UC Berkeley

Green Manufacturing and Sustainable Manufacturing Partnership

Title

Impact of the manufacturing phase on the life cycle of machined products

Permalink

https://escholarship.org/uc/item/5rs7n92f

Authors

Diaz, Nancy
Helu, Moneer
Ninomiya, Kevin
et al.

Publication Date

2012

Impact of the Manufacturing Phase on the Life Cycle of Machined Products

Nancy Diaz, Moneer Helu, Kevin Ninomiya, David Dornfeld

Laboratory for Manufacturing and Sustainability, Dept. of Mechanical Engineering, University of California, Berkeley

Abstract

Growing global energy demands require manufacturers to implement strategies to improve energy efficiency over the entire product life cycle. These strategies must consider the complexity of modern manufacturing systems by evaluating impacts at both the process- and facility-level while also considering the effect of any strategy on part quality to ensure a salable product that meets its intended function. This paper presents three studies that focus on how green machining strategies can be implemented on the shop floor and how they subsequently affect facility planning and the product use phase. The results of these studies highlight the need for a holistic perspective that emphasizes resource efficiency over consumption reduction to provide green products.

Keywords: Energy, green machining, product life cycle

1 INTRODUCTION

Global energy demand is expected to grow by 53% between 2008 and 2035 [1]. China and India are projected to more than double their energy demand by 2035. Previous literature has shown that the manufacturing phase can have a substantial effect on the environmental impact of a product, particularly when flows beyond electrical energy are considered [2]. This is especially true since manufacturing decisions can have a direct effect on a product's use phase impacts. Therefore, we must continue to propose and implement efficient and realistic strategies to reduce natural resource consumption in all phases of a product's life cycle.

This paper first characterizes energy in the manufacturing phase for both process- and factory-level assessments. We initially validate the energy model from Diaz et al. [3] for a toolpath with varied MRR [4]. The energy model is then utilized in a facility energy assessment conducted by means of a discrete event simulation (DES) to identify green operation strategies [5]. While it is important to implement green strategies during the manufacturing phase, we cannot ignore the effects of these strategies on machine tool service costs and surface quality. Effects on part quality are particularly important to consider since part quality must remain sufficient to ensure that the product meets its intended function and provides value to the manufacturer and customer. Furthermore, these effects can also impact resource efficiency over the entire product life cycle [6]. For example, improvements in part precision generally lead to greater operational efficiency and longer service life [7]. Thus, any change in the manufacture of a part must be holistically considered across the entire product life cycle.

2 VALIDATION OF THE ENERGY MODEL FOR VARIED PROCESS RATES

Gutowski et al. [8] showed that the specific electrical energy requirement of manufacturing processes was inversely proportional to the process rate. Based on this work, Diaz et al. [9]-[10] and Kara et al. [11] developed a method to model the specific electrical energy of machining centers that will be utilized in this paper. The model was previously used to predict the energy consumed to manufacture parts produced under a constant material removal rate (MRR) with 91.95% to 97.63% accuracy [11].

2.1 Methodology

To assess the validity of this model for complex parts, we conducted experiments on the Mori Seiki NVD1500 for a toolpath with variable MRR. 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 Figure 1; each feature indicates a change in the MRR. The same part was machined six times to gage repeatability.
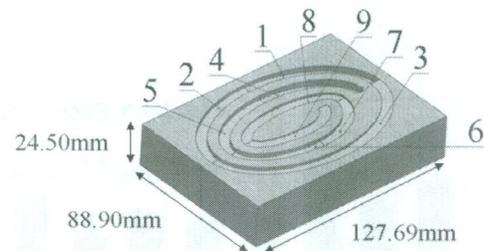

Figure 1: Spiral geometry and feature label of part design for energy characterization experiments

