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Environmental impact characterization of milling and implications for potential energy savings in industry

Nancy Diaz[a]*, Kevin Ninomiya[a], Joanna Noble[a], David Dornfeld[a]

[a]*University of California at Berkeley, 1115 Etcheverry Hall, Berkeley 94720-1740, United States of America*
* Corresponding author. Tel.: +1-510-642-8657; fax: +1-510-643-5599.E-mail address: ndiaz@berkeley.edu.

Abstract

Since machining is a prevalent process in product manufacture this study reviews the accuracy of a specific energy characterization model to predict the electrical energy consumed by a 3-axis milling machine tool during processing. The energy characterization model had an accuracy of 97.4% for the part manufactured under varied material removal rate conditions and highlighted the potential for energy reduction using higher cutting speeds. Interviews with cutting tool manufacturers and end users showed that there is a genuine potential for energy reduction during milling operations due to the extensive use of uncoated cutting tools in industry.

Keywords: Energy characterization; Milling; Cutting tool use

1. Introduction

Global energy demand is expected to grow by 53% between 2008 and 2035 [1]. China and India, two leading contributors to manufacturing, are projected to more than double their energy demand by 2035. It is therefore imperative to identify methods for estimating the energy consumption of manufacturing in order to propose efficient and realistic strategies for reducing the consumption of our natural resources.

Gutowski, et al. [2] showed that the electrical energy requirement of manufacturing processes was inversely proportional to the process rate. That is, the specific energy consumed to provide electrical power to the production equipment decreased as process rate increased. This is due to the dominance of the tare power demand in the electricity consumption of machine tools. When production equipment is turned on a significant portion of electricity is consumed by peripheral equipment in addition to the electricity needed to actually process material.

Diaz, et al. [3]-[4] and Kara, et al. [5] developed a method for modeling the specific energy of milling

Nomenclature

Δt	time subinterval of MRR profile
b	specific energy model constant
d	depth of cut
E	electrical energy of machine tool
f	feed rate
f_t	chip load
HSS	high speed steel
k	specific energy model constant
MRR	material removal rate
n	spindle speed
N	number of subintervals of MRR profile
V	volume of material removed
w	width of cut
x	feature with varied MRR
x+1	feature with constant MRR

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centers, which will be utilized in the analysis presented in this paper. The models predict the energy consumed to manufacture parts produced under a constant material removal rate (MRR) with an accuracy between 91.95% and 97.63% [5].Since parts are inherently complex, the goal of this research was to assess the accuracy of a machine tool energy characterization model in estimating the energy consumed to manufacture a part with varied material removal rate.

First, the methodology for modeling the specific energy of a machine tool will be presented. The model will then be used to estimate the energy consumed to manufacture a part, and the accuracy of this estimation will be determined. Lastly, the potential for energy consumption reduction in industry will be analyzed based on interviews conducted with cutting tool manufacturers and users.

2. Energy Estimation of Part Production

2.1. Specific energy model of machine tools

Following the findings of Gutowski, et al. [2], the possibility of modeling the electrical energy requirements of a machine tool as a function of the MRR was shown by Diaz, et al. [3]-[4] and Kara, et al. [5]. The research presented in this study utilized a model developed for a milling machine tool similar to that presented by Diaz, et al. [3]-[4], the Mori Seiki NVD1500. This machine tool, though, has a higher maximum spindle speed of 40000 rpm.

The electrical energy consumed while machining AISI 1018 steel was measured to develop the machine tool's energy model. In order to obtain energy data for a broad range of MRR's, peripheral cuts were made with three types of cutting tools: 2-flute uncoated, 2-flute TiN coated, and 4-flute TiN coated 8 mm diameter carbide end mills. The feedrate, *f*, and spindle speed, *n*, were varied with cutting tool type as recommended by the tool manufacturer for a constant chip load, f_t, of 0.0254 mm/tooth [6]. The machining parameters are summarized in Table 1. The depth of cut, *d*, was maintained at 2 mm, while the width of cut, *w*, was varied between 1 mm and 7.5 mm.

