Evaluating Trade-Offs Between Sustainability, Performance, and Cost of Green Machining Technologies

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Abstract

The growing demand to reduce environmental impacts has encouraged manufacturers to pursue various green manufacturing technologies and strategies. These solutions, though, may have a direct impact on several productivity metrics including availability, quality, service life, and cost. This study presents an approach to evaluate the trade-offs between the environmental, performance, and financial impacts of green machining technologies by combining green manufacturing principles into life cycle performance evaluation. The approach is validated by investigating the implications of reducing the processing time by increasing the cutting speed and chip load to green a horizontal milling process.

Keywords:
Life Cycle Cost; Green Machining; Data Acquisition

1 INTRODUCTION

Machine tool development has historically focused on reducing operating costs while simultaneously improving performance as measured by several metrics including availability, reliability, dimensional accuracy, and precision. To increase performance, machine tools have become more complex and automated in design, which has resulted in higher resource demands that have generally conflicted with rising resource costs due to growing scarcity and regulation. These trends have encouraged manufacturers and users to pursue various green machining strategies and technologies that enable increasingly efficient use of limited resources. Design and operation for the environment, though, has a direct impact on several factors including availability, quality, service life, and cost. Thus, it is important to quantify resource flows in machining to enable manufacturers to better guarantee performance as well as provide decision makers with tools that evaluate the trade-offs between the environmental, performance, and financial impact of any potential technology decision.

2 CURRENT ASSESSMENT TECHNIQUES

2.1 Environmental impact assessments

Life cycle assessment (LCA) has been traditionally used in the literature to quantify several resource flows (typically electrical energy) in machining. LCA is a quantitative tool that measures the resource and waste flows of a product from its fabrication to its end-of-life [1]. Much of the early LCA work focused on assessments of different green machining strategies and technologies. There was also an observed need to establish a set of quantifiable dimensions to determine the trade-offs in process planning decisions. This area of work focused on the development of models to capture the effects of machining physics on environmental and public health impacts. Munoz and Sheng [2] provided the seminal model that comprehensively links machining parameters (e.g. speed, feed, depth of cut) to the environmental impacts of a machining process (e.g. energy consumption, process rate, mass flow of generated wastes). This approach was extended to energy by developing a web-based energy estimation tool [3]. Subsequent work has connected LCA results from the literature to process planning to enable its use in the design of products [4]. While this research has provided initial tools for decision makers to evaluate current green machining strategies, these tools are based on theoretical models instead of captured data, which may limit the accuracy of these tools when gauging the trade-offs in process planning decisions [5], [6].

More recent work has addressed the deficiencies in previous process planning tools by developing methods to physically measure the environmental impacts of machine tools. Vijayaraghavan and Dornfeld [6] propose automated energy monitoring of machine tools using event stream processing to correlate measured energy consumption to machine tool usage. This enables full characterization of the machining process and the drivers of energy consumption. Similarly, Kuhrke, et al. [7] advocate a methodology to estimate the overall yearly energy consumption of a machine tool and any related costs by either measuring or calculating the energy consumption of individual components of the machine tool and considering the actual usage instead of assuming a constant power consumption. While calculating energy consumption inherently introduces inaccuracy into this approach, Kuhrke, et al. [7] argue that the feasibility of power measurements for highly specialized machine tools demands that calculations be used to simplify the approach for purchasing decisions. Dietmair and Verl [8] propose a nodular, component approach that also considers the actual usage of the machine tool to drive a modeling framework that estimates overall energy consumption using characteristic relationships between process parameters and energy consumption and other resource flows for each component. These characteristic relationships should be measured and can be found in the literature (e.g. Draganescu, et al. [9] modeled the specific energy of milling processes, and Klocke, et al. [10] modeled the specific energy of milling and drilling processes).