The MRR as a function of elapsed time was then used to estimate the energy consumption with Equations 1 and 2 for areas of constant (feature $x+1$ in Figure 2) and variable MRR (feature x in Figure 2), respectively:

$$E_{const} = V * (\frac{k}{MRR} + b) \tag{1}$$

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

where V is the volume of material removed, k and b are constants to the specific energy model [10], N is the subintervals per feature, and Δt the processing time for the feature. For each scenario, the average MRR of each subinterval, $MRR_{avg,i}$, was used to calculate the energy consumed per feature, E_{var}. The energy consumed for part manufacture was thereafter found by summing E_{var}
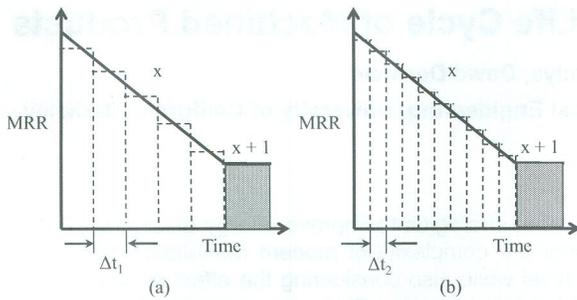
Figure 2: (a) MRR breakdown of feature x with N=5 subintervals; (b) MRR breakdown of feature x with N=10 subintervals

over all features and adding the energy consumed for the features produced under constant MRR, E_{const}.

The number of subintervals necessary for the energy estimate per feature converged within 1000 subintervals or less, so N of 1000 was used in the following results. 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.

2.2 Discussion of Results

Figure 3 shows the predicted energy ("Model") and the actual energy ("Experiment") consumed to machine the sample part [4]. The average percent error (over the six experiments) is also shown for each feature. The model typically overestimated the energy consumption for part production.
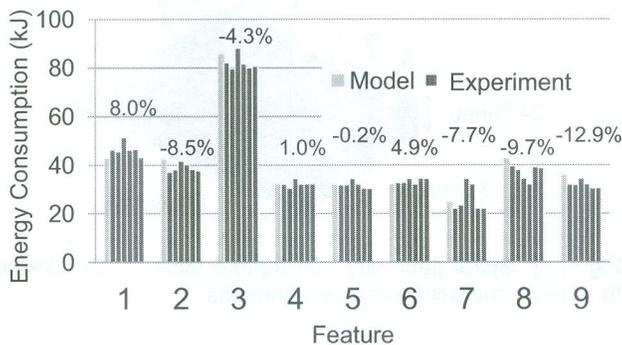

Figure 3: Energy consumed to create each feature of the sample part

The accuracy of the energy estimates were affected by several aspects of the manufacturing process. First, features machined under a low MRR (i.e., features 3 and 9) were hypothesized to have a large error between measured and predicted energy since at low process rates the specific energy model shows a steep change in energy. A second aspect affecting the accuracy is process time. More time is required for the power demand to reach a steady state because short process times provide fewer data points, the initial tool engagement causes a peak in the power demand, the power fluctuates over time (even in standby mode), and the internal cooling unit must do more work while machining to maintain precision. Conversely, with long process times when more data is collected at a constant MRR, the power required to create a feature can

reach a steady state and be closer to the energy predicted by the energy model. This fluctuation in power demand is more pronounced in machine tools with a small work volume [12]. Therefore, larger machine tools are expected to behave in accordance with the energy model. Lastly, the power demand is dependent on prior processing conditions. For example, the energy for feature 1 had a relatively high average error and range of errors since it was the first feature produced. In addition, the energy estimate was lower than the actual in all experiments. The feature was also produced over a short process time so the power did not reach a steady state even though it was milled at a high MRR, which is why we see a large range in power demand and predicted a lower energy consumption.

The predicted energy showed significant deviation from the measured energy when it was differentiated by feature. However, the average error of the part's energy estimate for the six parts produced was only -2.6% with a standard deviation of 3.8%. This shows that estimating the energy consumption for complex parts using our method is indeed promising since product designers and manufacturers may deem more valuable the estimated energy needed to create an entire part.

