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A MATERIAL-GENERAL ENERGY PREDICTION MODEL FOR MILLING MACHINE TOOLS

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ABSTRACT

Increasing awareness of energy consumption and its environmental impacts has prompted a need to better predict the energy consumption of various industrial processes, including manufacturing. Modeling can allow manufacturers to optimize the efficiency of their manufacturing processes. Highly accurate, data-driven models of energy consumption of CNC milling have been developed but these models are generated from experimental data and are not generally applicable. If any conditions are varied beyond the experimental parameter ranges, a data-driven model faces challenges in maintaining its prediction accuracy. In this work, two models based on the non-cutting power demand of the CNC machine and the specific cutting energy of the workpiece material are analyzed. These models are then used to predict milling energy consumption of several experimental parts. Both models predicted the total energy consumption of the experimental parts with an average relative total error of less than 3%, which is comparable to data-driven models. Unlike most models, the proposed models presented here can be applied to most workpiece materials.

NOMENCLATURE

P	Total power consumption [W]
P_0	Auxiliary power consumption [W]
a	Empirical chip thickness exponent
h	Average chip thickness [mm]
h_r	Normalizing chip thickness factor [mm]
k	Specific cutting energy [J/mm^3]
v	Volume of material removed [mm^3]
$\dot{v}$	Material removal rate [mm^3/s]

INTRODUCTION

Manufacturing is responsible for 90% of total energy consumption and 84% of CO2 emissions in the industrial sector [1]. The high usage of energy in manufacturing presents challenges but also potential for high impact of improved efficiency of manufacturing processing and planning. Energy modeling of machining processes can offer many benefits to manufacturers. Accurate energy prediction and subsequent optimization of manufacturing processes can help manufacturers increase resource efficiency, lower costs, and reduce the associated emissions. Predicting energy demand enables better integration with smart grids which is of increasing importance. Improved energy prediction can also lead to cost estimation based on maximum power demand which will enable manufacturers to optimize not just at the process level, but at a systems level. The work described here focuses on improving energy predictions for CNC milling.

Equations to predict energy consumption of milling based on cutting forces have existed for decades but their application is typically limited to choosing appropriate cutting parameters for manual milling [2]. Recent efforts have developed highly accurate models for prediction of energy consumption of CNC milling processes but these models are generated from experimental data and are not generally applicable [3-5]. If the workpiece material is changed from that used in the experiment, such a model tends to lose accuracy. This work describes two different models used to predict energy consumption of CNC milling. Both models can be applied to a range of materials. The accuracy of both models is compared with that of published models.

MATHMATICAL BASIS OF STUDIED MODELS

Rather than presenting a data-driven, experimentally-derived model, an attempt is made here to validate simple, material-general relationships that have been presented in literature before but not necessarily applied for the purpose of prediction. Both models presented here are based on the general equation for energy consumption in CNC machining as presented by Gutowksi [6]. The first model, which will be referred to as the Specific Cutting (SC) model, is an unmodified version of the equation Gutowski presented, where energy consumption is calculated from the material removal rate, $\dot{v}$, specific cutting energy, k, and the non-cutting power demand of the CNC machine, P_0 [6]. By integrating this equation from time t_1 to t_2, assuming a constant $\dot{v}$ over this interval, a model for the energy consumption can be obtained, as seen in Eq. (2).

$$P = P_0 + k\dot{v} \qquad (1)$$

$$E_{SC} = \int_{t_1}^{t_2} P\,dt = \int_{t_1}^{t_2} (P_0 + k\dot{v})\,dt = P_0\Delta t + k\Delta v \qquad (2)$$

A challenge of the model presented in Eq. (1) and Eq. (2) is that specific cutting energy is not a true constant. In actuality, specific cutting energy has a significant dependence on chip thickness: thin chips tend to consume more energy to machine per unit volume compared to large chips [7]. The exact reason for the dependence of k on chip thickness is unclear. The shear strength of the material has a similar dependence on average chip thickness. DeVries discusses a number of possible explanations for the dependence of the shear strength on average chip thickness, including the effects of work hardening ahead of the tool and the influence of shear strain rate [2].

To capture the dependence of k on average chip thickness, we proposed an additional term to modify k: a normalized chip thickness, h/h_r, raised to the power a, where $-1< a< 0$. Here, h is the average chip thickness and h_r is a normalizing chip thickness factor. As a first approximation, the values of a and h_r were assumed to be constant and equal to -0.8 and 0.32 mm respectively for the experiments described in this study. These values were derived from empirical data as described by DeVries [2]. The model now contains three empirical parameters: k, a, and h_r. This second model, referred to as the Modified Specific Cutting (MSC) model, is summarized in Eq. (3).

$$E_{MSC} = P_0\Delta t + k\left(\frac{h}{h_r}\right)^a \Delta v \qquad (3)$$

To obtain the model parameter P_0, the energy consumption of the machine tool was measured for an air-cut of the experimental toolpath. To implement both models, the predicted energy for each line of numerical control (NC) code was calculated following Eqn. (2) and (3). The volume removed and approximate cutting time can be calculated based on the NC code, machine parameters, and air-cut data. Energy consumption of non-cutting lines of code was calculated as the product of P_0 and the time elapsed for the line of code.