2.2 Performance and financial impact assessments

Increased competition and reduced profit margins have forced manufacturers to find ways to reduce operating costs and improve

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the performance of their facilities and equipment. So, many manufacturers have used life cycle cost (LCC) analysis as the primary tool to evaluate the performance and financial impact of their equipment and facilities. LCC analysis is a quantitative tool that compares the cost-effectiveness of different investment options from the perspective of a manufacturer or other business decision maker [11]. It takes into account all business costs over the life of the investment option including those costs associated with acquisition (e.g. sales price), ownership (e.g. maintenance), and disposal. The automotive sector has been one of the biggest drivers of LCC analysis techniques to help establish warranty demands with their suppliers [12].

Many approaches that seek to optimize the LCC of manufacturing equipment have focused on maintenance since these activities typically dominate costs. This has driven the development of life cycle performance (LCP) evaluation, which relates the overall equipment effectiveness (OEE) – a performance metric that combines reliability, availability, and quality – to the total monetary costs from the initial investment to disposal to generate an efficiency metric for a manufacturing system [13]. Thus, LCP evaluation broadens LCC analysis by relating the results of an LCC analysis to the performance of an investment option. LCP evaluation has been primarily used to optimize technical services (e.g. maintenance intervals and spare part provisions) and assess and control the risks associated with establishing warranty and servicing contracts [12], [13].

While the development of LCP evaluation from LCC analysis represented an important first step towards combining performance and financial assessments, neither approach addressed resource flows or environmental impacts, which can be highly significant to the OEE and financial costs of a manufacturing system. So, it has become very important to capture environmental impacts within both LCP and LCC approaches. Early attempts addressed these limitations by integrating LCA into LCC analyses. One example of this approach is economic input-output LCA (EIO-LCA), which was developed at Carnegie Mellon University. This approach relates the environmental impacts of each sector of an economy to the monetary value of that sector as defined by government economic input-output tables [1]. Norris [11] describes other approaches referred to as "partial solutions" that combine a full LCA with a partial LCC or vice-versa. The first type of partial solutions (full LCA and partial LCC) involves adding cost flows to a traditional LCA. The second type of partial solutions (partial LCA and full LCC) adds a truncated LCA (e.g. some resource flows from the main facility plus some first tier suppliers) to a full LCC. Norris [11] also highlights two "full solutions," PTLaser and TCAce. PTLaser includes dynamic LCA (i.e. time-varying flows), variable cost functions, and flexible investment, depreciation, accounting, and discounting tools in order to combine a full LCA with a full LCC. TCAce extends current LCA and LCC approaches to include all external costs including those that are less tangible (e.g. societal costs). Eco-efficiency is a last approach to combine LCA and LCC by normalizing the metrics from each analysis to enable an equal comparison [15].

2.3 Combined assessments and proposed approach

The current literature contains many tools that incorporate financial costs into either an environmental or performance assessment. However, these tools do not generally address all three factors simultaneously, which neglects their inherent interdependence. Recent work, though, has begun to develop methods that enable consideration of all three impacts. For example, Kuhrke, et al. [7] and Dietmair and Verl [8] demand a full understanding of actual machine usage even though the aim of both is to measure overall energy consumption. Similarly, Thiede and Herrmann [16] evaluate production criteria as well as energy consumption and related costs, but it is based on a simulation rather than a measurement approach. Also, Inamasu, et al. [17] include environmental (energy), performance (tool life), and financial factors when physically measuring the effect of cutting conditions on the energy consumption of a machine tool.

Niggeschmidt, et al. [13] provided a basic framework to incorporate green manufacturing principles into LCP evaluation so that environmental, performance, and financial impacts could be simultaneously considered. This framework comprised three steps:

1. Design and integration of appropriately targeted process monitoring systems to measure relevant data sources.
2. Characterization of the manufacturing system based on the collected data.
3. Optimization of the manufacturing system based on the developed characterization.

The goal of this paper is to apply the framework developed by Niggeschmidt, et al. [13] to develop a methodology that quantifies changes in environmental impact with respect to performance and cost. The approach is presented in Figure 1 and is based on data acquisition rather than modeling or simulation to ensure accurate calculation of impacts. By applying this approach to a baseline scenario (defined as "machining as usual") and other alternatives that implement a green machining strategy, the true costs of these technologies can be determined.