2.3 Scope of Analysis

Though the specific energy model provided accurate estimates for the part as a whole, it only accounts for the steady state electrical energy consumed during material removal. Machine tool users can account for air cutting power demand by estimating the power demand of components that contribute to the constant and variable power demand [13]. Also, the machine tool exhibits peaks in power demand many times throughout processing such as when the spindle starts, the cutting tool initially engages with the workpiece, and the cutting tool changes. Dietmair et al. [14] modeled the power demand of machine tools to account for these various states, but their methodology requires greater time to acquire data, which results in higher costs for model development.

3   ENERGY ANALYSIS OF THE FACTORY

Though resource use characterization and reduction for production equipment are important, machine tools rarely operate in isolation. Therefore, expanding the scope to at least the facility level is necessary to manufacture products in a sustainable manner. Previous consideration of sustainability of a facility is limited since the majority of facility level optimization has traditionally focused on financial costs. Research that accounts for the environmental impact of a facility include Fang et al. [15], who studied the energy consumption and peak power demanded by a two machine job shop; Heilala et al. [16] who developed a simulation tool for optimizing between production efficiency and environmental impact using a toy manufacturing plant as a case study; and Johansson et al. [17] who showed how discrete-event simulation (DES) and life-cycle assessment can be combined to evaluate the performance of a manufacturing system with the exemplary case study of a paint shop. In essence, these studies focused on manufacturing one type of product, manufacturing with preset processing conditions and equipment, or both. Since products change over time and facilities can manufacture a high mixture of products at a range of processing conditions, a method that adds

flexibility to the environmental impact assessment is needed to capture the evolution of facility operation.

We applied the energy model in a DES environment to estimate the energy of the production equipment within a factory [5]. Using this approach, we evaluated the energy consumption on smaller scales in the manufacturing system as well: the machine tool cells, the individual machine tools, and the parts produced. This spectrum of analysis allows the implementation of a broad range of sustainability strategies.

3.1 Methodology

DES was used to model the processing of three types of parts in a flexible manufacturing facility. The analyst may choose the types of parts that are manufactured by defining, for example, machine tool production constraints, process rates, process times, and interarrival times for the parts. The parts in this study are generically labeled types A, B, and C, and were produced in proportions of 45%, 30%, and 25%, respectively. We modeled the parts to have exponentially distributed interarrival times with a mean interarrival time of 10 minutes. Each part was processed using a first-in-first-out (FIFO) queuing discipline in a multi-server queuing model with five manufacturing cells.

Table 2: Uniformly distributed part processing parameters.

Type	Cell Constraints	MRR (mm³/s)	$t_{process}$ (min)
A	M1, M2, M3, or M4	500 to 600	45 to 50
B	M2, M4, or M5	305 to 350	95 to 105
C	M5	0.75 to 1.75	120 to 135

Table 2 shows the cell constraints placed on the machine tools capable of producing the different part types. That is, part type A could be produced with a machine tool in either cell M1, M2, M3, or M4, while part type C could only be produced by a machine tool in cell M5 (i.e., a micromachining center). The MRR and the processing time remained constant throughout the production of any given part. However, these parameters were uniformly distributed over the ranges outlined in Table 2 for each part type. Therefore, the facility produced a high mix of products. The conversion to low mix manufacturing can be achieved by constraining the process rates and times.

Since the parts could be produced by a range of machine tools, we programmed the selection criteria such that the machine tool was chosen to reduce the energy consumed while machining. The facility was modeled such that it had the machine tool cells provided in Table 3 with the cutting conditions (dry or wet). The cells were preferred in the following order based on lowest processing energy consumption: M1, M3, M2, M5, and M4 (i.e., a machine tool in cell M1 consumed the lowest energy while processing parts at a particular MRR and one in cell M4 consumed the highest energy at the same MRR).

