power measurement experiments, in which machine states are defined with subcomponents. Frigerio et al. (2013) extend the machine states with functional modules, and we can use some of the machine states for a specific case. Based on these micro-level energy investigations in machines, other researchers build energy models at a higher level. Johansson et al. (2009) apply

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discrete event simulation for estimating the manufacturing energy of a production line, and Liu et al. (2012) look into the standby mode of six different machines to save manufacturing energy. Devoldere et al. (2007) show the potential of saving discrete manufacturing energy when machine idle time is considered.

Ideas in these models, combined with those of Dahmus and Gutowski (2004), provide theoretical grounds for the factory energy simulation model presented by Prabhu, Jeon, and Taisch (2013). Prabhu, Jeon, and Taisch (2012) also extend the simulation model to the analytical queueing energy model. Apart from aspects of plant- or machine-level energy, Boyd, Dutrow, and Tunnessen (2008) apply stochastic frontier analysis (SFA) to evaluate the energy efficiency of cross-sectional auto industry data. The SFA model could be extended to general manufacturing plants.

Based on these previous studies, the present paper proposes energy evaluation methods and models for manufacturing plants. The proposed evaluation approach consists of modelling at four different levels, where models at one level are closely connected to parameters in other adjacent levels. We begin by parameterising product-level elements. A process plan with these elements is then used as input data for machine-level models, in which machine states, processing power and processing times (PT) are modelled. Using simulation experiments based on machine-level models, the analysis at the plant level identifies significant factors in energy footprints and provides the manufacturing energy equations in terms of factors for managerial decisions. Industry-level evaluation assesses the simulated plant-level footprints and provides energy efficiency percentile rankings of the simulated plant. A case study shows how the suggested approach can be applied for evaluating the energy footprints of discrete manufacturing plants.

The rest of this paper is organised as follows. Section 2 presents general energy evaluation methods and models for the analysis of the four levels. We show the case study with detailed proposed procedures for specific products in Section 3, and Section 4 presents conclusions and outlines future work.

2. Modelling and evaluating manufacturing energy

In this section, we show how product, machine, plant and industry levels are connected for energy footprint evaluation, and Figure 1 illustrates the summarised approach. More details about the models and methods of this section are introduced in Section 3 with a specific example.

2.1 *Parameterisation at the product level*

While LCA has served as grounds for product-level energy analysis, the required specific LCA data are not always available at early stages of manufacturing. Furthermore, the cost of analysing new products with LCA techniques can

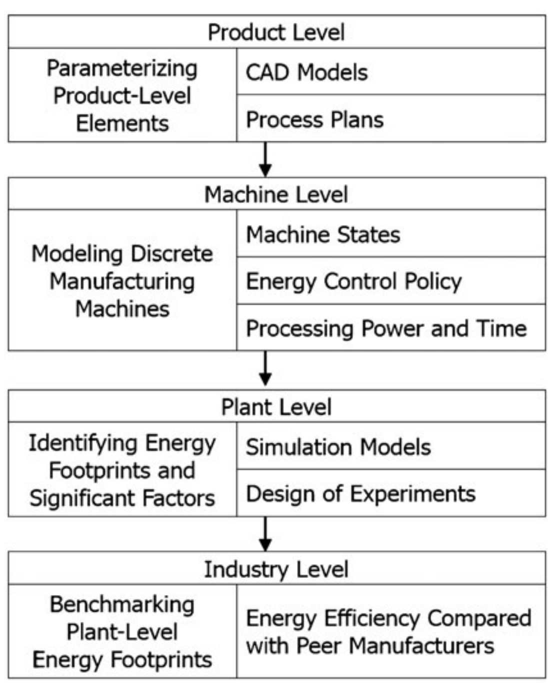

Figure 1. Approach for evaluating energy footprints.

be high, and an early analysis might not be updated to reflect subsequent managerial decisions. Thus, we consider a different approach to parameterise product-level energy factors based on CAD models of products. Using this approach, manufacturers can extract key energy parameters from a product design, and a brief process plan can be prepared. The parameters in the process plan are then connected to machine-level analysis. For instance, required manufacturing processes and machine types are parameterised at the product level for machine-level energy analysis.

2.2 *Models at the machine level*

Since a machine in use is always in one of several states, each of which has a specific power and time period, machine-level energy can be written as

$$\begin{gathered}\text{Energy} = \sum_{i=1}^{N} \text{Power}_i \times \text{Time}_i \\ \text{where } i = \text{index of machine states}\end{gathered} \tag{1}$$

Thus, machine-level energy can be modelled by identifying significant machine states at the machine level. After defining machine states, we assign adequate machine-level energy control policies to the defined states. For instance, an energy control policy to turn off idle machines can be considered.

