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A hybrid approach to integrate machine learning and process mechanics for the prediction of specific cutting energy

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ABSTRACT

Specific cutting energy is an important concept because it affects not only surface integrity but also process sustainability. However, the predictive power of traditional analytical models for specific energy is significantly limited by the complex mechanical–thermal coupling in cutting. This paper has proposed a new hybrid approach to integrate data-driven machine learning and process mechanics for the prediction of specific cutting energy. Compared to traditional analytical models, the accuracy of the hybrid approach has been validated in milling of H13 tool steel and Inconel 718. The predictive model is also transferable to other cutting processes.

1. Energy consumption in cutting

1.1. Specific cutting energy

Specific cutting energy (SCE), i.e., the energy consumed to remove a unit volume of material, is an important concept in cutting mechanics. Specific cutting energy consists of the plastic deformation energy in the primary and secondary shear zones, friction energy at the tool/material interface, and energy for new surface generation and momentum transfer to chips. Specific cutting energy has been used in turning, milling [1,2], sawing [3], and grinding [4] of different work materials to evaluate their machinability.

Specific cutting energy controls chip formation and surface generation which governs surface integrity of a machined part. Therefore, it could be a process signature for surface integrity [5]. Neugebauer et al. and Guo et al. have shown that the decrease in process energy worsens the surface finish [6,7]. Li et al. have reported that the decrease in specific energy consumption increases the surface roughness in grinding [8]. Malkin and Guo have found that specific energy may be a threshold for thermal damage in grinding [9]. Sealy et al. have demonstrated that net cutting specific energy based process signature reflects the relationship between the internal thermal-mechanical loads and surface integrity [10]. Buchkremer and Klocke showed that the material modification during machining is predictable using the mechanical and thermal energy inputs into the machined surface [11].

In addition to its influence on surface integrity, specific cutting energy is also important for sustainable machining. Although the energy consumed in actual cutting may contribute a relatively small portion to the total energy consumption, the reduction of specific cutting energy could be significant considering the enormous number of machine tools.

1.2. Related work on modeling of specific cutting energy

Specific cutting energy depends on not only cutting conditions but also thermal–mechanical properties of the work material. It has been reported that a smaller undeformed chip thickness results in a higher specific cutting energy [12]. Compared to cutting tool geometry, cutting speed has a moderate influence on specific cutting energy [13]. Tool wear has also been found has a great impact on specific cutting energy [14]. Therefore, a better understanding of specific cutting energy is beneficial for process optimization and cutting tool design as well.

This work focuses on specific cutting energy in milling. Table 1 summarizes the predictive models for calculating specific cutting energy in milling. Bayoumi et al. have developed a model of specific cutting energy based on a closed form mechanistic force model [1]. Specific cutting energy is predicted from cutting force which is estimated based on undeformed chip thickness. However, the undeformed chip thickness changes periodically in a milling process, which significantly complicates the model. Cutting force is dependent on cutting temperature which is a thermal–mechanical coupling parameter at different cutting speeds. Furthermore, the complex tool geometry and its evolution due to tool wear complicate the prediction of cutting forces. Thus, the predictive accuracy and application of the force-based specific cutting energy models are limited by the complex milling process.

Regression models have also been proposed to predict specific cutting energy for milling. Balogun and Mativenga proposed an empirical model to predict specific cutting energy based on the undeformed chip thickness for end milling [12]. However, only the undeformed chip thickness was considered in the model while other process conditions, e.g., tool wear, were not included. Sealy et al. proposed an empirical

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Table 1
Specific cutting energy for milling.

Model	Ref.
$SPEC_{eff} = \frac{K_{neff}(F + GK_{feff})}{\sin\ \theta_h} + \frac{k_{nfeff}k_{ffeff}\ \cos\ \theta_h l_f}{f_t(1 - \cos\ \ \alpha_{en})}$	[1]
$k_e = K_e\ h^{-x}$	[12]
$U_{nc} = \alpha_0\, a_p^{\alpha_1}\, a_e^{\alpha_2}\, v^{\alpha_3}\, f_z^{\alpha_4}(1 + VB)^{\alpha_5}$	[14]

model based on all related process parameters [14]. However, the prediction accuracy of these models is still limited since the complex relationship between the process conditions and specific cutting energy not follow the assumptions made by the simple analytical models.

1.3. Machine learning in cutting processes

Machine learning through data mining can be applied in manufacturing to discover hidden trends for establishing the relationship between manufacturing processes, cost, productivity, and quality, which provides a potential approach to process optimization. Machine learning is more powerful than the analytical solutions, in particular, for modeling of a complex system. One key strategy to improve the predictive power of a machine learning model is to utilize the prior knowledge of a concerned system. The expert knowledge of the concerned system is important to develop a machine learning models for effective prediction. In the manufacturing community, many analytical models have been developed to investigate process mechanics and optimize process conditions. However, those knowledge has not been efficiently utilized in developing a machine learning model for the predictive purpose. The prior understanding of process mechanics has rarely been incorporated into the development of a machine learning model.