The DES model tracked the number of available machine tools within a cell rather than the availability of each individual machine tool. If no machine tool was readily available to start production then the part entered the shortest queue. This machine tool selection strategy gives preference to high machine tool utilization to avoid the

consumption of energy for non-value added time during idling. Alternative strategies also can be studied, such as reducing the overall time spent in the facility (processing and wait time) or prioritizing parts in queues based on expected processing energy consumption or lead time. Since flexible manufacturing facilities, such as job shops, underutilize machine tools, it is also important to consider if it would be more beneficial for a part to wait for a less energy intensive machine tool to become available rather than immediately start production at an available machine tool especially if the part has a long processing time. Such a part scheduling strategy will be studied in future work.

Table 3: Parameters for process energy and idle power demand [9]-[11] for machine tool cells M1-M5.

	Machine Tool	K [J/s]	b [J/mm³]	P_{idle} [W]
M1	Fadal VMC 4020 (Dry)	1330	2.845	740
M2	Fadal VMC 4020 (Wet)	1396	3.082	740
M3	Mori Seiki DV 5500 (Dry)	1344	2.830	1020
M4	Mori Seiki DV 5500 (Wet)	2019	2.953	1020
M5	Mori Seiki NVD 1500 (Wet)	1481	3.678	924

3.2 Discussion of Results

With DES the energy consumed by the facility can be assessed at the level of the facility, cell, machine tool, and part in order to look at the effectiveness of green strategies. The total energy consumed by the five cells in this case study was 11.85 GJ, 92.8% of which was used for process energy and the remaining 7.2% for idle energy (see Figure 4). Cells M1, M2, and M5 consumed the greatest proportions of idle energy; we used this information to design six additional scenarios.
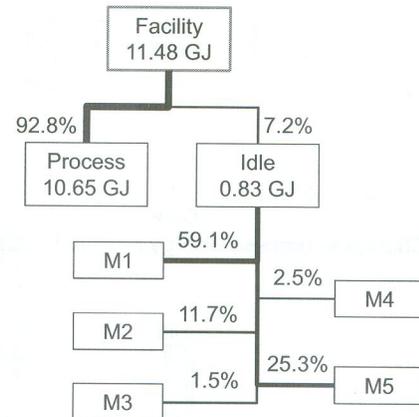

Figure 4: Breakdown of machine tool energy consumption.

Table 4 shows how the number of machine tools in each cell varied for the baseline scenario (case 1) and each subsequent case. The cells that were altered in this study relative to the base case are highlighted in gray.

The energy saved for the scenarios are shown in Figures 5-6. Case 4 is the only scenario that consumes more energy than the baseline; 11.1% of the total energy consumed by the machine tools (11.88 GJ) was spent on idling machine

tools. The idle energy consumption increased relative to the baseline case when a machine tool from cells M2 and M4 were removed in case 4 due to part queuing.

Table 4. Number of machine tools in each manufacturing cell for cases 1-7 where (*) represents the base case.

	Case 1*	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
M1	3	2	3	3	2	2	1
M2	2	2	2	1	2	2	2
M3	1	1	1	1	1	1	1
M4	1	1	0	0	0	0	0
M5	4	4	4	4	4	3	3

Even though we lowered the idle energy consumed in a facility by reducing the number of machine tools, part queuing became important in our analysis as overall machine tool availability was reduced. When a machine tool was removed from a cell that was highly utilized, the queue length grows at a potentially unstable rate; this occurred with cases 4, 6, and 7. Although cases 6 and 7 had lower energy consumption, parts spent a longer period of time in the facility. Thus, if additional criteria were used in the energy assessment, such as HVAC and lighting, these cases may not in fact be ideal scenarios since the time spent to produce parts will increase and the factory would have to operate for a longer period of time. The energy consumption of production equipment varied significantly with savings of up to 8.5% relative to the baseline case. Taking into consideration the stability of the cell queues, case 5 was the most promising design with a stable queue and energy reduction potential of 6.4%.
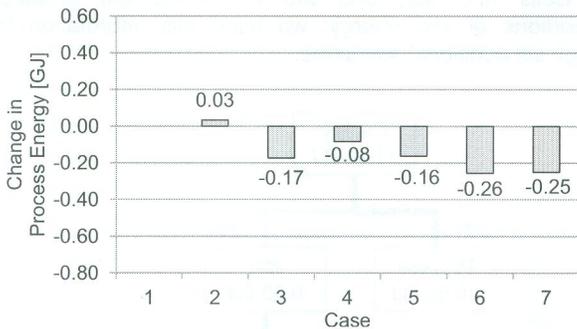

