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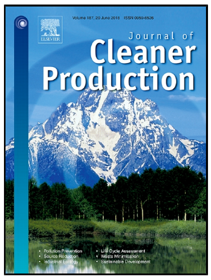

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An investigation into methods for predicting material removal energy consumption in turning

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Abstract: The wide use of machining processes has imposed a large pressure on environment due to energy consumption and related carbon emissions. The total power required in machining include power consumed by the machine before it starts cutting and power consumed to remove material from workpiece. Accurate prediction of energy consumption in machining is the basis for energy reduction. This paper investigates the prediction accuracy of the material removal power in turning processes, which could vary a lot due to different methods used for prediction. Three methods, namely the specific energy based method, cutting force based method and exponential function based method are considered together with model coefficients obtained from literatures and experiments. The methods have been applied to a cylindrical turning of three types of workpiece materials (carbon steel, aluminum and ductile iron). Methods with model coefficients obtained from experiments could achieve a higher prediction accuracy than those from literatures, which can be explained by the inability of the coefficients from literatures to match the specific machining conditions. When the coefficients are obtained from literatures, the prediction accuracy is largely dependent on the sources of coefficients and there is no definitive dominance of one approach over another. With model coefficients from experiments, the cutting force based model achieves the best accuracy, followed by the exponential function based method and specific energy based method. Furthermore, the power prediction methods can be used in process design stage to support energy consumption reduction of a machining process.

Keywords: Material removal; Energy consumption; Cutting force; Uncertainty; Cutting parameter selection

1. Introduction

Machining is widely applied in manufacturing industry and contributes to a significant portion of employment and economic growth. Unfortunately, machining also imposes large environmental burden due to energy consumption and related carbon emissions (Liu et al., 2016; Zhang et al., 2017). Many approaches are developed to save energy consumed during machining, such as energy efficient process planning and scheduling. However, the lack of accurate energy data has impeded the implementation of the aforementioned approaches (Hu et al., 2015; Wang et al., 2015). Therefore, accurate prediction of energy consumption in machining is of great importance.

Turning is the one of the most important machining processes and can produce a wide variety of parts. Considering large number of lathes used in manufacturing and the low energy efficiency, there have been significant potential in improving the energy efficiency of turning process. Consequently, it is important to forecast the energy use in turning, which will assist the process designers and machine operators to achieve energy efficient process design and operating.

The total energy during machining can be subdivided into three parts: the standby energy use, run-time operational energy and actual energy involved when removing material (Dahmus and Gutowski, 2004). The detailed energy flow in machining process in shown in **Fig. 1**. It is vital to investigate the material removal energy, since it is responsible for the new surface generation and determines the quality of a machined part (Sealy et al., 2016). There are three representative methods to predict the material removal power in existing research: specific energy based method (SEM), cutting force based method (CFM) and exponential function based method (EFM). The SEM considers the material removal power to be the product of the specific cutting energy and material removal rate (MRR). The CFM calculates the material removal power by multiplying the cutting force by cutting speed. The EFM predicts the material removal power using an exponential function of cutting parameters.

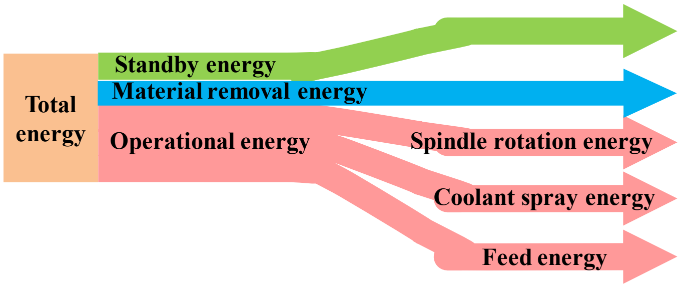

Fig. 1. Detailed energy flow in machining process.

The above three methods are widely used due to their easy application in engineering. In the three methods, many assumptions and simplifications have been made. The SEM and CFM consider that the material removal power is equal to cutting power, which is the power consumed through the tool tip to remove workpiece material. Actually, the material removal power also includes another part of the power called the loading loss which could reach up to 26% of the cutting power (Xie et al., 2016a). For the SEM, the material removal power is considered to be proportional to MRR, which means that material removal power is proportional to cutting speed, feed and depth of cut. However, this may not be true because the effects of each parameter on material removal power are not linearly proportional. Moreover, research showed that the specific energy is not a fixed value, but affected by the hardness and microstructure of the work material, feed rate, rake angle of the cutting tool (Boothroyd and Knight, 1989). In the CFM and EFM, cutting force and material removal power are assumed to be exponential models of cutting parameters. The assumptions may lead to inaccurate power prediction and costly errors in judgement which parameters are selected to reduce energy consumption for machining operations. There is an urgent need to evaluate the prediction accuracy of these methods.

This study was oriented to evaluate the material removal power prediction accuracy of existing methods based on experimental data. Although the focus is on the turning processes, the proposed studies can be used by any other machining processes, such as milling, drilling and grinding. The remainder of this paper is organized as follows. Section 2 reviews related work, and Section 3 introduces the three methods for predicting material removal power, concept of uncertainty and prediction accuracy. The methodology to acquire the model coefficients from literatures and experiments is described in Section 4. An evaluation of the three models is discussed in Section 5. The selection of cutting parameters for energy reduction based on the accurate power prediction is illustrated in Section 6. Finally in Section 7, the conclusions are drawn and future work is discussed.

2. Literature review

Energy consumption modelling and optimization has become a hot topic in recent years, especially in energy-intensive industries (such as steel production) (Sun et al., 2017; Sun and Zhang, 2016). In the machinery industries, a large number of research studies have been conducted to model the energy consumption of machining processes (Jia et al., 2017). One of the first studies addressed the energy consumption issues in machining processes was carried out by Gutowski et al. (2006). In this study, the energy consumption is calculated as the sum of idle power and material removal power. However, the detailed description of idle power and model validation is lacked. Diaz et al. (2011) adopted this model to estimate the power demand of matching and model the specific energy to be an inverse function of MRR. He et al. (2012) further broke the machining power into power consumed by servos system, fan motors, spindle motor, feed motor, tool changer motor and coolant pump motor. Similar work was carried out by Balogun and Mativenga (2013) and Priarone et al. (2016), in which the total power was divided into basic power, ready state power, coolant pumping power, air cutting power and cutting power. In the above researches, each part of power is usually obtained from power measurements of the machine tools. This detailed decomposition of power consumption could help to achieve a high energy prediction accuracy (over 90%).