Table 1.Cutting tool parameters

Cutting tool	f [mm/min]	N [rpm]
2-flute uncoated	170	3361
2-flute TiN coated	217	4278
4-flute TiN coated	860	7060

The electrical energy, *E*, consumed is given in Eq. (1) as a function of the *MRR* and the volume of material removed, *V*:

$$E = (\frac{k}{MRR} + b) * V \qquad (1)$$

where the constants *k* and *b* are 1556 and 1.475, respectively for this model of the Mori Seiki NVD1500 and the *MRR* and *V* are in mm^3/s and mm^3, respectively. Fig 1 portrays the inverse relationship of the specific energy and MRR. The specific energy approaches zero as the MRR increases, reducing significantly until approximately50mm^3/s. Therefore, energy reductions by means of increasing the process rate for MRR's higher than 50 mm^3/s would only be worthwhile for long processing times.

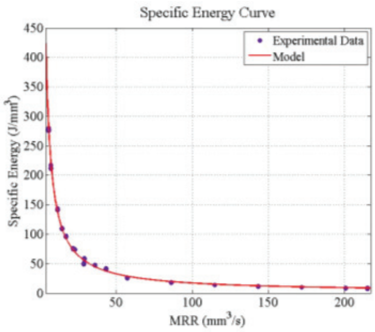

Fig. 1. Specific energy model of Mori Seiki NVD1500

2.2. Part design for energy estimation of milling

The electrical energy required for milling was estimated for an inclined spiral design on an ANSI 1018 steel workpiece with flood cooling. Machining occurred over 87% of the total cycle time of 259 seconds. The part design was broken down into 9 features as shown in Fig 2; each feature indicates a change in the MRR.

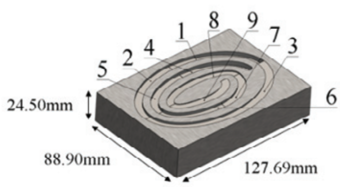

Fig.2.Spiral geometry and feature label of part design for energy characterization experiments

The test cuts used to obtain the specific energy models in Diaz, et al. [4] and Section 2.1 were completed at a constant depth of cut and a constant MRR with movement along only the x- or y-axis at any given time. The production of the part in Fig 2 required movement along the x-, y-, and z-axes simultaneously. The part was designed such that the MRR profile could be easily constructed since current CAM software does not output MRR as a function of time for a generated toolpath.

2.3. Material removal rate profile

The MRR was calculated based on the depth of cut, *d*, width of cut, *w*, and feed rate, *f*. The recommended feedrate for slotting conditions with an uncoated 6mm carbide end mill of 164mm/min was used with a spindle speed of 3558 rpm [6]. The MRR as a function of elapsed time was then used to estimate the energy consumption.

The width of cut throughout the experiment was maintained at a constant 6 mm. Features 2, 5, and 7, were milled while maintaining a constant depth of cut; the depth of cut varied for the remaining features. The MRR was varied as shown in Fig 3 and Fig 4. The corresponding part features are labeled in the figures.

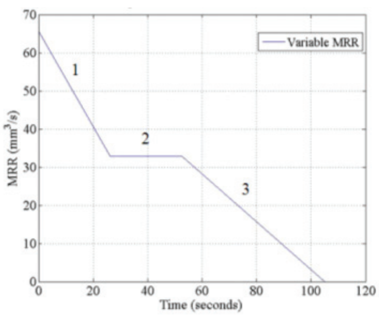

Fig.3. MRR as a function of elapsed time for features 1-3

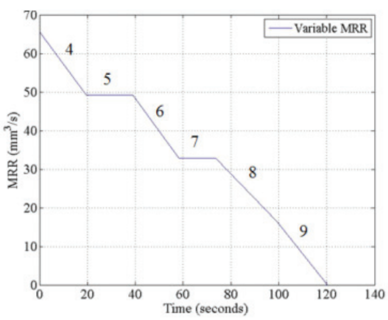

Fig.4. MRR as a function of elapsed time for features 4-9

2.4. Energy estimate of part manufacture

Complex toolpaths result in a MRR profile that cannot necessarily be represented by a simple function. Therefore, the energy consumption was calculated with a generalized energy estimate approach. The MRR profile is first divided into sections of constant and varied MRR. For areas of constant MRR (feature *x+1* in Fig 5), the energy consumption is calculated directly from Eq. (1). Areas with variable MRR were broken down into *N* subintervals as shown in Fig 5 for feature *x*.