Processing power and time of each state in (1) are modelled by following the process plan written at the product level. In general, processing power can be modelled as a function of a material processing rate, and the parameters of the function are determined by raw material, required process and machine type, all of which are available in the process plan. This general modelling of power and time is, however, able to include only two machine states, processing and idling. In order to build a more accurate model of machine states, we need to extend the general processing power and time model.

2.3 *Analysis at the plant level*

Using previously defined parameters, we run simulation experiments to see which factors have the significant impact on plant-level energy footprints. Since the parameters of product and machine levels are closely connected to simulation factors, we can check dynamics on energy footprints at product-, machine- and plant-level factors. In running the simulation, we use the design of experiments (DOE) technique. For instance, if we have N different factors to check, we can use 2^N full factorial design with 2^N treatment combinations. After ANOVA is performed, the manufacturing energy footprints can be written in regression equations of managerial factors for decisions. In analysing plant-level energy consumption, we assume that the manufacturing energy needs are mainly driven by production lines. The energy consumption of production-supporting equipment such as HVAC is considered in the industry-level analysis.

2.4 *Evaluation at the industry level*

The simulated energy footprints in 2.3 can be analysed as the total energy consumption or energy consumption per product (EPP) unit. This evaluation of a given plant may provide more insight, however, if it is considered from the perspective of a manufacturing industry. For this evaluation method, we propose two different energy efficiency criteria.

We introduce a criterion based on fitting probability distributions first. The approach is straightforward. We assume that plants in the same industry segment are producing the same or similar products. Then, for all cross-sectional plant data in which energy consumption and total number of products are available, EPP is calculated. EPP values are fitted to a well-known probability distribution. After checking the goodness-of-fit, we write the fitted cumulative distribution function (cdf) F by integrating the probability density function f as in (2).

$$\begin{gathered}F(\text{EPP}) = \int_{0}^{\text{EPP}} f(x)dx \\ \text{where EPP} \geq 0\end{gathered} \tag{2}$$

Using (2), we define the energy efficiency criterion (EEC_1) as

$$\begin{gathered}\text{EEC}_1(\text{EPP}_i) = 1 - F(\text{EPP}_i) = P(\text{EPP}_i < \text{EPP of peers}) \\ \text{where EPP}_i = \text{EPP of plant } i\end{gathered} \tag{3}$$

When EPP_i is plugged into (3), EEC_1 returns the probability that other peer manufacturers would spend more energy in producing the same product. Hence, we can use $EEC_1(EPP_i)$ as the percentile rank of the energy efficiency of plant i.

The other energy efficiency criterion involves the energy inefficiency component u_i of the SFA. In SFA, E_i (energy consumption of plant i) is regarded as a function of various independent variables X_j (j = 1, 2, …, m). These independent variables include economic plant inputs such as annual production and the number of employees, as well as other energy-related variables such as weather. Then, with E_i and X_j, we build a regression model using the maximum likelihood estimation (MLE) as

$$E_i = \sum_{j=1}^{m} \beta_j X_j + \epsilon_i, i = 1, 2, \ldots, N \tag{4}$$

$$\epsilon_i = u_i + v_i \tag{5}$$

Thus, for plant i, we have a random error term ϵ_i, which would have been distributed as $N(0, \sigma_\epsilon^2)$ in the ordinary least square (OLS) regression. However, in SFA, we assume that ϵ_i is asymmetrically distributed and consists of two random parts as in (5), where u_i is an energy inefficiency component following a one-sided distribution $(u_i \geq 0)$, and v_i is a random noise component following $N(0, \sigma_v^2)$. In other words, when the MLE algorithm tries to maximise the log-likelihood function of ϵ_i, the algorithm estimates β_j and parameters of u_i and v_i in (4) and (5) all together. Then, using distribution functions and estimated parameters, we can separate u_i from ϵ_i for all plants i as in

$$u_i = E_i - \sum_{j=1}^{m} \beta_j X_j - v_i \tag{6}$$

In (6), since $\left(E_i - \sum_{j=1}^{m} \beta_j X_j\right)$ is the distance between actual energy consumption (E_i) and estimated energy consumption in the plant $\left(\sum_{j=1}^{m} \beta_j X_j\right)$, we can understand u_i as the energy inefficiency combined with a random noise factor v_i. Thus, the other energy efficiency criterion EEC_2 can be defined for plant i as in (7).

$$\begin{gathered} EEC_2(u_i) = 1 - F(u_i) \\ \text{where } F \text{ is cdf of } u_i \end{gathered} \tag{7}$$

The insight of EEC_2 is similar to EEC_1 in that if u_i is applied into (7), $EEC_2(u_i)$ gives the probability that other peer manufacturers would consume more energy, based on input variables X_j. Likewise, we can use $EEC_2(u_i)$ as the percentile rank of energy efficiency of plant i. Greene (1990) and Kumbhakar and Lovell (2003) provide more technical details on SFA.