The material removal power is an important part of machining power. It can be predicted by theoretical formulas or empirical models. Munoz and Sheng (1995) analysed the mechanics of machining processes and provided theoretical formulas for cutting power of orthogonal turning and oblique milling processes. However, it is difficult to obtain the coefficients and set-up parameters, such as tool rake angle and tool oblique angle, involved in the theoretical formulas. Thus this theoretical formula is rarely used in industry. In comparison, empirical models are often used to predict the material removal power in engineering, which are summarized in **Error! Reference source not found.**.

The specific energy model is most widely used because of its simplicity to apply to a range of machining processes, such as turning, milling and drilling. The specific energy is the only coefficient and the key for model prediction accuracy. Kellens et al. (2012) estimated the machining power of drilling grey cast iron, of which the specific cutting energy is 1.3 J/mm^3 from literatures. Aramcharoen and Mativenga (2014) indicated that the specific cutting energy depends on types of workpiece material and sharpness of cutting tool. Dull tools cause higher cutting power. The specific cutting energy of stainless steel was evaluated as 4.72 J/mm^3 using regression analysis of measured total power required for machining and MRR. Priarone et al. (2016) calculated the specific energy by dividing the measured material removal power by MRR. They observed that increased tool wear lead to higher values of specific energies due to higher increased force. This is especially true for milling case, as the specific energy increased significantly when tool wear increased (Liu et al., 2016).

Table 1 A summary of empirical models for material removal power prediction in machining.

Model	Machining processes	Author(s)	Model coefficients obtained by
Specific energy model	Drilling of grey cast iron	Kellens et al. (2012)	Averaging specific energies from different literatures
	Milling of stainless steel	Aramcharoen and Mativenga (2014)	Regression analysis of measured power and MRR
	Turning of Ti-6Al-4V alloy	Priarone et al. (2016)	Dividing measured material removal power by MRR
	Milling of AISI H13 tool steel	Liu et al. (2016)	Dividing measured material removal power by MRR
Cutting force based model	Milling of aluminum 7022	Avram and Xirouchakis (2011)	Referencing theoretical cutting force formulas
	Milling of aluminum 6061	Zhou et al. (2015)	Referencing machining technology handbook
	Turning of aluminium alloy and S45C carbon steel	Xie et al. (2016b)	Referencing mechanical engineering manual
Exponential model	Milling of steel	Xie et al. (2016a)	Regression analysis of material removal power
	Turning and milling of AISI 1045 steel	Lv et al. (2016)	Regression analysis of material removal power
Second-order regression model	Milling of S45C steel	Yoon et al. (2014)	Regression analysis of material removal power

The cutting force based model are also used to predict the material removal power by many researchers. Avram and Xirouchakis (2011) modelled the cutting force through the estimation of instantaneous values of the feed and feed perpendicular forces. Zhou et al. (2015) used empirical formulas to calculate the cutting forces for the milling of aluminium 6061 (Yang et al., 2011):

$$F_Z = C_F K_F a_w^{0.86} a_f^{0.72} d_0^{-0.86} Z a_p \tag{1}$$

where F_Z is cutting force, C_F, K_F are coefficients obtained from machining manual, a_w, a_f, d_0, Z and a_p are the width of cut, feed per tooth, cutting tool diameter, number of cutting tooth and depth of cut, respectively. Xie et al. (2016b) also employed empirical exponential function from mechanical engineering manual to calculate the cutting force for the turning processes.

The exponential model and second-order regression model are empirical models. Xie et al. (2016a) measured the material removal power for milling of steel plate and fitted the material removal power model as an exponential function of spindle speed, depth of cut, feed and width of cut. Errors of the fitted model were within 8%. Lv et al. (2016) took a similar approach and modelled the material removal power of turning process as an exponential function of cutting speed, feed and depth of cut. Yoon et al. (2014) employed an empirical model to predict both material removal power and power increase due to tool wear for milling process. The model is a second order regression function of rotational speed, feed and depth of cut.

While the material removal power has been modelled using various types of models, the accuracy for predicting the material removal power has not been well investigated. In fact, the material removal power may vary a lot if it is predicted by different models and using different sources of model coefficients. This could affect the prediction accuracy of energy consumption for whole machining processes. Therefore, the aim of this work is to evaluate the accuracy of different methods (including model and sources of model coefficients) for material removal power prediction.

3. Background

This section introduces three power prediction methods used in this study, SEM, CFM and EFM. Then the performance metrics for prediction accuracy evaluation is described.

3.1. Specific energy based method

The SEM predicts the material removal power based on the specific energy model which is expressed in Equation (2) (Gutowski et al., 2006):

$$P_{\mathrm{m}} = k\dot{v} \tag{2}$$

where P_{m} is the power used for material removal operation [W], k is the specific energy requirement in cutting operations [W·s/mm^3], $\dot{v}$ is material removal rate (MRR) [mm^3/s] and can be calculated from machining parameters, for turning processes, $\dot{v}$ can be expresses as (Kalpakjian and Schmid, 2006):

$$\dot{v} = 1000 \times v \times f \times a_{\mathrm{p}} \tag{3}$$

where v is cutting speed [m/s], f is feed [mm/r] and a_p is the depth of cut [mm].

The specific energy k is the key coefficient for the application of this method. It can be obtained from literatures or by regression analysis of experimental data. When obtaining the coefficients experimentally, experiments are conducted and the material removal power is measured at various MRR. Then linear regression analysis is employed to obtain the value of specific energy. Here, the dependent variable is material removal power and independent variable is the MRR. With the machining parameters and the values of specific energy, the material removal power can be predicted using this specific energy based method.

3.2. Cutting force based method

For the CFM, the cutting force is used to calculate the material removal power, which is expressed as follows:

$$P_m = F_C v \tag{4}$$

where F_C is the primary cutting force [N], v is cutting speed [m/s]. The cutting force is strongly related to the cutting parameters. However, the metal cutting mechanics is quite complicated and it is very difficult to develop a precise model to describe the relationship between the cutting force and its related parameters. As a result, a generic exponential model is used to describe the cutting force (Wang, 2008):

$$F_C = C_F v^{n_F} f^{y_F} a_p^{x_F} k_{MF} k_{\gamma M} \tag{5}$$

where C_F is the coefficient of cutting force, f is feed [mm/r], a_p is the depth of cut [mm], n_F, y_F and x_F are exponential coefficients of cutting speed, feed and the depth of cut, respectively, k_{MF} is the correction coefficient for yield and tensile strength of the workpiece material, $k_{\gamma M}$ is the correction coefficient for tool angles.