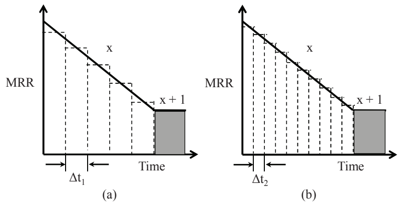

Fig. 5.(a) MRR breakdown of feature *x* with 5 subintervals; (b) MRR breakdown of feature *x* with 10 subintervals

The number of subintervals, *N* was varied from 1 to 10000 per feature to determine the smallest number of subintervals necessary for convergence of the energy estimate. For each scenario, the average MRR of each subinterval was used to calculate the energy consumed per feature, E_x (see Eq. (2)). The energy consumed for part manufacture was thereafter found by summing E_x over all features and adding the energy consumed for the features produced under constant MRR.

$$E_x = N * \Delta t \sum_{i=1}^{N} (k + b * MRR_{avg,i}) \quad (2)$$

The number of subintervals necessary for the energy estimate to converge for a particular feature varied given the difference in process time, but all estimates converged within 1000 subintervals or less. The corresponding subintervals were between 0.02 seconds and 0.11 seconds in size. The point of convergence would be expected to vary by machine tool and toolpath.

Since the optimal approach in proceeding with the energy estimate would utilize the smallest number of subintervals necessary for convergence, *N* of 1000 was used in the following results. The specific energy model provided an accurate estimate of the energy consumed to machine a part with varied MRR. Fig 6 shows the predicted energy and the actual energy consumed during the machining of the sample part, which was conducted six times to gage repeatability.

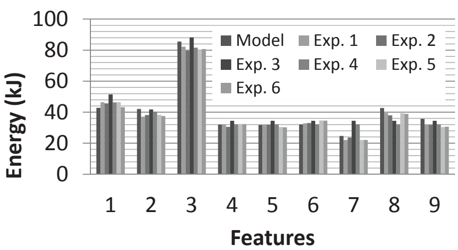

Fig. 6. Energy consumed for each feature

The predicted energy and the average of the measured energy from the six experiments per feature and per part are shown in Table 2. The accuracy of the predicted energy is evaluated based on the average (Avg) error, and the standard deviation (Std Dev) and range of the error relative to the energy measurements. The largest error occurred with feature 9. As seen in Section 2.1 the specific energy model showed the greatest variation in MRR's less than 50 mm^3/s, and feature 9 was fabricated with a low MRR. Had the MRR during the feature construction been on the order of 75 mm^3/s or greater, the variance in the model error is hypothesized to be even lower.

The range of the error amongst the features shows a significant fluctuation. For some features the measured energy is always greater than the predicted energy (features 1 and 6), while for other features the measured energy is always less than the expected energy (features 2, 8, and 9). The remaining features, though, are not skewed in any one direction. This fluctuation may be attributed to the inherent variability of the power demand of a machine tool over time; a trend observable even while in standby mode. This trend is more pronounced in machine tools with a small work volume [7] so the accuracy is also expected to improve for larger machine tools.

Though the predicted energy showed a significant deviation from the measured energy when evaluated by feature, the average error of the energy estimate for the part in its entirety was only -2.6% with a standard deviation of 3.8%. Therefore, estimating the energy consumption for complex parts proves to be promising as the toolpath for this part had a variable MRR.

Table 2. Energy consumption model results and error analysis per feature and per part, where (*) denotes a feature made with a constant MRR.