DESCRIPTION OF VALIDATION EXPERIMENTS

Two experiments were undertaken to validate and compare the SC and MSC models. The first, Experiment I, was used to compare the accuracy of these two models to an existing published model, namely the Gaussian Process Regression (GPR) model developed by Bhinge et al. [8]. The second experiment was used to verify that the proposed models can be used for different types of materials with comparable accuracy.

The total power of the machine tool was measured at a frequency of 100 Hz. The MTConnect standard [9] was used to collect and record machine operation information, such as feed rate, spindle speed, and tool position. This enables a richer data set because energy consumption data is contextualized with the corresponding machine parameters as dictated by the NC code. Each block of NC code in a given toolpath becomes an experiment in itself, allowing for better understanding of what effect each machine parameter has on energy usage. Although the experiments described here included machining only a few parts, the data from each part contained hundreds of measurements of machine parameters and energy usage.

Experiment I

As part of the validation of the GPR model, four test parts were machined using four different milling strategies, namely zigzag in X, zigzag in Y, contour in, and contour out, to create the same geometry, as illustrated in Fig. 1. These parts were milled from a 2.5"x2.5"x1" block of 1018 steel on a Mori Seiki NV1500 DCG milling machine tool. Spindle speed (ranging from 1500 to 3000 rpm) and feed rate (ranging from 75 to 300 mm/min) were varied throughout the toolpath. As part of Experiment I, the SC, MSC, and GPR models were used to predict the energy consumption of the four parts, Parts A through D.

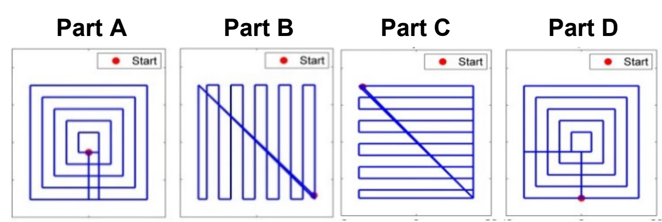

Figure 1: Toolpaths used in Experiment I

Experiment II

A second experiment was performed to explore the ability of the SC and MSC models to predict energy consumption for different workpiece materials. This work was completed on a different Mori Seiki NV1500 DCG milling machine tool. The part geometry, called Part E, used a more complicated toolpath, including pocketing, slotting, and drilling operations, as shown in Fig. 2. This toolpath was used to machine 2.5"x2.5"x1" blocks of several different materials.

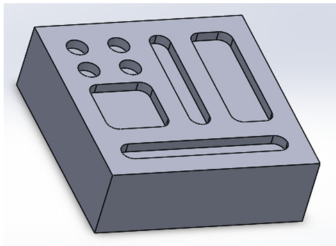

Figure 2: Final geometry of Part E

Workpiece materials for Experiment II were chosen with the goal of capturing a wide range of materials. This goal was limited by the fact that all materials were to be machined with the same set of feed rates (ranging from 150 to 900 mm/min) and spindle speeds (ranging from 1500 to 4500 rpm). Another limitation was the need to select materials with a published value of k. Although it is possible to obtain a rough estimate of k based on hardness, it was desired to eliminate uncertainty of k as a possible source of error so only materials with a published value of k were chosen. The materials chosen included 1018 steel (used for Experiment I), as well as 6061 aluminum, 2024 aluminum, and C36000 brass. This is summarized in Table 1.

Table 1. Summary of experimental parts

Material	Temper	Part Types	Model Parameters
1018 Steel	As cold drawn	Parts A, B, C, D, E*	k=2.07; a= -0.8; h_r=0.32
C36000 Brass	H02	Part E*	k=0.68; a= -0.8; h_r=0.32
Al 6061	T6511	Parts E*	k= 0.76; a=-0.8; h_r=0.32
Al 2024	T351	Parts E*	k=0.87; a=-0.8; h_r=0.32

*Part E was machined with three levels of depth of cut

The feed rate and spindle speed were varied throughout the toolpath to obtain a wide range of material removal rates. Part E was cut three times for reach material, using a constant depth of cut of 0.5 mm, 1.0 mm, and 1.5 mm for each part.

RESULTS

Experiment I

The GPR model was used to predict the energy consumption for Parts A through D. The SC and MSC models were used to predict the energy consumption for the same four parts and the accuracy of the predictions were compared with the predictions of the GPR model.

The predicted and measured energy consumption are compared using the normalized mean absolute error (NMAE) and relative total error (RTE). The NMAE is the average absolute error of all lines of NC code for a part, while the RTE is the absolute error between the total predicted energy (i.e. the sum of the predicted energy for all lines of NC code) and the actual total energy consumption. These errors are summarized in Table 2, along with the experimental energy consumption and predictions of each model. For Parts A through D, the average number of data, or NC blocks of code and the corresponding energy usage and machining parameters, was 94 per part.