The coefficients in the CFM can be obtained from literatures or experimentally. One way is to obtain the coefficients by referring to the handbook of manufacturing engineers, mechanical processing or principles of machining. Another way is to obtain the coefficients experimentally. The cutting experiments are conducted and the cutting forces are measured with different combinations of cutting parameters. Before conducting regression analysis, the exponential model of cutting force in Equation (5) is converted into linear form by logarithmic transformation:

$$\log F_{\mathrm{C}} = \log\left(C_{\mathrm{F}} k_{\mathrm{MF}} k_{\gamma\mathrm{M}}\right) + n_{\mathrm{F}} \log v + y_{\mathrm{F}} \log f + x_{\mathrm{F}} \log a_{\mathrm{p}} \quad (6)$$

Based on the above linear equation, the unknown coefficients $\log\left(C_{\mathrm{F}} k_{\mathrm{MF}} k_{\gamma\mathrm{M}}\right)$, x_{F}, y_{F} and n_{F} are acquired by multiple linear regressions of the experimental data.

3.3. Exponential function based method

The EFM is based on the postulated exponential model. The exponential model assumes the material removal power as an exponential function:

$$P_{\mathrm{m}} = C_{\mathrm{P}} v^{n_{\mathrm{P}}} f^{y_{\mathrm{P}}} a_{\mathrm{p}}^{x_{\mathrm{P}}} \quad (7)$$

where C_{P}, n_{P}, y_{P} and x_{P} are coefficients of material removal power, cutting speed, feed and the depth of cut, respectively. The nonlinear Equation (7) can be converted into linear form by logarithmic transformation:

$$\log P_{\mathrm{m}} = \log C_{\mathrm{P}} + n_{\mathrm{P}} \log v + y_{\mathrm{P}} \log f + x_{\mathrm{P}} \log a_{\mathrm{p}} \quad (8)$$

In order to obtain the unknown coefficients C_{P}, n_{P}, y_{P} and x_{P} in the postulated exponential model, cutting experiments are conducted with different combinations of cutting parameters and the cutting power is measured. The coefficients are acquired by multiple linear regressions of the experimental data based on the measured data and Equation (8).

3.4. Uncertainty and prediction accuracy

The measurement data contains both average values and uncertainty. The uncertainty can be characterized by repeated measurements. If the measurements are repeated N times, the average value is estimated to be:

$$x_{\mathrm{avg}} = \frac{x_1 + x_2 + \ldots + x_N}{N} \quad (9)$$

where x_i(i=1, 2, …, N) is the value obtained in i^{th} measurement. The uncertainty in the mean value of measurements is:

$$\Delta x_{\mathrm{avg}} = \frac{x_{\max} - x_{\min}}{2\sqrt{N}} \tag{10}$$

When z is a linear equation by addition or subtraction, such as:

$$z = x \pm y \tag{11}$$

The uncertainty Δz can be calculated through the propagation of uncertainty as:

$$\Delta z = \sqrt{(\Delta x)^2 + (\Delta \mathrm{y})^2} \tag{12}$$

where Δx and $\Delta \mathrm{y}$ are the uncertainty of x and y, respectively. In this study, we use linear regression analysis to obtain the empirical equations. For a multiple linear regression model $y = \mathrm{b}_1 x_1 + \mathrm{b}_2 x_2 + \ldots + \mathrm{b}_m x_m + \mathrm{c}$, the uncertainty of model coefficient b_i is written as follows (Jeter, 2003):

$$u_{bi} = \frac{SEE}{\sqrt{\sum_{j=1}^{n} x_{i,j}^2 - n x_{i,\,ave}^2}} \tag{13}$$

where SEE is the standard error of estimate, n is the number of observations, $x_{i,j}$ is the j-th data of independent variable x_i, $x_{i,\mathrm{ave}}$ is the average value of variable x_i. The standard uncertainty of the model is then determined by combining the uncertainty of each independent variables (Jeter, 2003):

$$u_{\mathrm{model}} = \sqrt{\frac{\mathrm{SEE}^2}{n} + \left(x_1 - x_{1,\mathrm{ave}}\right)^2 u_{b1}^2 + \ldots + \left(x_m - x_{m,\mathrm{ave}}\right)^2 u_{bm}^2} \tag{14}$$

To construct a (1-α)×100% confidence interval, the expanded uncertainty of the model is calculated as:

$$U_{\mathrm{model}} = t_{n-p,\,1-\alpha/2}\, u_{\mathrm{model}} \tag{15}$$

where $t_{n-p,\,1-\alpha/2}$ is the value obtained from the t-distribution table, and p is the number of model parameters. The prediction accuracy is taken as performance metric, which is calculated by the predicted and measured power:

$$Acc = \left(1 - \frac{\left|P_{\mathrm{pred}} - P_{\mathrm{mes}}\right|}{P_{\mathrm{mes}}}\right) \times 100\% \tag{16}$$

where P_{pred} and P_{mes} are the predicted and measured material removal power [W], respectively.

4. Methodology

This work uses three methods for material removal power forecasting: SEM, CFM and EFM. For application of each method, the coefficients in the models are key and can be acquired from literatures or experiments. This section first describes the acquisition of the coefficients from literatures. Next, experimental setup and design is introduced. Finally, this section describes the regression analysis of experimental data to obtain the coefficients experimentally and uncertainties of the model coefficients.

4.1. Coefficients acquisition from literatures

For the SEM, the coefficients can be obtained from handbook of machining calculations (Wu, 2012), machinery's handbook (Oberg et al., 2008) or thesis (Rajemi, 2011), as shown in **Table 2**. It can be seen that the specific energies vary significantly, and there is a lack of knowledge to get the exact specific energy value for given machining conditions. For instance, the specific energies range from 1.96 to 4.3 J/mm^3 for steel, with the maximum value being more than twice the minimum one. This could be explained by that they were obtained under different machining conditions.

Table 2 Specific energies for different workpiece materials.

Materials	Specific energies [J/mm^3]			
Steel	1.96 (hot rolled)	2.59 (260-280 HB[a])	4.3	2.7-9
Aluminum alloy	0.83	0.90 (rolled)	0.7	0.4-1
Cast iron	1.41 (ductile)	1.72 (175-200 HB[a])	1.2	1.1-5.4
Source	Wu (2012)	Oberg et al. (2008)	Rajemi (2011)	Kalpakjian (1984)

[a] Brinell Hardness

For the CFM, the values of coefficients can be obtained from manufacturing engineers handbook (Yang, 2012), mechanical processing handbook (Meng, 1991) or the text book of principles of machining (Kaczmarek, 1976) for the material properties and tool conditions in this study, as shown in **Table 3**. Similarly, the coefficients from different sources vary a lot even for the same material. As a result, the use of coefficients from literatures could result in large power prediction errors.