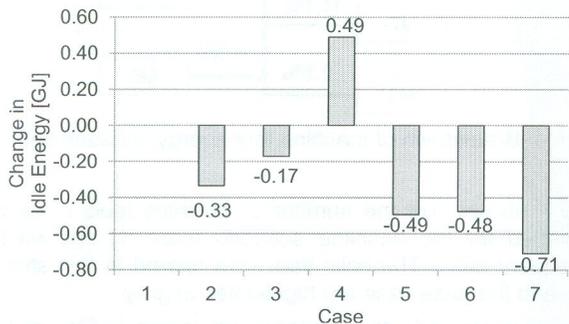Figure 5: Change in process energy relative to case 1.

Figure 6: Change in idle energy relative to case 1.

The methodology for energy consumption optimization that utilizes DES was presented for a manufacturing facility with high product variability and relatively low production volume. However, the simulation of a facility with a low mix, high volume of parts can be accomplished as well by increasing the interarrival rate and reducing the number of part types produced.

4   IMPACT TO OTHER LIFE CYCLE STAGES

Aside from characterizing and reducing energy during the manufacturing phase, changes to the manufacturing phase will also inevitably impact other life cycle stages, particularly the product's use phase [6]. We now conclude our paper with an analysis of how green machining strategies can impact the overall product life cycle.

4.1   Direct Impacts: Achieved Surface Quality

[18] investigated the effect of process time reduction and dry machining on both the machining process and achieved surface quality of titanium alloy (Ti-6Al-4V) parts. Experiments were conducted on a 4-axis horizontal machining center using uncoated carbide inserts to turn a test part from an initial diameter of 25 mm to a final diameter of 16 mm with cuts of length 80 mm. These experiments utilized separate inserts to rough and finish, and new inserts were used for each test part. A "baseline" part was created first from the tool manufacturer's recommended process parameters.

4.1.1   Process time reduction

Process time reduction was explored by increasing the MRR by individually varying the cutting speed, feed rate, and depth of cut for both the rough and finish cuts to study the effect of each parameter [18]. Helu et al., [18] found that the specific electrical energy decreased as the process time decreased. These results agreed with the literature (e.g., Dahmus et al. [19]; Diaz et al. [9]-[10]; Kara et al. [11]). Furthermore, the specific electrical energy varied at the same rate for each parameter, which indicates that energy requirements are directly tied to the process time (see Figure 7).
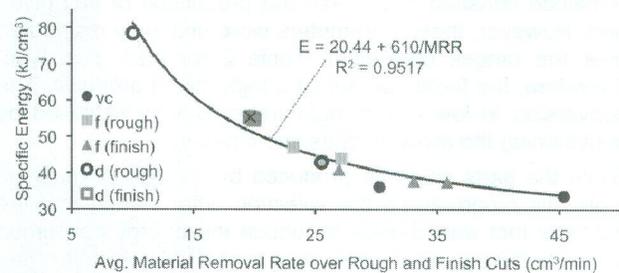

Figure 7: Total specific energy consumed to create one test part for varied cutting speed, v_c, feed, f, and depth of cut, d; the specific energy for the baseline case is marked with an "x" [18].