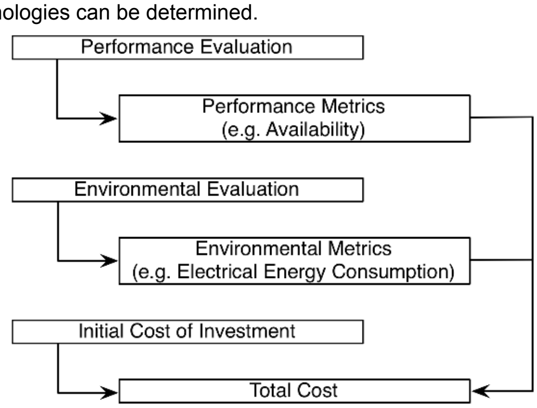

Figure 1: Proposed methodology to combine environmental, performance, and financial impacts when evaluating investment options.

3 GREEN MACHINING TECHNOLOGIES

Many green machining approaches have focused on process and design level improvements through new technologies and machining strategies. To validate the approach described in Figure 1, though, this study focuses on processing time reductions [3]. The power demand of a machine tool can be divided into three components: constant, variable, and processing (or cutting) power (see Figure 2). Constant power demand is due to auxiliary components that are always powered and have a demand irrespective of the selected machining parameters (e.g. computer panels and lights). Variable power demand is due to those components that have a constant baseline demand but that may not always be active (e.g. spindle and drive motors). Finally, processing or cutting power demand is the power demand dependent on the material removal process.

Constant and variable power demand are together referred to as tare power demand since this is the minimum amount of power that is required to run the machine tool whether or not chips are formed. Dahmus and Gutowski [18] found that the tare power demand increases with automation, which means that the energy consumption of many modern machine tools is dominated by this constant power demand. Thus, reducing the processing time better amortizes these constant charges and may effectively reduce the specific cutting energy.

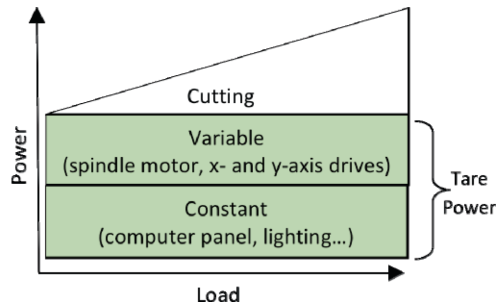

Figure 2: The typical power demand of a machine tool [3].

4 METHODOLOGY

Machining experiments were conducted on a Haas VF-0 vertical milling machine tool to study the impacts of a reduced processing time strategy. A baseline scenario was selected as well as alternative scenarios that reduce processing time by increasing the feed rate. Relevant data for a performance and environmental analysis were collected during each machining experiment.

4.1 Baseline and alternative scenario design

The test piece chosen for this investigation was developed by Behrendt [19] (see Figure 3). This part is meant to compare the energy consumption of various three-axis machine tools that have a work area (defined by the x- and y-travel) between 0.1 and 1 m^2. It has been designed to fully exercise the machine tool by requiring every combination of axes to create eighteen different features using four tools: a 50 mm, 5 insert face mill; an 8 mm end mill; a 16 mm end mill; and an 8 mm drill. The initial workpiece material is an 82 mm x 82 mm x 25.4 mm 1018 AISI steel blank. The cutting speed is kept constant at 50 m/min. The chip load is kept constant for every feature except the face cut, which requires a chip load of 0.1 mm/tooth, and the small and large grooves sets, which require a chip load of 0.5, 0.6, and 0.7 mm/tooth for each subsequent groove. The depth of cut is also incrementally increased for each of the three machining passes used to machine each feature except the drilled holes.