Table 3 Coefficients of primary cutting force models of turning processes

Workpiece material	Coefficients					
	C_F	k_{MF}	$k_{\gamma\mathrm{M}}$	n_{F}	y_{F}	x_{F}
Steel	1434	1.02	0.89	-0.15	0.75	1.0

Aluminum	390	1.00	1.00	0	0.75	1.0
Cast iron	790	1.02	0.89	0	0.75	1.0
Source	Yang (2012)					
Steel	1706	1.00	1.00	0	0.75	1.0
Aluminum	617	1.00	1.00	0	0.75	1.0
Cast iron	1046	1.00	1.00	0	0.75	1.0
Source	Meng (1991)					
Steel	1874	1.00	0.89	0	0.75	1.0
Aluminum	-	-	-	-	-	-
Cast iron	1422	1.00	1.00	0	0.82	0.92
Source	Kaczmarek (1976)					

4.2. Experimental setup and design

In order to obtain the model coefficients experimentally, experiments were designed and conducted on a CK6153i computer numerical control (CNC) lathe. A flowchart of experimental procedure is shown in **Fig. 2**. The lathe, workpiece and cutting tools were first selected. This lathe was made by Jinan First Machine Tool Group Co., Ltd. of China. Three different types of workpiece materials including AISI 1045 steel, AISI 6061 aluminum and AISI 80-55-06 ductile iron were selected for experiments due to their wide use in manufacturing industry. The dimension of the workpiece is Φ80 mm×150 mm. The material properties and chemical composition of the workpiece materials are shown in **Table 4**. For cutting experiments, a TiCN coated carbide insert was used for the turning of steel and ductile iron, and an uncoated carbide insert was used for aluminum. The details of tool conditions are presented in **Table 5**. All cutting experiments were conducted under dry conditions.

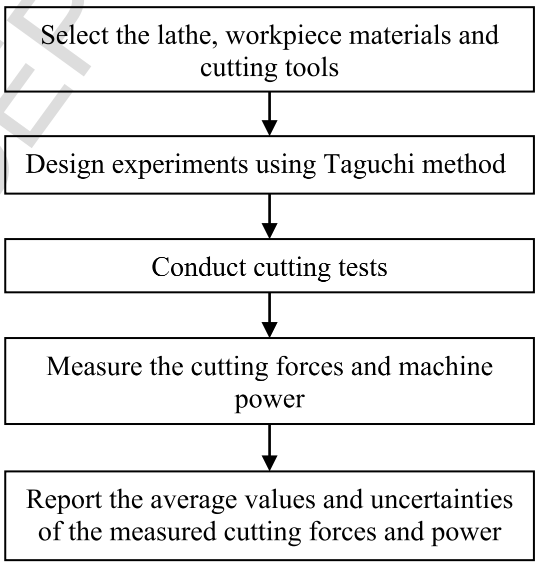

Fig. 2. A flowchart of experimental procedure.

Table 4 Material properties and chemical composition of the workpiece material.

	AISI 1045 steel	AISI 6061 aluminum	AISI 80-55-06 ductile iron
Yield strength (Mpa)	385	290	320
Tensile strength (Mpa)	665	325	500
Elongation (%)	24.5/25	13	7
Hardness (HB)	262	97	200
Chemical composition (wt %)	C(0.44); Si(0.23); Mn(0.61); P(0.012); S(0.024); Ni(0.02); Cr(0.03); Cu(0.05); Pb(0.0020); Fe(Remainder)	Fe(0.32); Si(0.55); Cu(0.27); Mg(1.02); Mn(0.03); Zn(0.03); C(0.15); Ti(0.01); Al(Remainder)	C(2.96~3.35); Si(2.34~2.86); Mn(0.50~0.68); S(0.015~0.019); P(0.038~0.053); Fe(Remainder)

Table 5 Tool conditions used in the experiments.

Workpiece material	Steel and ductile iron	Aluminum
Insert	VNMG160408N-UX-AC820	CCGT09T304-AK-H01

Tool holder	MVJNR2525M16	SCLCR2525M09
Clearance angle	0º	7º
Cutting edge angle	93º	95º
Nose radius	0.8 mm	0.4 mm
Manufacturer	Sumitomo	Korloy

During cutting tests, the cutting forces were measured using a three-component force dynamometer (Kistler Type 9257A) mounted on the turret of the CNC lathe via a custom designed fixture. The charge generated at the dynamometer was amplified using three single channel charge amplifiers YE5850A made by Jiangsu Lianneng Electronic Technology Co., Ltd. of China. Power consumption of the machine tool was measured using voltage and current transducers, and the electrical signals were acquired by data acquisition cards and chassis. A laptop was connected to the chassis, and a LabVIEW programming interface was developed to record and process the electrical signals. The sampling rate was 5000Hz. Data was averaged and output every 0.1 s. The experimental setup is illustrated in **Fig. 3**.

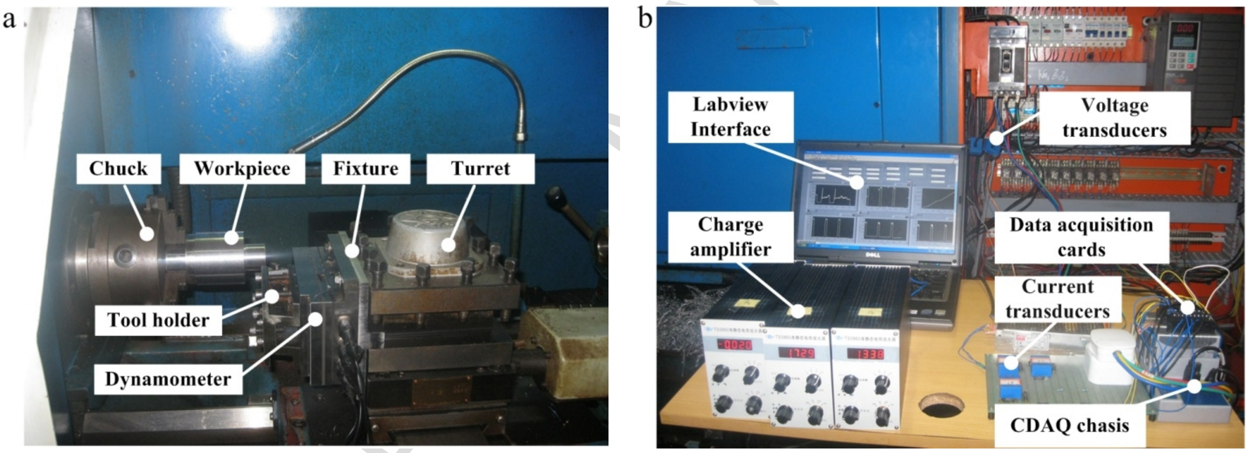

Fig. 3. Experimental setup (a) Cutting force dynamometer mounting and (b) Power transducers and data acquisition device.