3. Simulation experiments

In order to demonstrate how proposed models in Section 2 are implemented for manufacturing energy analysis, we conduct a case study with IME Inc., a hypothetical manufacturing firm. In this case study, we estimate the firm's energy footprints first, and then compare its energy efficiency with those of peers in the same industry segment. For products to manufacture, we use six machined chess pieces, designed by Penn State students as a part of their coursework (Pennsylvania State University).

3.1 *Energy footprints estimating*

In this subsection, we show how energy footprints can be estimated using the approaches of Subsections 2.1–2.3. Thus, in each of the product, machine and plant levels, parameters are extracted and models are built based on the parameters.

For parameterisation at the product level, we first prepare process plans of final products, using CAD models. For example, we make the process plan of the rook pieces in Table 1 based on the CAD model in Figure 2.

In preparing process plans, we assign a lathe (L) to cut a cylindrical or torus shape and milling machine (M) to cut other shapes. For instance, (L1) in Figure 2 requires the removal of a partial torus shape and therefore, we assign a lathe. Then, as in Table 1, the volume to remove (VTR) for each process is computed based on the CAD model, and we write MRRs of interest together. Computing (VTR/MRR), we estimate the PT of each cut in Table 1. Following the same procedures, we create process plans for the other five pieces.

Table 1. Process plan for rook.

Process name	Process description	Machine type	VTR (mm^3)	PT (seconds) MRR = 44,245 (mm^3/min)	PT (seconds) MRR = 27,858 (mm^3/min)
Raw material = low carbon steel cylinder of radius 16.00 mm					
L1	Partial torus	Lathe	942.19	1.28	2.03
L2	Outer cylinder of obelisk	Lathe	17032.84	23.10	36.68
M1	Part of obelisk (hexahedron)	Milling	6869.54	9.32	14.80
M2	Top of obelisk (pyramid)	Milling	748.92	1.02	1.61

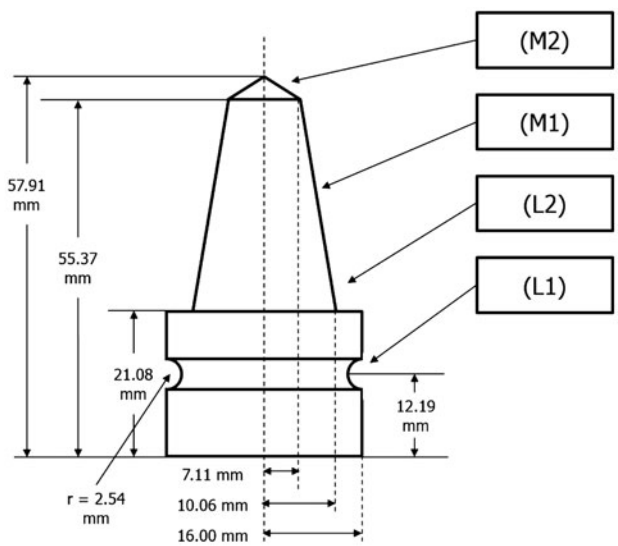

Figure 2. CAD model of rook.

For power models at the machine level, we define three machine states and two machine-level energy control policies for the firm (Prabhu, Jeon, and Taisch 2013), as follows. The P state indicates the general processing state of a machine; a machine making cuts on materials is in this state. The nominal power idling state (N) is used for a typical idle period; after finishing one part, a machine stays in this state before working on new parts. The low power idling state (L) is the other idle state. It consumes less energy than the N state, but it is defined only under the active energy control policy EC_1. If an idle period is longer than the time threshold τ, a machine is assumed to stay in the L state for the idle period. An idle period shorter than τ is considered in the N state. The idle states L and N are roughly analogous to the power saving and idle modes in mobile devices.

The first energy control policy EC_0 does not consider any machine-level energy control. Since a machine is either working or idling with this policy, only the P and N states are defined under EC_0. The other energy control policy, EC_1, allows machines to enter the L state if idle periods are longer than τ. Thus, the P, N and L states are defined under EC_1. Figure 3 illustrates how the P, N and L states are defined under EC_0 and EC_1.