While process time reduction improved energy efficiency, it also created tool wear and service cost issues. Flank wear on the tool increased with increased cutting speed and feed rate and in several cases far exceeded the tool manufacturer's recommendation. The service costs per part also substantially varied due to unexpected breakdowns; this variation increased for the most aggressive strategies

on the spindle, such as increasing the depth of cut, where the authors found the highest service costs per part. When unexpected breakdowns were excluded, production loss and service technician costs primarily drove service costs, and process time reduction strategies reduced service costs per part because of increased production volume. So, while process time reduction can improve energy efficiency, the potentially detrimental effects on tool wear and machine tool maintenance may not allow process time reduction to viable green titanium machining.

The viability of any green machining strategy also depends on its ability to produce parts of sufficient quality. Helu et al. studied two measures of surface quality: surface roughness and local strain hardening [18]. They measured the average height surface roughness, R_a, in the feed direction after both the final rough and finish cuts. Even though the experiments varied the cutting speed and depth of cut, the surface roughness was primarily influenced by the feed rate, which agreed with expectations since the surface roughness was primarily caused by feed marks. More importantly, though, the finish cut most strongly affected the final achieved surface roughness (see Figure 8). So, process time reduction may be implemented best during any rough cuts since it would not negatively impact the final achieved quality of a part. Furthermore, these results also may support any strategy that relies on aggressive rough cuts, such as the use of a "sleep mode" where roughing should occur while the machine re-stabilizes itself back to production conditions.
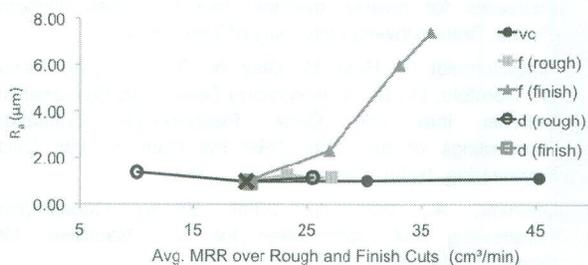

Figure 8: Final measured surface roughness for varied feed rate, f, cutting speed, v_c, and depth of cut, d, during either the rough or finish cuts as indicated; the baseline case is marked with an "x" [18].
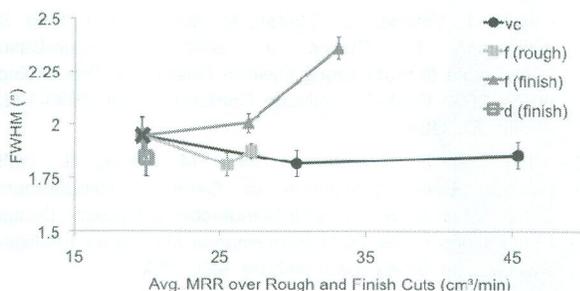

Figure 9: Measured full width at half maximum on the finished surface for varied feed rate, f, cutting speed, v_c, and depth of cut, d, during either the rough or finish cuts as indicated; the baseline case is marked with an "x" [18].

To measure the local strain hardening, [18] conducted x-ray diffraction analyses after the final finish cut to measure the full width at half maximum (FWHM) of the resultant x-ray interference patterns. The FWHM correlates to the degree of cold working since it increases as dislocation density

increases. The feed rate had the largest impact on local strain hardening due to the increased elastic-plastic deformation that occurs in the shear zone and is driven by increased tool wear and surface roughness (see Figure 9). So, despite its negative consequences, increased feed rate increases work hardening, which may improve fatigue performance and overall resource efficiency by extending service life. In addition, the finish cut had the strongest influence on the FWHM just as it did with surface roughness. These results further support green machining strategies that target roughing operations.