Feature	Predicted Energy [kJ]	Avg Energy [kJ]	Percent Error		
			Avg [%]	Std Dev [%]	Range [%]
1	42.7	46.6	8.0	5.1	0.9 to 16.9
2*	42.1	38.9	-8.5	4.8	-13.4 to -0.9
3	85.5	82.1	-4.3	3.8	-7.4 to 3.0
4	32.0	32.3	1.0	3.8	-4.7 to 7.3
5*	31.7	31.7	-0.2	4.0	-4.9 to 6.2
6	32.0	33.7	4.9	2.7	2.2 to 7.5
7*	24.7	23.1	-7.7	7.6	-12.7 to 6.6
8	42.6	38.9	-9.7	1.8	-12.2 to -7.8
9	35.7	31.7	-12.9	3.7	-17.3 to -7.1
Part	369	360	-2.6	3.8	-5.4 to 4.9

When estimating the energy consumption of a machine tool, a toolpath under a constant MRR for a long period of time is expected to have greater accuracy than a cut processed within a short time span. Power demand is also dependent on the prior processing conditions. Though feature 1 was milled at a high MRR, it was the first feature produced so the error is still relatively high because the power demand has not stabilized and the machine requires internal cooling for temperature management.

Though the energy estimation with the specific energy model proved to be accurate, there are some limitations to the approach regarding the inclusion of air cutting time and the effects of cutting tool engagement. The analysis presented herein only accounts for the electrical energy consumed during the removal of material, i.e. it does not include air cutting time as defined by Niggeschmidt, et al. [8]. Machine tool users can account for air cutting power demand by including estimates for components contributing to the constant power demand. This is comprised of the machine tool's power demand in standby mode including peripheral equipment and that required for the spindle and axis drives; typically the spindle power demand dominates over the power required for the axis drives except during rapid feed.

Lastly, the machine tool experiences peaks in power demand such as with the initial engagement of the cutting tool with the workpiece. So if a toolpath has a multitude of cutting tool changes or multiple instances of air cutting, the machine tool will typically consume more electrical energy than predicted because of the accumulation of peaks in power demand. The modeling of power demand of machine tools has been conducted by Dietmair, et al. [9], but the methodology expenses greater time in data acquisition resulting in higher costs for development.

3. Cutting Tool Use in Industry

As mentioned previously, increasing the process rate reduces the energy consumed for product manufacture. This could be achieved by toolpath modification [10] or increasing MRR as verified by the specific energy model. Use of carbide end mills, coated end mills, or end mills with a higher number of flutes all allow for higher cutting speeds, and thus increased MRR. In order to ascertain the prevalence of these energy-saving types of end mills and explore the potential for energy savings in industry, we researched end mill sales by cutting tool manufacturers and end mill use in manufacturing facilities. End mill sales data was evaluated from the United States economic census for1992 through 2002 (only aggregated end mill data was available after 2002). Fig 6 displays the percentage of annual product shipment values for high speed steel (HSS), carbide, non-indexable insert, indexable insert, and miscellaneous end mills.

These percentages are not necessarily representative of number of cutting tools sold since cost per tool varies across and within categories. HSS tools are less expensive than carbide end mills, yet still represent a plurality of product shipments by value. The ratio based on number of tools is likely even higher. However, carbide tools allow for higher cutting speeds, typically leading to lower energy consumption [8].

Aside from upgrading the cutting tool material, MRR can also be increased by increasing the number of flutes or tool diameter, if the material and part feature allows, or by using a coated tool. However, while MRR increases, ease of chip exit becomes problematic as the number of flutes and cutting speed increase. When machining aluminum or difficult to machine materials such as titanium or inconel, chip exit becomes critical to achieving optimal tool life because of the concentration of heat at the cutting tool edge and workpiece interface. If the cutting tool wears too quickly, the cost and power demanded from having to change the cutting tool could overshadow energy savings from increased cutting speeds.

The application of a coating on a cutting tool allows for increased cutting speeds and tool life. The effect of coatings on tool life has been previously studied by Gu, et al. [14] for tool inserts used for face milling applications. Tool life enhancement factors for TiN, TiAlN, and ZrN coated inserts over uncoated inserts were provided, where the enhancement factor is the length of cut without wear using a coated versus uncoated insert.