Then, experiments were designed using Taguchi method. Cutting speed, feed and depth of cut were defined as process variables. The ranges of the turning parameters of each material were selected as recommended from the tool manufacturers. The turning factors and their levels are shown in **Table 6**. For the machining experiments of each material, Taguchi's orthogonal design L_{16} (3^4) was employed to study the factors influencing the material removal power, as shown in **Table 7-Table 9**. Here, the three factors of cutting speed, feed and depth of cut are coded as A, B and C. Four levels of factors A, B and C were represented by "1", "2", "3" and "4" in the matrix. As shown in each row of the matrix represents one trial, and 16 experiments were conducted for turning processes of each material. The length of cut for each test was 30 mm in axial direction. Each run was repeated three times during the cutting tests and the primary cutting forces F_C [N] and machine power were measured. The material removal power P_m [W] was computed by subtracting the power measured during air-cutting from the power acquired during the normal cutting. The average values and uncertainty of the three measurements of cutting forces and power were obtained using Equations (9)-(12). The uncertainties of cutting force ΔF_C are smaller (within 2.5%), while the uncertainties of material removal power ΔP_m are larger (up to 7.5%). This could be explained by that the former values are only related to workpiece material, cutting tool and parameters while the later values depend on both air-cutting and normal cutting power variations of the machine tool.

Table 6 Cutting parameters and their levels in turning experiments.

Material	Coded factors	Cutting parameters	Level 1	Level 2	Level 3	Level 4
Steel	A	Cutting speed [m/s]	0.83	1.67	2.50	3.33
	B	Feed [mm/rev]	0.05	0.1	0.15	0.2
	C	Depth of cut [mm]	0.5	1.0	1.5	2.0
Aluminum	A	Cutting speed [m/s]	1	2	3	4
	B	Feed [mm/rev]	0.1	0.2	0.3	0.4
	C	Depth of cut [mm]	0.6	1.2	1.8	2.4
Ductile iron	A	Cutting speed [m/s]	0.67	1.33	2.00	2.67
	B	Feed [mm/rev]	0.05	0.1	0.15	0.2
	C	Depth of cut [mm]	0.5	1.0	1.5	2.0

Table 7 Design matrix and measurements of cutting force and material removal power of steel.

Experimental order	Factors and levels			Cutting force		Material removal power	
	A	B	C	F_C [N]	ΔF_C [N]	P_m [W]	ΔP_m [W]
1	1	1	1	116.5	2.1	103.0	7.7
2	1	2	2	379.9	2.1	323.9	2.7
3	1	3	3	739.5	1.7	668.7	7.2
4	1	4	4	1277.0	9.1	1204.2	8.2
5	2	1	2	270.2	5.0	462.7	9.3
6	2	2	1	221.8	1.8	372.3	12.1
7	2	3	4	874.7	0.8	1552.0	9.9
8	2	4	3	812.9	0.2	1438.8	2.8
9	3	1	3	340.8	1.3	870.9	6.8

10	3	2	4	646.6	1.5	1683.1	28.1
11	3	3	1	253.8	0.9	659.1	11.3
12	3	4	2	564.2	1.0	1453.4	9.5
13	4	1	4	422.9	2.6	1478.1	32.9
14	4	2	3	494.0	2.8	1686.1	31.6
15	4	3	2	448.4	1.4	1506.1	10.0
16	4	4	1	304.3	2.4	1027.1	16.0

Table 8 Design matrix and measurements of cutting force and material removal power of aluminum.

Experimental order	Factors and levels			Cutting force		Material removal power	
	A	B	C	F_C [N]	ΔF_C [N]	P_m [W]	ΔP_m [W]
1	1	1	1	66.3	0.5	67.5	3.3
2	1	2	2	228.0	0.5	235.7	9.5
3	1	3	3	443.9	1.6	483.8	5.9
4	1	4	4	732.0	1.7	795.3	7.8
5	2	1	2	118.5	2.7	267.3	7.6
6	2	2	1	109.2	0.3	238.4	2.9
7	2	3	4	515.8	1.2	1084.3	19.5
8	2	4	3	521.1	2.0	1090.3	20.9
9	3	1	3	169.0	1.3	571.3	38.7
10	3	2	4	395.6	9.4	1194.2	31.1
11	3	3	1	142.4	0.9	449.9	26.7
12	3	4	2	353.7	1.1	1110.6	15.4
13	4	1	4	200.2	1.4	837.1	35.0
14	4	2	3	271.7	2.7	1127.8	60.8
15	4	3	2	280.5	5.2	1173.7	40.7
16	4	4	1	171.6	1.9	764.9	23.8

Table 9 Design matrix and measurements of cutting force and material removal power of ductile iron.

Experimental order	Factors and levels			Cutting force		Material removal power	
	A	B	C	F_C [N]	ΔF_C [N]	P_m [W]	ΔP_m [W]
1	1	1	1	72.9	0.2	52.1	1.9

2	1	2	2	228.2	0.7	167.0	0.6
3	1	3	3	453.5	1.3	321.9	1.9
4	1	4	4	780.7	1.3	542.9	1.6
5	2	1	2	131.6	0.1	179.6	3.4
6	2	2	1	133.1	0.2	187.0	12.2
7	2	3	4	630.0	1.3	864.2	45.2
8	2	4	3	603.5	0.7	829.1	31.2
9	3	1	3	194.7	3.0	398.9	8.0
10	3	2	4	464.2	1.0	957.5	5.1
11	3	3	1	170.5	0.6	346.1	8.5
12	3	4	2	417.4	0.7	849.7	4.1
13	4	1	4	321.2	3.0	856.7	21.0
14	4	2	3	390.6	1.2	1063.1	16.0
15	4	3	2	361.2	0.4	976.2	16.7
16	4	4	1	237.6	0.2	647.5	12.7

4.3. Regression analysis of the measured data

Based on experimental data in **Table 7-Table 9**, linear regression was used to acquire the model coefficients for the above three methods. There are five main assumptions which justify the use of linear regression models: linearity, homoscedasticity, normality, independence and no multicollinearity. Assumption of linearity and homoscedasticity were first checked using a plot of residuals versus predicted values. The residuals are randomly dispersed around the zero horizontal line, which indicates linear regression models are appropriate for the data. In addition, there is no clear pattern in the residual distribution, which indicates that the assumption of homoscedasticity is satisfied. Then the assumption of normality is verified using the normal probability plot of residuals. The residuals lie reasonably close to a straight line, giving support that the normal distributed of residuals is satisfied. Next, assumption of independence is verified by the Durbin-Watson statistic. The values of Durbin-Watson are greater than the upper critical values in most cases, which means that the assumption of independence is satisfied. Finally, the variance inflation factor (VIF) values are used to test the no multicollinearity assumption. All the values of VIF equal to 1, which indicates that the there is no correlation among the predictor variables. The analysis of variance (ANOVA) was applied to test the significance of the regression. The values and uncertainties of coefficients and the results of ANOVA for the fitted models are summarized in **Table 10**. On average, the values of uncertainties are much smaller than the values of the model coefficients. This analysis was carried out at the 95% confidence level, as shown in **Table 11**. The R-square values of all the models exceed 0.982, which indicates that regression is capable of providing good fits to obtain the model coefficients, and more than 98.2% of the variance of the observed data can be explained within the empirical models. The large F-values (exceed 326.0) imply a strong correlation between the responses and the variable chosen in the model under various cutting parameters. The fact that the P-values are less than 0.0001 means the obtained models are statistically significant.