Table 2. Experimental results, model predictions, and model errors for Experiment I

		GPR		SC		MSC	
Part	Exp. Energy (kJ)	Pred. Energy (kJ)	RTE [NMAE] (%)	Pred. Energy (kJ)	RTE [NMAE] (%)	Pred. Energy (kJ)	RTE [NMAE] (%)
A	849.8	877.7	3.3 [11.0]	848.1	0.2 [17.5]	859.4	1.1 [16.9]
B	943.3	997.4	5.7 [15.4]	983.5	4.3 [7.7]	998.1	5.8 [7.6]
C	1018.2	1051.4	3.3 [11.7]	1010.0	0.8 [4.7]	1026.2	0.8 [4.6]
D	938.3	969.2	3.3 [16.0]	896.7	4.4 [11.7]	911.4	2.9 [11.5]

The results from Experiment I indicate that the SC and MSC models can predict energy consumption with relative error similar to the GPR model. While the GPR model predicted an energy consumption higher than the actual value for all parts, the SC and MSC models under-predicted the consumption for some parts, and over-predicted for others. The NMAE error of MSC model is consistently lower than that of the SC model. Despite these differences, all three models accurately predict that the lowest energy toolpath is that of Part A, namely contour out.

Experiment II

For Experiment II, the SC and MSC models were applied to the toolpath of Part E. Part E was machined using three different depths of cut. The average number of data, or NC blocks of code and the corresponding energy usage and machining parameters, was 269. The measured energy consumption, along with the SC and MSC model predictions are shown in Fig. 3 for a depth of cut of 1 mm.

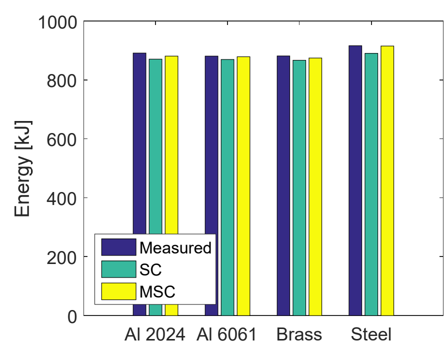

Figure 3: Measured and predicted energy consumption for Part E, depth of cut=1 mm

As seem in Fig. 3, although the majority of the energy is consumed by the non-cutting operation of the machine, represented by the $P_0\Delta t$ term in Eq. (2) and (3), energy consumption is affected by the workpiece material. The cutting energy accounted for ~5% of the total energy consumption. The energy consumption for all three depths of cut are similar, with an average percent deviation of 5.8%. For ease of reference, the results for the three depths of cut are averaged and summarized in Table 3.

Table 3. Average model error for Experiment II

	SC		MSC	
	RTE (%)	NMAE (%)	RTE (%)	NMAE (%)
Al 2024	1.80	4.31	1.78	3.81
Al 6061	1.87	4.13	0.83	3.74
C36000 Brass	0.76	8.90	1.11	8.74
1018 Steel	2.44	8.52	0.33	8.55

The results show that the SC and MSC models can predict the total energy consumption with less than 3% RTE for several materials. As seen in Experiment I, the NMAE error for the MSC model is generally lower than that of the SC model.

DISCUSSION

The results indicate that the SC and MSC models have a comparable accuracy to the GPR model as well as other similar models [10]. The SC and MSC models have varying accuracy for different parts and materials. For example, the results for Experiment II indicate the NMAE for the aluminum is considerably smaller than that of brass and steel for both the SC and MSC models. One possible explanation for this behavior is better accuracy of the value of k used for aluminum versus that of steel and brass, as the model accuracy is very sensitive to k.

Generally, the MSC model has a lower NMAE than the SC model, which implies that it is better at capturing the cutting physics. The MSC model also has a low RTE (an average of ~1% for Experiment II). The MSC model may further be improved by experimentally determining the model's novel empirical parameters (a and h_r) for each material, rather than using the same values for all materials.

However, the increase in accuracy of the MSC model is accompanied by increased complexity, with three empirical parameters compared to one. Additionally, the fraction of total energy consumption used by the cutting process varies for different machine tools so the tradeoff between complexity and accuracy needs to be considered on a case-by-case basis.. Further experimentation on different machine tools would enable better understanding of this trade off.

Though data-driven models like the GPR model can be adapted to different machine tools and different conditions, they are data-intensive and require training data. The accuracy improves as more training data is collected. However, in many cases such as process planning and toolpath planning, where prior data may not be available, it is more feasible to use an empirical model such as the models described in this paper. The SC and MSC models can be used for accurate, efficient, and material-general energy prediction where no training data is available.

CONCLUSION

The models described here, the SC and MSC models, provide similar accuracy to the data-driven models but are considerably simpler and can be applied to most materials. The SC and MSC models can be updated for any material for which a specific cutting value is known. Further, the SC and MSC models can be easily calibrated for a new machine tool by analyzing the power consumption of that machine tool during an air-cut. Future work could better determine the models' accuracy over a wider range of machine tools and machining parameters like depth of cut.

Because of their simplicity and flexibility, the models presented in this work provide a useful tool for making better informed decisions related to energy consumption in manufacturing.

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