4.1.2 Dry machining

[18] implemented dry machining by running the baseline case without any coolant. The largest impact occurred for specific electrical energy since dry machining required less energy than the baseline case because none of the coolant pumps in the machine tool demanded power. Thus, the effect of dry machining on specific electrical energy was to essentially lower the curve shown in Figure 7 by a constant amount. However, this does not take into account the embodied energy of the coolant, which would further improve energy efficiency. Dry machining also affected flank tool wear. This agreed with expectations since a lack of coolant increases thermal gradients, friction, and cutting forces, which all increase tool wear. Aside from these effects, though, dry machining did not significantly affect the manufacturing process or achieved surface quality; the resulting service costs per part, surface roughness, and local strain hardening were all comparable to the baseline case.

4.2 Indirect Impacts: Operational Efficiency

Because the precision and quality of a part influences the part's operational efficiency in addition to its salability, it is important to ensure that any change to the manufacturing process does not offset environmental impacts to the part's use phase. [7] investigated the effect of reduced surface roughness of automotive drivetrain components on their environmental impacts during use. The study focused on the manufacture and use of a final drive reduction unit. Recent research suggests that the gear mesh efficiency of these components is directly influenced by the RMS surface roughness, R_q, and inlet lubricant temperatures among other factors [20]. While the inlet lubricant temperature is a function of the drivetrain design, the RMS surface roughness of the gear mesh can be directly controlled by the gear finishing processes.

To study the effect of changing the gear finishing process to improve the surface roughness of the final drive reduction, [7] studied a drivetrain and vehicle modeled after a Honda Civic, which was identified as a representative fuel-efficient sedan on the market. They found that decreasing the R_a by 20-60% of that achieved for a standard automotive gear finish can be accomplished for less than 0.5 MMBtu PE per final drive reduction. While this may be a significant additional resource expenditure for a manufacturer, the savings potential during the use of the final drive reduction is quite great: decreasing R_q over the range of values expected for a final drive reduction can save 2 to 5 MMBtu PE in gasoline alone over the life of the part. Even though the surface roughness measures used in both analyses are different by necessity, this comparison shows how small investments in the manufacturing phase can actually be

leveraged into large overall resource reductions over the entire life cycle of a product.

5 SUMMARY

This paper first 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 to estimate the energy required to machine a part. Overall accuracy of the energy model is hypothesized to improve with higher MRR's, longer process times, and large machine tools – instances when more stabilized power demand is achieved.

In addition, a methodology for energy consumption optimization utilizing DES modeling was studied for a manufacturing facility with high product variability and a relatively low volume of production. Additional types of facilities may be simulated by changing parameters such as the interarrival rate, the number of part types produced, and the type and number of available machine tools.

Lastly, Helu et al. [7] and [18] both display how changes to the manufacturing phase can have far reaching impacts on a product's overall resource efficiency. Often, engineers may adjust a manufacturing process to reduce resource consumption without realizing that these strategies may have deleterious effects on part quality that can ruin a product's value or decrease its operational efficiency and/or service life. Ultimately, a holistic perspective is required when considering any change to manufacturing phrase. All resources should be considered, and improved resource efficiency (i.e., minimum resource consumption for maximum value-added, efficiency, etc.) should be the primary goal instead of simple resource consumption reduction. In this way, manufacturers can meet the increasing challenge of providing customers with truly green products.

6 REFERENCES

[1] U.S. Energy Information Administration (EIA). "China and India Account for Half of Global Energy Growth through 2035 - Today in Energy." Accessed 10 Dec. 2011. <http://www.eia.gov/todayinenergy/detail.cfm?id=3130>.

[2] Diaz, N., Helu, M., Jayanathan, S., Chen, Y., Horvath, A., Dornfeld, D., 2010, Environmental Analysis of Milling Machine Tool Use in Various Manufacturing Environments, IEEE Intl. Symp. on Sustainable Systems and Technology.

[3] Diaz, N., Behrendt, T., Choi, S., Kong, D., Ninomiya, K., Dornfeld, D., 2011, Environmental Impact Accounting of Machining, the Proceedings of MTTRF 2011 Annual Meeting, Chicago, IL, USA.