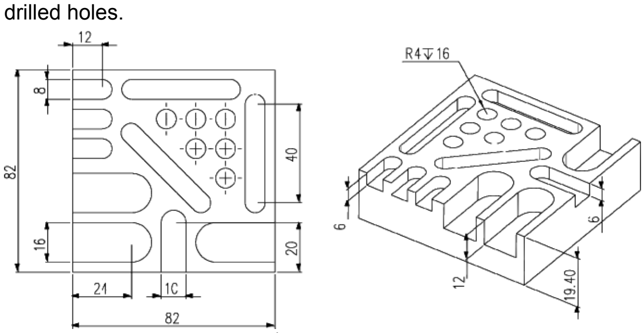

Figure 3: Standard part machined for each machining scenario (units in mm) [19].

The baseline scenario followed the standard presented by Behrendt [19]. To reduce the processing time, one may increase the number of flutes on the tool, increase the cutting speed, or increase the chip load. The latter two options were pursued in this study since they are typically the parameters that a machinist has most control over. While the cutting speed and chip load should be simultaneously increased to ensure a stable cut and good surface quality, each parameter was increased independently to better study the effects of each on the overall environmental and performance impacts. Two scenarios were considered for each parameter to initially validate our approach. The cutting speed was increased to 55 m/min and 60 m/min, which represented a feed rate increase of 10% and 20% respectively. Each chip load was increased by a 20% and 40% for the increased chip load scenarios, which represented a feed rate increase of 20% and 40% respectively. The chip load was increased further than the cutting speed due to stability limitations (increased cutting speed without an increase in feed rate typically induces chatter).

4.2 Energy based environmental assessment

The overall power demand of the machine tool was measured to evaluate the environmental impact of each machining scenario by determining the electrical energy consumption. A Yokogawa CW-240 wattmeter was used in a three-phase, three-wire, three-current setup. The current transducers and voltage clamps were installed at the power input and a sampling frequency of 10 Hz was used. Figure 4 shows the measured power demand for the baseline scenario.

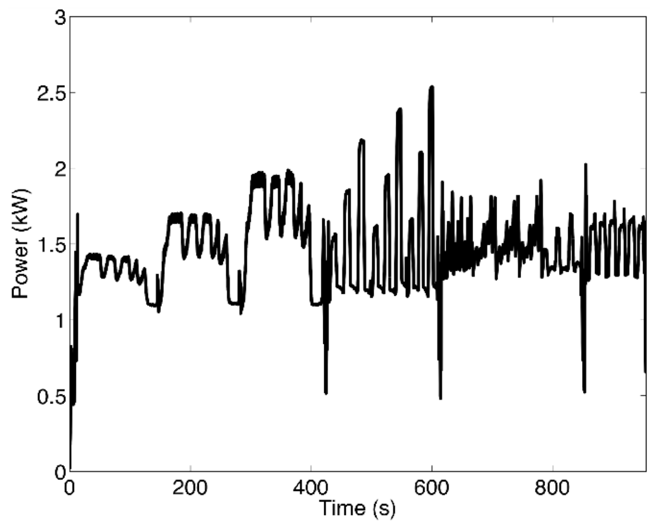

Figure 4: Measured power demand for the baseline scenario (a 2 second moving average was used to smooth the plot).

The power demand was assumed to be constant for the 0.1 seconds immediately after a measurement. This allowed the total electrical energy consumption to be estimated using Equation 1:

$$E_{total} = \sum_{i=1}^{k} \left(\frac{0.1 P_i}{3600} \right), \quad (1)$$

where E_{total} is the total electrical energy consumed (in kWh), k is the total number of data samples, and P_i is the ith measured real power demand. Real power (the portion of power used towards productive work) was used as opposed to apparent power (the total power including any losses in the electrical system) since power companies charge facilities based on real power as long as the power factor (a measure of efficiency defined as real to apparent power) of a facility is above a defined threshold (85% in California) [20]. Equation 1 was then used to estimate the change in total electrical energy consumption caused by each alternative scenario.