Applying the introduced machine states and energy control policies, however, requires machine-specific considerations. In this case study, our fictional IME Inc. is assumed to use Haas VF3 for milling machines and Haas SL30 for lathes, both of which have the auto power saving mode, which turns off idle machines after the predefined time duration of inactivity. Thus, we redefine the N state as in being idle and the L state as in being turned off, assuming that the mode is on in all machines.

While we can save energy by turning idle machines off, turned-off machines require time to start-up. Thus, τ for EC_1 can be determined as the starting-up time of VF3 and SL30, since production delay is assumed by EC_1 to not be allowed. In order to investigate the starting-up time and other power parameters of the two CNC machines, we conduct power measurement experiments with VF3 and SL30 cutting low carbon steel parts. In these experiments, machine power is assumed to be a function of MRR, and the pairwise data of MRR and average power are collected. Based on

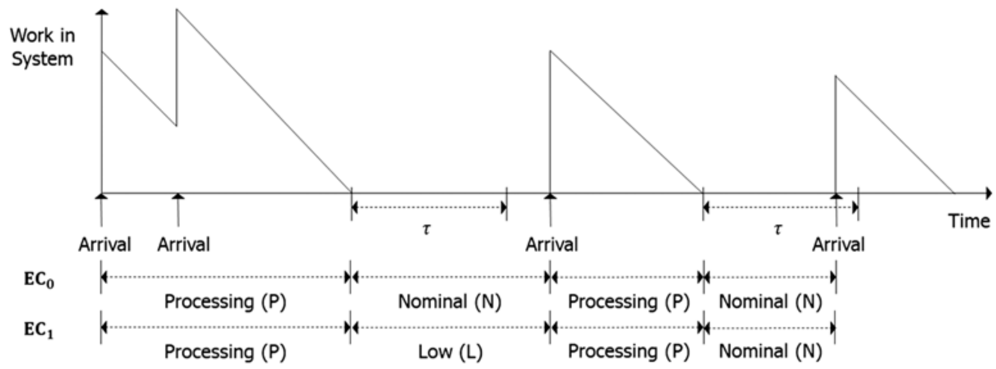

Figure 3. Machine states and energy control policies.

the collected experimental data, linear regression models are built as in (8) and (9) with R^2 98.2% (VF3) and 93.7% (SL30). We plot the data and estimated equations in Figure 4.

$$W_{\text{milling(VF3)}} = 2005 + 4.76 \times 10^{-2} \times \text{MRR} \tag{8}$$

$$W_{\text{lathe(SL30)}} = 2603 + 3.06 \times 10^{-2} \times \text{MRR} \tag{9}$$

We then specify W_P, W_N and W_L (power levels of the defined machine states) as follows. Given MRR during the P state, W_P is computed from (8) and (9). For W_N, 625 W (VF3) and 808 W (SL30) are measured, and 0 W is assumed for W_L. VF3 and SL30 take 0.5 min to start-up, and average power during start-up is measured to be less than W_N in both machines (262 W for VF3 and 526 W for SL30). This suggests that the proposed energy control policies are economically well grounded and, therefore, τ is set as 0.5 min.

For plant-level simulation, we use the hybrid simulator for production, energy and emission dynamics (HySPEED) (Prabhu, Jeon, and Taisch 2013). Since HySPEED can simulate the energy consumption of a discrete manufacturing system with various production parameters, this is a suitable choice for this analysis. Important factors that can vary in HySPEED are as follows: number of machines in a production line, mean interarrival time (IAT) of raw materials to a system, mean machine PT, machine utilisation (PT/IAT), power consumption levels of machine states, energy control policies, τ, start-up energy and probability distribution for random IAT and PT.