Table 10 Values and uncertainties of coefficients for the fitted models.

Model	Materials	k [J/mm^3]	
		Value	Uncertainty
Specific energy model	Steel	3.269	0.228
	Aluminum	0.803	0.029
	Ductile iron	2.358	0.150

Model	Materials	$\log(C_F k_{MF} k_{\gamma M})$		n_F		y_F		x_F	
		Value	Uncertainty	Value	Uncertainty	Value	Uncertainty	Value	Uncertainty
Cutting force based model	Steel	3.243	0.036	-0.0724	0.035	0.655	0.035	0.902	0.035
	Aluminum	2.835	0.013	-0.104	0.016	0.803	0.016	0.924	0.016
	Ductile iron	3.154	0.028	0.0856	0.028	0.779	0.028	0.935	0.028

Model	Materials	$\log(C_P)$		n_P		y_P		x_P	
		Value	Uncertainty	Value	Uncertainty	Value	Uncertainty	Value	Uncertainty
Postulated exponential model	Steel	3.282	0.038	0.893	0.037	0.668	0.037	0.929	0.037
	Aluminum	2.860	0.018	0.896	0.023	0.799	0.023	0.915	0.023
	Ductile iron	3.174	0.029	1.047	0.029	0.777	0.029	0.926	0.029

Table 11 The results of ANOVA for the fitted models.

Models	Materials	R^2	R^2 Adjusted	F-value	P-value
Specific energy model	Steel	0.982	0.915	807.3	<0.0001
	Aluminum	0.995	0.929	3099.5	<0.0001
	Ductile iron	0.985	0.918	967.9	<0.0001
Cutting force based	Steel	0.988	0.985	326.0	<0.0001
	Aluminum	0.998	0.997	1889.5	<0.0001

model	Ductile iron	0.994	0.992	631.6	<0.0001
Postulated	Steel	0.992	0.990	506.9	<0.0001
exponential	Aluminum	0.997	0.997	1449.1	<0.0001
model	Ductile iron	0.996	0.995	1001.9	<0.0001

The methods, models and sources of coefficients for predicting the material removal power were summarized in **Table 12**.

Table 12. Summary of methods, models and sources of coefficients for predicting the material removal power in turning.

Methods	Models for different types of materials			Sources of coefficients
	Steel	Aluminum alloy	Cast iron	
Specific energy based method	$P_{\mathrm{m}} = 1.96\dot{v}$	$P_{\mathrm{m}} = 0.83\dot{v}$	$P_{\mathrm{m}} = 1.41\dot{v}$	Wu (2012)
	$P_{\mathrm{m}} = 2.59\dot{v}$	$P_{\mathrm{m}} = 0.90\dot{v}$	$P_{\mathrm{m}} = 1.72\dot{v}$	Oberg et al. (2008)
	$P_{\mathrm{m}} = 4.3\dot{v}$	$P_{\mathrm{m}} = 0.7\dot{v}$	$P_{\mathrm{m}} = 1.2\dot{v}$	Rajemi (2011)
	$P_{\mathrm{m}} = 3.269\dot{v}$	$P_{\mathrm{m}} = 0.803\dot{v}$	$P_{\mathrm{m}} = 2.358\dot{v}$	Experiments
Cutting force based method	$P_{\mathrm{m}} = 1302v^{0.85}f^{0.75}a_{\mathrm{p}}$	$P_{\mathrm{m}} = 390vf^{0.75}a_{\mathrm{p}}$	$P_{\mathrm{m}} = 717vf^{0.75}a_{\mathrm{p}}$	Yang (2012)
	$P_{\mathrm{m}} = 1706vf^{0.75}a_{\mathrm{p}}$	$P_{\mathrm{m}} = 617vf^{0.75}a_{\mathrm{p}}$	$P_{\mathrm{m}} = 1046vf^{0.75}a_{\mathrm{p}}$	Meng (1991)
	$P_{\mathrm{m}} = 1668vf^{0.75}a_{\mathrm{p}}$	-	$P_{\mathrm{m}} = 1422vf^{0.82}a_{\mathrm{p}}^{0.92}$	Kaczmarek (1976)
	$P_{\mathrm{m}} = 1750v^{0.928}f^{0.655}a_{\mathrm{p}}^{0.902}$	$P_{\mathrm{m}} = 684v^{0.896}f^{0.803}a_{\mathrm{p}}^{0.924}$	$P_{\mathrm{m}} = 1426v^{1.086}f^{0.779}a_{\mathrm{p}}^{0.935}$	Experiments
Exponential function based method	$P_{\mathrm{m}} = 1914v^{0.893}f^{0.668}a_{\mathrm{p}}^{0.929}$	$P_{\mathrm{m}} = 724v^{0.896}f^{0.799}a_{\mathrm{p}}^{0.915}$	$P_{\mathrm{m}} = 1493v^{1.047}f^{0.777}a_{\mathrm{p}}^{0.926}$	Experiments

5. Results and discussion

This section discusses the prediction accuracy of above three methods using unseen testing data. Twelve new combinations of cutting parameters were selected for confirmation experiments. The test parameters are within the range of the parameters defined previously (see **Table 13**). Fig. 4 illustrates the measured and predicted material removal power. The measured power was obtained by conducting cutting tests on CK6153i under dry condition. The prediction uncertainties were calculated using Eqs. (14)-(15). The error bar represents the uncertainty with 95% confidence interval for the predicted power. When using coefficients form literatures, the power predicted by

SEM and CFM varies a lot. This could be attributed to the variations of coefficients obtained from literatures. When using coefficients obtained experimentally, the power predicted is very close to the measured value. In this case, most measured power values fall within the 95% confidence bound on the predicted power. The width of the confidence bound changes depending on how the machining parameters for a test experiment are distributed relative to the average values of machining parameters used in the training dataset. In general, the width of the confidence bound increases toward the end points of the range of machining parameters. Another observation is that there is no significant difference in power prediction accuracy for different materials.