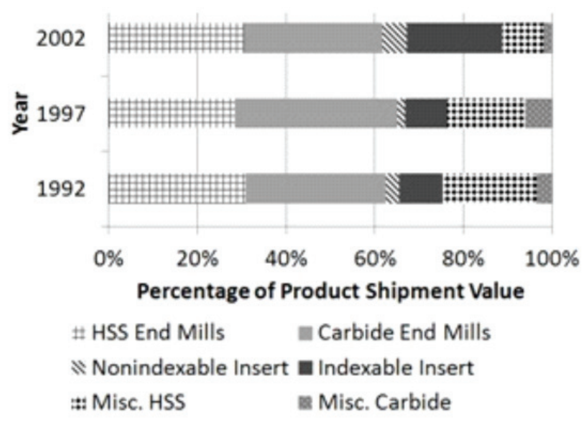

Fig. 6.USA end mill sales data 1992-2002 [11]-[13]

The tool life enhancement factor varied based on the feed per tooth and cutting speed. The point of tool failure was defined as flank wear of 0.1 mm. TiAlN performed the best, achieving a tool life of up to 70 times more than an uncoated insert. The TiN performed the second best, achieving up to 35 times longer tool life than the uncoated insert. ZrN followed the performance of TiN achieving only approximately 4 times the tool life of the uncoated inserts. Thus, aside from achieving higher cutting speeds, coatings extend the life of cutting tools, which allows for even greater energy savings.

As the economic census data did not include a sales breakdown based on coatings, we also conducted interviews with cutting tool manufacturers and end users of cutting tools to gain further insight into cutting tool use in industry. Sales of uncoated tools by RobbJack Corporation (a cutting tool manufacturer) represent 70% of their end mill sales. RobbJack states that the primary motivations in cutting tool selection are material and type of cut. Another cutting tool manufacturer questioned stated that price considerations drive users towards uncoated tools, while performance considerations drive users towards coated tools.

Two of the three manufacturing facilities surveyed use at least 95% uncoated tools, which is consistent with the large percentage of uncoated tools sold by cutting tool manufacturers. Site B, though, only utilizes coated cutting tools, allowing for a more energy-efficient use of the machine tool. The manufacturing facilities listed tool life, price, feedrate limits, and size as their primary motivations in end mill selection.

The use of coated tools allows for a higher cutting speed. Although the user must pay a higher upfront cost, energy savings can be achieved if optimal cutting conditions for the coated tools are maintained [15]. Additionally, all of the manufacturing sites questioned use less than 15% indexable tools. Indexable end mills though are generally used for larger feature dimensions, so this could be a direct result of the size of the part features being produced.

End mill end-of-life practices are also important in estimating the environmental impact of manufacturers. The aforementioned cutting tool manufacturers both offer regrinding/reconditioning services for used end mills, and all of the manufacturing sites surveyed regrind end mills at least once except for Site B who regrinds their end mills a minimum of four times. The results from the manufacturing sites are summarized in Table 3.

These end mill usage trends may not apply to niche industries. For example, a cutting tool manufacturer that caters primarily to the composites industry has over 60% of sales consisting of diamond-coated end mills. Diamond-coated tools cannot be resharpened, and thus no regrinding service is offered.

As previously stated, coated tools and a higher number of flutes both allow for decreased power consumption. Regrinding also decreases environmental impact by increasing cutting tool lifespan. Based on these criteria, Sites A and C show the most potential for reducing energy consumption at their facility through modification of end mill usage.

Table 3. Summary of interview results with manufacturing facilities with the following breakdown: (1) uncoated, (2) unspecified coating, (3) TiCN, (4) AlTiN

	Site A	Site B	Site C
Operating hours (hrs/yr)	2160	36000	171000
Solid/	91%	89%	95%
Indexable	9%	11%	5%
Coating	95%1	0%1	95%1
	5%2	72.5%3	5%2
		22.5%4	
# Flutes	2, 3&4	Mostly 4	Mostly 2
End mill lifespan (mins)	151-200	200+	150+
Regrinding	1 time	>4 times	1 time

4. Summary of Conclusions

This study presented a method for estimating the energy consumption of a milling machine tool for the production of a part with a varied MRR toolpath. The model showed an average accuracy of 97.4%, validating the use of the model. Overall accuracy is expected to improve with higher MRR's and longer process times to allow for the stabilization of power demand.

The extent of sustainable practices in facilities was found to vary tremendously based on the industry interviews conducted. Both economic census data and survey results from industry show significant potential for reducing the environmental impact of some manufacturing facilities. Simple measures can be taken to adopt green practices such as upgrading and regrinding the cutting tools used for processing.

Acknowledgements

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