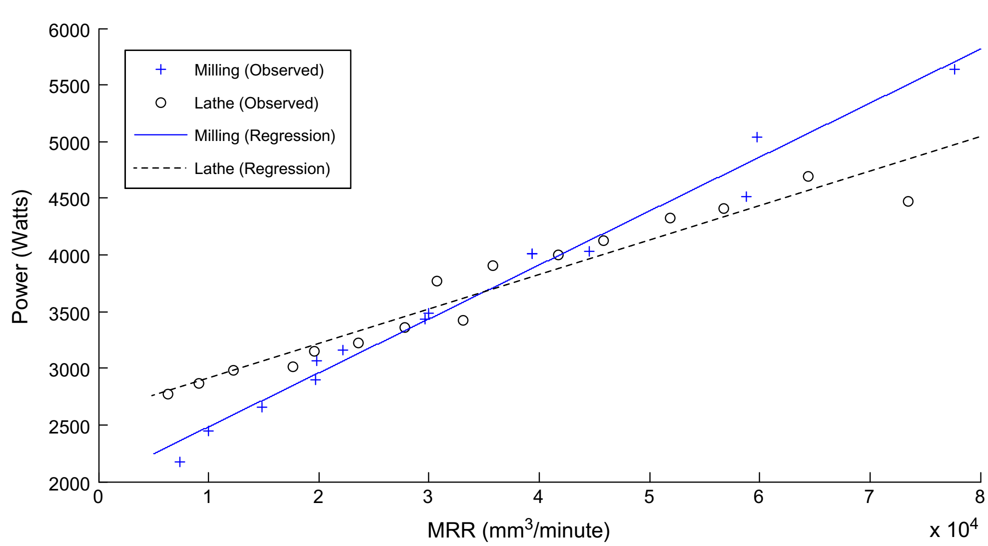

Figure 4. Milling and lathe machine power with MRRs.

In the plant-level analysis, we use the DOE method in the 2^5 full factorial design in order to identify the significant factors on energy consumption. For five factors to vary, we consider material route, market demand, product quality, size and energy control policy (EC). For six chess pieces, we assume independent production lines. Then, the material route is considered to be milling machines only (−1) or milling and lathe machines together (+1), as in the planned process. Market demand (machine utilisation) controls IATs of each production line. Thus, we control the utilisation of the busiest machine in each line with this factor, since PTs are already determined in process plans. We also consider product quality (MRR) as a factor, since a high MRR has a negative impact on product quality, while it increases the number of products. This factor also governs W_P based on (8) and (9). Product volume (size) is a factor that changes the product size. (−1) is used for the same size as CAD models, and (+1) for 120% of CAD models. EC decides between EC_0 and EC_1 policies. The raw material is assumed to be a low carbon steel cylinder with the necessary height for each piece. IAT and PT are assumed to be normally distributed. We consider two responses: Y_1 = the total energy spent (kJ) and Y_2 = energy spent per product (kJ/piece). Level of significance α is 0.05 in DOE analysis. DOE factors with levels are summarised in Table 2.

After all 32 runs are simulated, we apply the natural log transformation to Y_1 and Y_2 in order to cope with the violation of the normality assumption of the residuals. Then, we have two half-normal plots of effects for $\ln Y_1$ and $\ln Y_2$ in Figure 5. Among five main factors and higher order interactions, we build regression models only with terms that have the absolute effect > 0.05, since other terms contribute less to the responses. The resulting regression models are provided in Table 3.

From Table 3, we can identify significant factors, and this result can be interpreted as follows. When VF3 and SL30 are used together (route = +1), both Y_1 and Y_2 increase, since the starting-up power and W_N of SL30 are greater than those of VF3. With higher market demand (+1), Y_1 is increased (more products), but Y_2 is decreased (less wasted energy during the N state). For higher quality (+1), Y_1 is decreased, since the number of products is decreased (low MRR), while Y_2 is increased, since more energy is consumed for each product. To make a larger size of products (size = +1), more energy is consumed for each product, but Y_1 is not closely related to the product size. Obviously

Table 2. DOE factors with levels.

Factors and Levels	(−1)	(+1)
Material route	Only milling (VF3)	Milling and lathe (VF3 and SL30)
Market demand	Machine utilisation = 0.3	Machine utilisation = 0.7
Quality (MRR)	$44,245 \text{mm}^3/\text{min}$ (low quality)	$27,858 \text{mm}^3/\text{min}$ (high quality)
Size (product volume)	Regular (100%)	Large (120%)
Energy control policy	EC_0	EC_1