4.3 Load based performance evaluation

An LCP evaluation requires an understanding of the failure behavior of machine tool components. The failure behavior can be estimated using a reliability analysis that begins with the load profile on the machine tool components. Because these load profiles were difficult to obtain, the overall cutting forces were measured and assumed to affect all components equally. The cutting forces were measured for each scenario using a Kistler 9257A three-component dynamometer on which the workpiece was mounted. A Kistler 5004 dual mode amplifier set to a sensitivity of 200 N/V converted the dynamometer charge output to a voltage signal that was then recorded using LabVIEW Signal Express via a National Instruments NI USB-6009 multifunction I/O card. The load profile was generated using a sampling frequency of 1 kHz. Figure 5 shows the measured load profile for the baseline scenario.

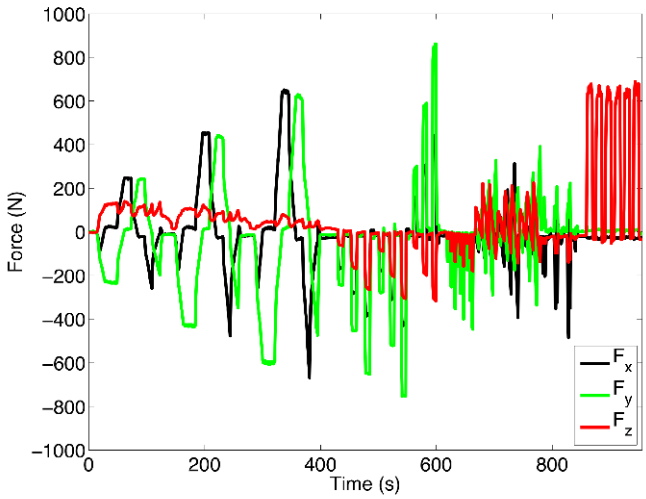

Figure 5: Measured load profile for the baseline scenario (a 5th order Butterworth filter with cutoff frequency 0.005 Hz has been used to smooth the plot).

A Weibull distribution approach is typically used to describe the stochastic failure behavior of machine tool components and statistically estimate their service life, but an alternative approach was required since the load profile on a machine tool is expected to vary with different machining processes [14]. So, the load-dependent reliability model was derived using an approach based on the Weibull Cumulative Damage Model, which relates the cumulative damage of varied loads to the Weibull distribution, and the Generalized Log-Linear Model. Cumulative damage, or cumulative exposure, is the effect caused by different stresses that decrease the service life of equipment. The general form of the Weibull Cumulative Damage Model is given by Equation 2:

$$F(t,L) = 1 - e^{-(W(t,L))^{\beta}}, \qquad (2)$$

where F is the probability of failure due to cumulative damage, t is time, L is the load vector, W is the normalized cumulative damage, and β is the shape parameter. W is written in the Generalized Log-Linear Model as given by Equation 3:

$$W(t,L) = \int_0^t e^{a_0 + \sum_i a_i X_i(t')} dt', \qquad (3)$$

where a_0 and a_i are model parameters, and X_i is a transformation of the load levels, L_i, that depends on the type of load. For example, the power law offers that the natural logarithm is the appropriate transformation for mechanical stresses.

The normalized cumulative damage presented in Equation 3 can be simplified to Equation 4:

$$W(t,L) = \sum_j \left(e^{a_0 + \sum_i a_i X_{ij}} \bullet t_j \right), \qquad (4)$$

where t_j is the measuring interval, and X_{ij} is the transformation of the characteristic load value measured over t_j. Equations 2 and 4 were then used to estimate the change in cumulative damage caused by each alternative scenario. For a given conditional probability based on previous loads and a predicted future load profile, the cumulative damage then allows for a calculation of the remaining service life of the machine tool.