Table 13 Cutting parameters and the measured material removal power for evaluation of the methods.

Workpiece material	Test No.	Cutting parameters			Power P_m [W]
		Cutting speed [m/s]	Feed [mm/rev]	Depth of cut [mm]	
Steel	1	1.33	0.08	0.8	402.7
	2	2.00	0.08	1.2	782.3
	3	2.00	0.18	1.8	1770.6
	4	1.33	0.18	1.2	883.1
Aluminum	1	2.17	0.15	1.2	362.8
	2	3.67	0.26	1.2	933.7
	3	3.67	0.2	0.8	484.6
	4	2.17	0.2	1.6	576.3
Ductile iron	1	1.67	0.12	0.6	272
	2	1.67	0.18	1	642.6
	3	2.50	0.12	1.2	873.9
	4	2.00	0.12	1	577.3

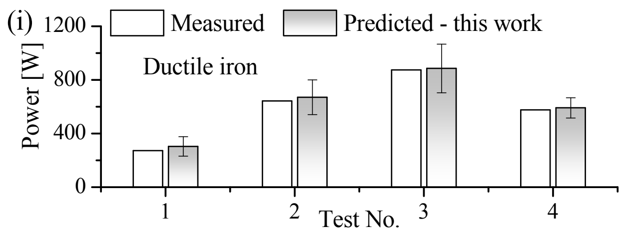

Fig. 4. Comparison of measured and predicted power. Power predicted by SEM for (a) steel, (b) aluminum and (c) iron. Power predicted by CFM for (d) steel, (e) aluminum and (f) iron. Power predicted by EFM for (g) steel, (h) aluminum and (i) iron.

Table 14 shows the average prediction accuracy of the material removal power for the three methods. When coefficients are obtained from literatures, no single method, SEM or CFM, is better than another. For SEM, the average prediction accuracy is low, ranging from 52.1% to 74.6% for steel and ductile iron. This low accuracy could be explained by the large difference between the values of specific energy k given in literatures and the real k values. The values of prediction accuracy were over 82.5% for aluminum. This implies that for some material, like aluminum, the k values from literatures could provide an effective prediction of material removal power. For CFM, all values of the average prediction accuracy are below 68.8% using coefficients from Yang (2012). This low accuracy may be due to the inaccurate coefficients from literatures, which were obtained by experiments conducted decades ago. The machining conditions such as workpiece material properties, tool coating material have changed a lot over the past years, which may result in large changes of power value. When using coefficients from Meng (1991) and Kaczmarek (1976), a higher prediction accuracy which is ranging from 75.1% to 91.2% could be observed, and the CFM performs better than the SEM. It can be seen that sources of coefficients could have a great influence on the prediction accuracy of the method. Therefore, proper selection of literatures is very important to increase the prediction accuracy.

Table 14 Average prediction accuracy of material removal power for the three methods.

Methods	Sources of coefficients		Prediction accuracy [%]		
			Steel	Aluminum	Ductile iron
SEM	1-	Wu (2012)	56.3	96.7	61.2
	2-	Oberg et al. (2008)	74.4	92.3	74.6
	3-	Rajemi (2011)	72.0	82.5	52.1
	4-	Experiments	80.8	94.6	95.3
CFM	1-	Yang (2012)	58.0	68.8	51.5
	2-	Meng (1991)	82.0	91.2	75.1

	3-	Kaczmarek (1976)	80.1	-	89.3
	4-	Experiments	95.0	97.4	97.0
EFM	1-	Experiments	94.0	95.5	94.9

When coefficients are obtained from experiments, the prediction accuracy has been improved a lot. Overall, the highest prediction accuracy, ranging from 95.0% to 97.4%, was achieved with the CFM. In the case of EFM, the average prediction accuracy varies from 94.0% to 95.5%, which is slightly lower than that predicted by the CFM. The prediction accuracy was lowest with SEM. Thus the material removal power could be expressed as an exponential function of cutting parameters rather than the product of the cutting parameters.

Another important aspect in evaluating a prediction method is the implementation difficulty. It is easy to implement the methods using coefficients from literatures. In this case, only the handbooks or text books are needed to review to get the coefficients. For the case of coefficients obtained experimentally, experiments are specially designed and conducted and the cutting forces or power of the machines are measured. The measurement of cutting force is limited by high cost and layout constraints. For instance, the Kistler Type 9257B dynamometer costs more than 30,000 USD. To fix the dynamometer on the turret of machine tool, special fixture is needed to be designed and manufactured. The measurement of machine power could be cheaper and easier. The current and voltage sensors (such as LEM sensors) used to for the power measurement are cheaper (less than 30 USD for each sensor). The sensors can be easily connected to the three-phase electrical wires in the main electrical cabinet of the machine tools.

In summary, the average prediction accuracy and implementation requirements of the three methods are summarized in **Table 15**. Overall, no method outperformed the others when using coefficients from literatures. When coefficients were obtained from experiments, the CFM and EFM provided more accurate prediction of material removal power, and the predictions gave quite consistent results where same levels of errors were obtained for all types of materials.

Table 15 Average prediction accuracy and implementation requirements of different methods in this study.

Methods	Coefficients from	Ranges of average prediction accuracy [%]			Implementation requirements
		Steel	Aluminum	Ductile iron	
SEM	Literatures	56.3-74.4	82.5-96.7	52.1-74.6	Review handbooks or theses.
	Experiments	80.8	94.6	95.3	Conduct experiments and measure power data.
CFM	Literatures	58.0-82.0	68.8-91.2	51.5-89.3	Review handbooks or text books.
	Experiments	95.0	97.4	97.0	Conduct experiments and measure force data.

EFM	Experiments	94.0	95.5	94.9	Conduct experiments and measure power data.

In industrial application, not only the prediction accuracy but also the implementation difficulty is considered in the process of method selection. If the required prediction accuracy is not high, for instance, to verify if spindle motor can provide enough machining power in process planning stage, the SEM or CFM are recommended to be used with coefficients from literatures. If higher prediction accuracy is required, for instance, to get accurate machining power data for energy optimization, methods with coefficients obtained experimentally should be adopted. Although the CFM can provide the most accurate prediction of material removal power, the force measurement is difficult to apply. Comparatively, the EFM might be a compromise solution, which could provide a relatively high prediction accuracy with moderate implementation difficulty, since the power measurement is less expensive and easier to be implemented than the measurement of cutting force.

6. Selection of cutting parameters for energy efficient machining

In the process design stage, there are often several feasible combinations of cutting parameters to machine a part. The material removal power of each combination of cutting parameters can be predicted with the above three methods. Then machining parameters that uses the least amount of energy to machine a part can be selected before actually machining the part. In the following section, a case study is employed to demonstrate the effect of accurate power prediction on energy savings.