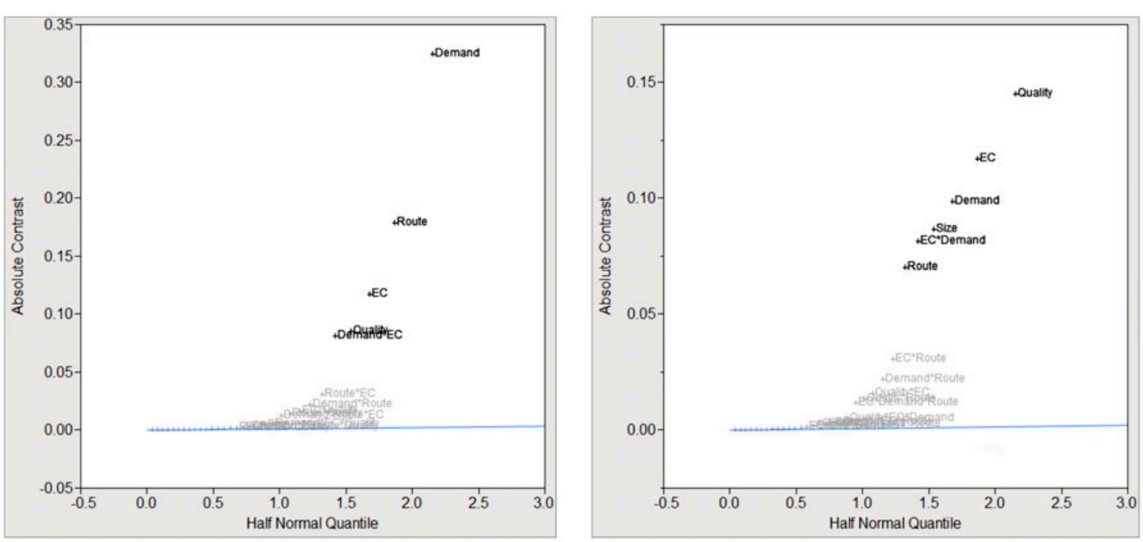

Figure 5. Half normal plots of effects for $\ln Y_1$ (left) and $\ln Y_2$ (right).

Table 3. Linear regression models of energy footprints for IME Inc.

Variables	$Y = \ln Y_1$		$Y = \ln Y_2$	
	Coefficient	P Value	Coefficient	P Value
Regression equation: $Y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_2x_5$				
Constant (b_0)	14.0	0.000	5.146	0.000
Route (x_1)	0.179	0.000	0.070	0.000
Demand (x_2)	0.324	0.000	−0.098	0.000
Quality (x_3)	−0.085	0.000	0.145	0.000
Size (x_4)	–	–	0.086	0.000
EC (x_5)	−0.117	0.000	−0.117	0.000
Demand × EC ($x_2 \times x_5$)	0.081	0.000	0.081	0.000
R^2	98.7%		96.8%	

when EC_1 is applied, we could save energy with both responses. The second-order interaction between demand and EC is found to be significant, and this suggests that more energy can be saved when demand and EC are considered together. For example, when market demand is low (−1), Y_1 would decrease further with EC (+1) since the signs of demand and (demand × EC) effects are positive, while the sign of EC effect is negative. For energy-saving opportunities, we can check EC, which is a significant factor in both responses. This implies that IME Inc. can save a non-negligible amount of energy by implementing EC_1. More specifically, when the other four factors are the same, average difference in Y_1 between EC_0 and EC_1 is 249 MJ per day (19.7% saving), or approximately $1717 for a year ($18.92/GJ). In both models, R^2 is greater than 96%, and the residual normality assumption is met, suggesting that the regression equations are reliable.

3.2 *Energy efficiency benchmarking*

In this subsection, we describe how the probabilistic approaches of 2.4 can be used for industry-level analysis. Thus, the distribution fitting method and SFA are applied here.

For evaluating the simulation data at the industry level, the Industrial Assessment Centers (IAC) data-set is used. The IAC is a government-sponsored programme to evaluate the energy efficiency of US industrial plants, and its assessment results provide useful data, including annual energy consumption and production levels of more than 16,000 plants. The full data-set is downloadable from the IAC database (IAC).

Before using the data, we filter and modify it as follows. All types of energy consumption are aggregated as annual energy consumption (MJ). In order to consider HVAC effects, we add the cooling/heating degree days (CDD/HDD) of plants with respect to each state and fiscal year. CDD and HDD are collected from the US National Climatic Data Center (NCDC). For clustered plants, all plants are categorised by their Standard Industrial Classification codes between 2000 and 3899, which represent all manufacturing industries. Since each SIC segment consists of 100 codes, all plant data are classified into 19 different segments, starting from 2000. We analyse only the plants of which a final product unit is ‘piece’, so that we can assume that plants in each SIC segment produce the same or similar products. We also consider only the plants of annual production level > 100,000 pieces, in order to have plant data with mass production.