5 RESULTS

5.1 Energy based environmental assessment

The total electrical energy consumed during the baseline scenario was 0.387 kWh and the maximum power recorded was 13.1 kW. Table 1 summarizes the total electrical energy consumed and maximum power demanded during each alternative scenario relative to the baseline scenario. As expected, the total electrical energy consumed by the machine tool decreased for every scenario since it is most strongly dependent on the processing time. The slight difference between both 20% increase scenarios is likely due to measurement error. The greater decrease in energy consumption for larger increases in feed rate occurred because the effect on energy amortization per part is greater than that of the increased power required to run the higher feed rate. This suggests that an operating point exists that requires minimal specific cutting energy consumption [3], [10]. Also, the maximum power demanded by the machine tool increased for every scenario due to the increased power that the spindle and axes motors require for higher speeds.

	ΔE_{toal}	ΔP_{max}
Increased cutting speed scenarios		
10% increase	-26.0%	+5.6%
20% increase	-29.7%	+12.6%
Increased chip load scenarios		
20% increase	-31.0%	+7.6%
40% increase	-40.7%	+13.8%

Table 1: % change in total electrical energy consumption and filtered maximum power demand of the machine tool for each alternative scenario relative to the baseline case.

5.2 Load based performance evaluation

Table 2 summarizes the cumulative damage on each axis of the machine tool for each alternative scenario relative to the baseline scenario. These values were calculated by considering the stress-life relationship of bearings as an initial validation of our approach since bearings are an important part of many machine tool components. The cumulative damage on the x and y axes decreased with increased cutting speed. This was due to the slight decrease in cutting force created by the increased heat generation at the tool-chip interface. Conversely, the cumulative damage on the z-axis increased with increased cutting speed despite the previously noted trend. This was due to the added stresses on the z-axis during the face mill cut created by run out of the face mill tool. Finally, the cumulative damage of all axes increased with increased chip load because of the strong, direct dependence of the cutting force on the chip load. The y-axis was unique in that increasing the chip load seemed to initially decrease the cumulative damage. This could likely be due to a suboptimal choice for the chip load for the baseline scenario from the perspective of cutting forces.

	Δ***Damage***$_x$	Δ***Damage***$_y$	Δ***Damage***$_z$
Increased cutting speed scenarios			
10% increase	-8.7%	-37.9%	+39.8%
20% increase	-12.5%	-39.8%	+33.2%
Increased chip load scenarios			
20% increase	+18.7%	-14.1%	+52.9%
40% increase	+31.2%	-0.2%	+113.2%

Table 2: % change in cumulative damage on each axis of the machine tool for each alternative scenario relative to the baseline case.

5.3 Total costs of alternative scenarios

Industrial facilities are typically charged for electricity based on both overall usage and peak power demand. In addition, the rates for both charges differ depending on the time of day (peak, off-peak, or partial-peak) and the time of year (summer or winter). Using the current rate schedule for the Pacific Gas and Electric Company (PG&E) in California [21], Table 3 shows how each alternative scenario may affect the electrical energy price per part. To determine the amount to which the increased power demand shown in Table 1 becomes amortized per part, it was assumed that a machine tool creates only the test piece for 12 hours per day (6 hours during peak and 6 hours during partial-peak in the summer; all 12 hours during partial-peak in the winter), 20 days per month, and that set up requires 30 seconds per part.

	Summer		Winter	
	ΔCost/Part	% Diff	ΔCost/Part	% Diff
Increased cutting speed scenarios				
10% increase	-$0.001	-0.2%	-$0.008	-16.4%
20% increase	+$0.010	+4.3%	-$0.009	-17.6%
Increased chip load scenarios				
20% increase	$0	0%	-$0.010	-19.9%
40% increase	+$0.004	+1.9%	-$0.013	-26.6%

Table 3: Electricity cost to produce 1 part using each alternative scenario relative to baseline scenario.