[4] Diaz, N., Ninomiya, K., Noble, J., Dornfeld, D., 2012, Environmental Impact Characterization of Milling and Implications for Potential Energy Savings in Industry.

[5] Diaz, N., Dornfeld D., 2012, Cost and Energy Optimization of Product Manufacture in a Flexible Manufacturing System, Proceedings of the 19th CIRP Intl Conf on Life Cycle Engineering, Berkeley, CA, USA: (to appear).

[6] Hauschild, M., Jeswiet, J., Alting, L., 2005, From Life Cycle Assessment to Sustainable Production: Status and Perspectives, Annals of the CIRP, 54/2: 1-21.

[7] Helu, M., Vijayaraghavan, A., Dornfeld, D., 2011, Evaluating the relationship between use phase environmental impacts and manufacturing process precision, Annals of the CIRP, 60/1: 49-52.

[8] Gutowski, T., Dahmus, J., Thiriez, A., 2006, Electrical Energy Requirements for Manufacturing Processes, Proceedings of the 13th CIRP Intl Conf on Life Cycle Engineering.

[9] Diaz, N., 2010, Process Parameter Selection for Energy Consumption Reduction in Machining, Master of Science Project Report from the Dept of Mech Eng at the University of California, Berkeley.

[10] Diaz, N., Redelsheimer, E., Dornfeld, D., 2011, Energy Consumption Characterization and Reduction Strategies for Milling Machine Tool Use. Proc of the 18th CIRP Intl Conf on Life Cycle Engineering, pp. 263-7, Braunschweig, Germany.

[11] Kara, S., Li, W, 2011, Unit Process Energy Consumption Models for Material Removal Process, Annals of the CIRP, 60/1: 37-40.

[12] Behrendt, T., 2010, Development of a simulation-based application to derive and estimate potentials of efficiency measures for diverse machine tool processes, Diploma Thesis, Braunschweig University of Technology.

[13] Niggeschmidt, S., Helu, M., Diaz, N., Behmann, B., Lanza, G., Dornfeld, D., 2010, Integrating Green and Sustainability Aspects into Life Cycle Performance Evaluation, Proceedings of the 16th CIRP Intl Conf on Life Cycle Engineering, Hefei, China.

[14] Dietmair, A., Verl, A., 2009, Energy Consumption Forecasting and Optimisation for Tool Machines. MM Science J Mar 2009; 62-6.

[15] Fang, K., Uhan, N., Zhao, F., Sutherland, J.W., 2011, A New Shop Scheduling Approach in Support of Sustainable Manufacturing, Proceedings of the 18th CIRP International Conference on Life Cycle Engineering, pp. 305-310, Braunschweig, Germany.

[16] Heilala, J., Vatanen, S., Tonteri, H., Montonen, J., Lind, S., Johansson, B., Stahre, J., 2008, Simulation-Based Sustainable Manufacturing System Design, in: Proceedings of the 2008 Winter Simulation Conference, pp. 1930-1922, Austin, TX, USA.

[17] Johannson, B., Skoogh, A., Mani, M., Leong, S., 2009, Discrete Event Simulation to Generate Requirements Specification for Sustainable Manufacturing Systems Design, Proceedings of the 2009 Performance Metrics for Intelligent Systems, pp. 38-42, Gaithersburg, MD, USA.

[18] Helu, M., Behmann, B., Meier, M., Dornfeld, D., Lanza, G., Schulze, V., 2012, Impact of green machining strategies on achieved part quality, Annals of the CIRP, 61/1: (to appear).

[19] Dahmus, J., Gutowski, G., 2004, An Environmental Analysis of Machining, Proceedings of the 2004 ASME International Mechanical Engineering Congress and RD&D Exposition, Anaheim, CA, USA.

[20] Xu, H., Kahraman A., Anderson N. E., Maddock, D. G., 2007, Prediction of Mechanical Efficiency of Parallel-Axis Gear Pairs, J. Mechanical Design, 129: 58-68.