Using the IAC data for EEC_1, we calculate EPP values of all plants as described in 2.4. EPPs of each segment are then fitted to the Weibull distribution (W). If the Weibull fit is not good, EPPs are fitted to the Burr Type XII distribution (BT), since the Weibull has a smaller number of parameters than the BT. As Kolmogorov–Smirnov (KS) and Anderson–Darling (AD) tests show good fits for all 19 segments, we can write EEC_1 in terms of the Weibull (F_W) and BT (F_{BT}) cdfs as in (10) and (11). Details about the distributional parameters of each SIC segment are shown in Table 4. One thing to note is that although this result is handy to implement, careful use is required for segments with small sample sizes (including tobacco, petroleum and leather segments), since significant bias can be included in fitted models.

$$\mathrm{EEC}_{1(\mathrm{W})}(\mathrm{EPP}) = 1 - F_W(\mathrm{EPP}) = \exp\left(-\left(\frac{\mathrm{EPP}}{p_1}\right)^{p_2}\right) \quad \text{where EPP} \geq 0 \text{ and } p_1, p_2 > 0 \tag{10}$$

$$\mathrm{EEC}_{1(\mathrm{BT})}(\mathrm{EPP}) = 1 - F_{\mathrm{BT}}(\mathrm{EPP}) = \left(1 + \left(\frac{\mathrm{EPP}}{p_1}\right)^{p_2}\right)^{-p_3} \quad \text{where EPP} \geq 0 \text{ and } p_1, p_2, p_3 > 0 \tag{11}$$

Table 4. Fitted distribution parameters for 19 SIC segments.

SIC segment	Typical Products	Sample Size	Distribution	p_1	p_2	p_3	KS & AD tests ($\alpha = .05$)	Constraints
2000–2099	Food	239	Burr	5.037	0.795	1.225	Passed	Annual Production > 100,000 & Production Unit = 'piece'
2100–2199	Tobacco	4	Weibull	1.605	0.268		Passed	
2200–2299	Textile	45	Weibull	10.190	0.771		Passed	
2300–2399	Apparel	111	Weibull	9.774	0.640		Passed	
2400–2499	Lumber	94	Weibull	39.419	0.600		Passed	
2500–2599	Furniture	104	Weibull	91.171	0.752		Passed	
2600–2699	Paper	136	Burr	0.013	1.454	0.235	Passed	
2700–2799	Printing	219	Burr	0.378	0.920	0.886	Passed	
2800–2899	Chemicals	96	Burr	0.368	1.198	0.442	Passed	
2900–2999	Petroleum	11	Weibull	30.969	1.108		Passed	
3000–3099	Rubber	397	Burr	1.373	0.728	0.957	Passed	
3100–3199	Leather	40	Weibull	25.276	0.795		Passed	
3200–3299	Glass	103	Weibull	35.651	0.396		Passed	
3300–3399	Primary metal	83	Weibull	30.628	0.531		Passed	
3400–3499	Fabricated metal	491	Weibull	17.423	0.428		Passed	
3500–3599	Machinery	240	Weibull	42.086	0.531		Passed	
3600–3699	Electronic	302	Weibull	27.473	0.485		Passed	
3700–3799	Transportation equipment	217	Weibull	41.620	0.557		Passed	
3800–3899	Photo/medical/optical	107	Weibull	15.835	0.514		Passed	

Among the SIC segments in Table 4, we use the distribution of the 'fabricated metal' segment, since this is the segment the IME would belong to. Thus, we apply p_1 and p_2 of the segment in Table 4 to (10) for IME Inc. For EPP of IME Inc., a pair of simulated data from 3.1 is used, with all treatments the same except for EC. However, since the EPP is too small compared with the IAC data, we assume that the number of machines in IME Inc. has been extended 100 times, and we give the firm a new name, IME100 Inc. Then, plugging EPPs of 34.59 MJ (EC_0) and 20.24 MJ (EC_1) into (10), we have $EEC_{1(W)}(34.59)$ = 26th and $EEC_{1(W)}(20.24)$ = 34th, suggesting that EC_1 can improve the energy efficiency of IME100 as compared with its peers.

In order to perform EEC_2 analysis for IME Inc., we also use the same segment in the IAC data. For the distribution of u_i, we assume the Gamma distribution, since it has a more flexible fit. After careful examination of alternative models, we determine the final regression model and its estimated parameters in Table 5 and (12).

$$\begin{gathered}\sqrt{Y_i} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 \sqrt{X_3} + \beta_4 X_4 + \beta_5 \ln(X_5) + u_i + v_i \\ \text{where } v_i \sim N\left(0, \sigma_v^2\right) \text{ and } u_i \sim F_G(x) = \int_0^x \frac{\theta^P \exp(-\theta s) s^{P-1}}{\Gamma(P)} ds, \quad x \geq 0, P, \theta > 0\end{gathered} \tag{12}$$

As shown in Table 5, all estimates are statistically significant at the significance level α = 0.05, except for σ_v. In the likelihood ratio test against the OLS model, the chi-squared statistic (df = 1) is found to be 194.1. This implies that the

Table 5. Estimated SFA parameters of fabricated metal segment (N = 491).