The absolute cost difference per part was low for both the summer and winter pricing periods because the test piece is a simple part that is relatively cheap to produce. Also, the Haas VF-0 does not have too much auxiliary equipment, which means that the processing power is a relatively large portion of the overall power demand. So, reducing the processing time should not have had as significant an effect on the Haas VF-0 as it would have had on a larger or more automated machine tool where the processing power can be as little as 10% of the overall power demand [18]. Nonetheless, the percentage difference in electricity costs may still be substantial and did generally increase with increasing processing rate as seen in the winter pricing period. This trend should continue until a minimal operating point is reached due to the greater power required to operate the machine tool at greater loads. The summer pricing period did not have the same trend as the winter pricing period because of the relatively high demand costs ($12.67/kW and $2.81/kW for peak and partial-peak periods respectively [24]). Again, though, the summer pricing period would have more closely followed the winter pricing period if a larger or more automated machine tool were considered.

The increase in damage that is shown in Table 2 also impacts costs because of its indirect relationship with the lifetime of a machine tool component. For example, the spindle bearings should be strongly affected by the increased damage in the z-axis for both of the increased cutting speed scenarios. So, a 20% increase in the cutting speed increased the damage in the z-axis by 33.2%, which will decrease the service life of the spindle bearings by about 75% (that is, the machine tool will be able to machine 75% less parts before the spindle bearings will need to be replaced). In fact, because service life is measured in terms of parts produced in this approach, the relative change in damage is exactly equal to the cost of a component per part produced (e.g. if a spindle bearing costs $100 and has a life of 1000 parts, then they would cost $0.10/part for the baseline scenario and $0.133/part when the cutting speed is increased 20%, which is an increase of 33.2%). Thus, the increased cutting speed scenarios should generally decrease maintenance costs (if the damage in the z-axis is neglected since it was likely due to run out of the face mill), while the increased chip load scenarios should generally increase maintenance costs.

6 SUMMARY AND FUTURE WORK

This paper has presented an approach that considers environmental, performance, and financial impacts when evaluating green machining technologies and strategies. To begin the validation of this approach, a series of cutting experiments were performed to study the true costs of a reduced processing time strategy. The initial results indicate that such an approach may not provide great benefit for smaller machines or those will lower levels of automation such as the Haas VF-0 due to the increased loads on the bearings and other components of the machine tools and the marginal reductions in the electricity costs. However, these initial results do suggest that increasing the process rate could have significant benefits to larger and/or more automated machine tools were the processing power is a much smaller percentage of overall power demand and the machine tool components are designed to withstand greater forces. There are also other potentially significant costs that have yet to be included in this approach such as tool wear (which should be important for increased processing time strategies) and power factor. Furthermore, the performance evaluation should be improved to provide greater detail on the extent to which increased loads affect individual machine tool components.

The preliminary results of this study suggest that power factors could be a promising green machining strategy since power companies provide many financial benefits to ensure a high power factor so that the electricity grid is most efficiently utilized. For example, for facilities that have greater than 400 kW demand, PG&E rewards power factors above 85% by reducing its fees by 0.06% for each percentage point above 85% [20]. Similarly, PG&E also discourages power factors below 85% by increasing its fees in the same manner. Many facilities generally operate at or above 85% when all powered systems are considered. However, machine tools tend to reduce the power factor due to the high resistive losses typical in motors. For example, a power factor of ~68% was typical for the Haas VF-0. There are two general ways to increase the power factor of equipment: use more power towards productive work, or change electrical components (e.g. motors) to higher efficiency models. Both are technologies that should be investigated further, especially the former option as many existing strategies may serve to promote this effect.

Future work will focus on extending the current approach to consider other environmental impacts (e.g. water and machining fluid consumption, compressed air) and tool wear in addition to load and energy data on individual machine tool components to provide greater detail in characterizing the costs of green machining strategies. In addition, useful metrics such as energy reduction per Dollar of cost to implement the technology will be developed so that decision makers have the most relevant information when considering investment options. Through continued development, this approach may hopefully contribute towards existing cataloguing efforts such as the CO2PE! Initiative by providing true cost information for machining technologies and tools.

7 ACKNOWLEDGEMENTS

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