The objectives of this study are to (1) develop a data-driven machine learning model by incorporating process mechanics for the prediction of specific cutting energy; (2) compare the machine learning model with the traditional mechanics models; and (3) validate the machine learning model in milling of H13 tool steel and Inconel 718.

2. Experimental measurement of specific cutting energy

End milling experiments of H13 and Inconel 718 were performed on a CNC milling machine. The cutting conditions are summarized in Table 2. H13 was milled at dry condition while Inconel 718 was milled at both dry and flood conditions. A Fluke power analyzer was used to measure the spindle power. The specific cutting energy was calculated based on the net cutting power (i.e., the difference in spindle power between air cutting and actual cutting) and material removal rate (MRR). Since this study focuses on precision cutting, the spindle load due to actual cutting is small. Therefore, the power loss due to spindle bearing friction between air cutting and actual cutting is negligible. Furthermore, the power loss due to motor and drive system is canceled largely when calculating the net cutting power. In addition, cutting insert flank wear was measured using an online digital microscope.

Table 2
Experimental design.

Cutting tool diameter D (mm)	20
Number of teeth n	2
Tungsten carbide inserts	(Ti,Al)N/TiN coating
Work materials	H13 (HRC 52), Inconel 718
Cutting speed v (m/min)	100–300 for H13 40–80 for Inconel 718
Feed per tooth f_z (mm/tooth)	0.05–0.20
Radial DoC a_e (mm)	0.3–0.5
Axial DoC a_p (mm)	0.5–2.5 for H13 0.5 for Inconel 718
Flank wear VB (mm)	0–0.2
Milling mode	Up, Down
Cutting fluid supply	Dry for H13 Dry and flood for IN 718

3. Process mechanics model of specific cutting energy

As shown in Fig. 1, the energy consumption E and material removal volume V for a single chip in a milling process are given by Eqs. (1) and (2), respectively. Only the tangential force F_t contributes to the net cutting power $P(\varphi)$ which can be calculated by Eq. (3).

$$E = \int_0^{t_s} P(\varphi(t))dt = \frac{1}{\omega}\int_0^{t_s} P(\varphi)d\varphi \tag{1}$$

$$V = a_p a_e f_z \tag{2}$$

$$P(\varphi) = F_t\ (\varphi)v \tag{3}$$

where t_s and φ_s are the time and swept angle for the cutting tool to form a single chip; φ is the cutting tool location angle; ω is the angular velocity.

The swept angle φ_s is given by Eq. (4).

$$\varphi_s = arccos\,\frac{D - 2a_e}{D} \tag{4}$$

The tangential cutting force can be calculated by multiplying specific cutting pressure K_t and chip cross-section area $A(\varphi)$ (Eq. (5)) [15]. The specific cutting pressure K_t is a function of the undeformed chip thickness $h(\varphi)$ calculated by Eq. (6). The average chip thickness h_{avg} and chip cross-section area $A(\varphi)$ can be calculated by Eqs. (7) and (8), respectively.

$$F_t\ (\varphi) = K_t(\varphi)\ A(\varphi) \tag{5}$$

$$\mathrm{h}(\varphi) = f_z\ \sin\ \varphi \quad 0 \le \varphi \le \varphi_s \tag{6}$$

$$h_{avg} = \frac{\int_0^{\varphi_s} h\ (\varphi)\ d\varphi}{\varphi_s} = \frac{\int_0^{\varphi_s} f_z\ \sin\ \varphi d\varphi}{\varphi_s} = \frac{f_z(1\ -\ \cos\ \varphi_s)}{\varphi_s} \tag{7}$$

$$A(\varphi) = a_p\, h\ (\varphi) \tag{8}$$

The relationship between specific cutting pressure and undeformed chip thickness can be calculated by Eq. (9).

$$K_t(\varphi) = k[h\ (\varphi)]^{\beta} \tag{9}$$

where k and β are parameters which depend on the cutting tool, work material, and process conditions. k is related to the flow stress while β presents the size effect. k and β are often treated as constants for a given set of cutting tool and work material in the literature. However, the cutting conditions also influence k and

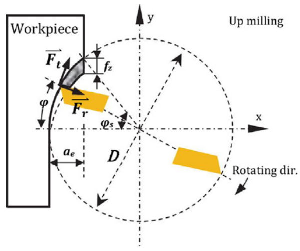

Fig. 1. Schematic of cutting forces in end milling.