In this case study, an AISI 1045 steel round bar with a diameter of 76 mm is machined on the CK6153i CNC lathe. Three feasible combinations of cutting parameters are selected as shown in **Table 16**. The energy consumption of machining is determined by the product of machining time and power. The machining time is approximately equal because the material removal rates are nearly the same for the three sets of parameters. Thus less energy is consumed with lower material removal power. The above three methods with coefficients from experiments are used to predict the material removal power. Then this prediction is compared to the measured power (see **Fig. 5**). It can be seen that the values of power predicted with the SEM are not accurate enough and nearly the same. This may mislead the selection of cutting parameters. When the power is predicted with CFM and EFM, the prediction accuracy has been improved a lot and the measured power values all fall within the 95% confidence bound on the predicted power. In this case, the first set of parameters which consumes the least amount of power will be selected. This selection could achieve energy savings of up to 19%. Therefore, accurate prediction of material removal power could support the selection of cutting parameters for energy saving, thereby reducing the environmental impact of machining.

Table 16 Cutting parameters used in the case study.

Levels	Cutting speed [m/s]	Feed [mm/r]	Depth of cut [mm]
1	1.95	0.2	1.5
2	2.61	0.15	1.5
3	3.90	0.1	1.5

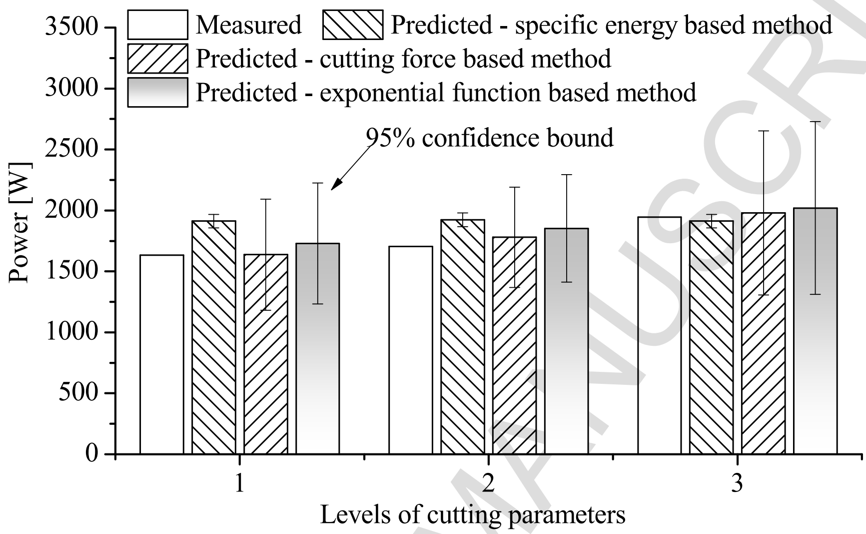

Fig. 5. Material removal power comparison for different sets of cutting parameters.

7. Conclusions and future work

The material removal power is an essential part of energy consumed during machining, three types of methods: the SEM, CFM and EFM, are usually used to predict the material removal power. However, there is a lack of evaluation and comparison of the accuracy of these methods. Inappropriate use of the methods may lead to low prediction accuracy, which cannot support accurate energy evaluation and energy reduction of machining processes. In the current work, the accuracy of the three types of methods is analyzed and compared. According to analysis results, conclusions are drawn as follows:

1. The prediction accuracy of the methods is largely influenced by the sources of coefficients. When using coefficients from literatures, the prediction accuracy of the methods varies a lot, ranging from 51.5% to 96.7%. In this case, the material removal power prediction of aluminum demonstrated better performance than that of the steel and ductile iron.

2. The prediction accuracy of the methods has been improved a lot when using coefficients obtained experimentally. Most measured power values fall within the uncertainty bound (95% confidence) on the predicted power. In this case, the CFM can provide the most accurate prediction of material removal power, followed by the EFM and then the SEM.

3. The SEM and CFM are easy to implement when using coefficients from literatures. When using coefficients from experiments, the implementation difficulty of the SEM and EFM is moderate and the CFM is the most difficult to implement.

The accurate prediction of material removal power can be used to improve the energy efficiency of machining. Machining parameters that use the least amount of energy can be selected in the process design stage. One limitation of the study is that this study was only conducted for turning processes. Further studies should extend this research into other machining processes (such as milling and drilling) and development energy saving methods, such as cutting parameters optimization and tool path selection.

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Nomenclature

Acc	prediction accuracy
C_F	coefficient of cutting force
C_P	coefficient of material removal power
F_C	primary cutting force [N]

F_Z	cutting force of milling process [N]
K_F	coefficient of milling force
P_{m}	power used for material removal operation [W]
P_{mes}	measured material removal power [W]
P_{pred}	predicted material removal power [W]
SEE	standard error of estimate
U_{model}	expanded uncertainty of the model
Z	number of cutting tooth
a_f	feed per tooth [mm/tooth]
a_p	depth of cut [mm]
a_{w}	width of cut [mm]
d_0	cutting tool diameter [mm]
f	feed [mm/r]
k	specific energy requirement in cutting operations [W·s/mm^3]
k_{MF}	correction coefficient for yield and tensile strength of the workpiece material
$k_{\gamma\mathrm{M}}$	correction coefficient for tool angles
n	the number of observations
n_{F}	exponential coefficient of cutting speed
n_{P}	coefficient of cutting speed
p	number of model parameters
$t_{n-p,1-\alpha/2}$	value obtained from the t-distribution table
u_{bi}	uncertainty of model coefficient b_i
u_{model}	standard uncertainty of the model
v	cutting speed [m/min]
$\dot{v}$	material removal rate (MRR) [mm^3/s]
x_{avg}	average value measured for N times
x_{F}	exponential coefficient for depth of cut

x_{P} coefficient of depth of cut

x_i value obtained in i^{th} measurement

$x_{i,\mathrm{ave}}$ average value of variable x_i.

$x_{i,j}$ the j-th data of independent variable x_i

y_{F} exponential coefficient of feed

y_{P} coefficient of feed

ΔF_{C} uncertainties of cutting force [N]

ΔP_{m} uncertainties of material removal power [W]

Δx uncertainty of x

Δx_{avg} uncertainty in the mean value of N times measurements

Δy uncertainty of y

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Highlights

- Three methods can be used to predict material removal energy.
- The accuracy and implementation difficulty of three methods are investigated.
- The coefficients for the methods can be obtained experimentally.
- The cutting force based method can provide the most accurate power prediction.
- The methods should be selected according to the required accuracy in industry.