Variable	Description	Estimated coefficient	P value (Wald test)	Unit
Y	Annual energy consumption			MJ
β_0	Constant	-7.524×10^3	0.0073	
X_1	Number of employees	5.886	0.0000	
X_2	Plant area	7.290×10^{-3}	0.0000	m^2
X_3	Annual production level	4.227×10^{-2}	0.0000	pieces
X_4	Annual production hours	3.286×10^{-1}	0.0002	hours
X_5	HDD	6.418×10^2	0.0327	
θ	Parameter 1 of u_i	5.800×10^{-4}	0.0000	
P	Parameter 2 of u_i	2.891	0.0000	
σ_v	Standard deviation of v_i	1.744×10^{-2}	1.0000	

Table 6. Energy efficiency and saving for IME20 and IME100.

Factory	Energy policy	Key parameter	Percentile ranking	Energy saving
IME100	EC_0	EPP $= 34.59(\mathrm{MJ})$	$EEC_{1(W)}(EPP) = 26$th	14.36 (MJ/unit) ≈ 0.27 ($/unit)
	EC_1	EPP $= 20.24(\mathrm{MJ})$	$EEC_{1(W)}(EPP) = 34$th	
IME20	EC_0	$u_i = 2166$	$EEC_2(u_i) = 85$th	3.879×10^6 (MJ/year) ≈ 73,000 ($/year)
	EC_1	$u_i = 1448$	$EEC_2(u_i) = 94$th	

SFA model in (12) is better than the usual OLS regression model, since the SFA model increases the log-likelihood function value statistically more than the OLS model does at $\alpha = 0.05$. Since estimated $|v_i| < 0.01$ and $u_i = [194, 35350]$, these ranges and insignificant σ_v together suggest that residuals in (12) mostly come from the energy inefficiency component u_i, and the random noise v_i does not statistically contribute to (12). Then, we can write EEC_2 in terms of the Gamma distribution cdf $F_G(u_i)$ as

$$EEC_2(u_i) = 1 - F_G(u_i) = 1 - \int_0^{u_i} \frac{\theta^P \exp(-\theta s) s^{P-1}}{\Gamma(P)} ds, \quad u_i \geq 0 \tag{13}$$

where P and θ are found in Table 5

Applying EEC_2 to IME Inc., we use the same pair of simulated data as we use with EEC_1. Also for the same reason, we assume that the number of machines in IME Inc. has been extended 20 times, and we call the new firm IME20 Inc. Since independent variable data in (12) are not available for IME20, we assume that the firm has the average level of input data of the segment, except for the annual energy consumption and production level. From Table 5, (12) and (13), we have $u_i(EC_0) = 2166$ and $u_i(EC_1) = 1448$ as well as $EEC_2(2166)$ = 85th and $EEC_2(1448)$ = 94th. This result shows again that EC_1 can improve the energy efficiency of IME20. We summarise the results of the energy efficiency evaluation in Table 6.

Although we can benchmark the energy efficiency of plants with two methods introduced here, any result based on the methods is dependent on the assumption that all the manufacturers produce the same or very similar products. The benchmarking method must be performed very carefully if this assumption is significantly violated.

4. Conclusion

This paper aims to provide holistic but pragmatic approaches for estimating and evaluating manufacturing energy footprints by integrating and improving energy research and studies. The proposed methods start by extracting parameters at the product level, and link the parameters to machine-level power and plant-level energy footprints, thereby enabling comparison of manufacturing energy footprints at the industry level. A case study shows in detail how parameterised information at each level is systemically used as input data for the next level. Simulating the energy consumption of a hypothetical plant with five managerial factors, the case study presents the total energy consumption and the energy consumption per unit product in closed-form equations. By using the equations, the manufacturing energy can be estimated with the factors at different levels, and ways to reduce manufacturing energy consumption can be analysed in consideration of a higher order interaction.

Our case study focuses on offering practical, useful tools in the early stages of planning new products or plants to estimate and evaluate energy consumption. Thus, machine power equations are estimated based on experimental data from real CNC machines. Furthermore, theoretical energy control policies and machine states are refined for use in the existing power saving mode of the CNC machines, suggesting that the proposed approach can be implemented in actual manufacturing plants. The results from the proposed methods are used for comparing the energy efficiency of plants with peers in the US manufacturing sector.

This paper presents useful tools for assessing manufacturing energy use, but the proposed methods would benefit from more thorough analytical analysis and are currently time consuming in implementation. We expect to address these points in future work.

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