The International Journal of Advanced Manufacturing Technology (2018) 98:565–577
https://doi.org/10.1007/s00170-018-2281-6

ORIGINAL ARTICLE

A carbon emission quantitation model and experimental evaluation for machining process considering tool wear condition

Guanghui Zhou[1,2] · Shengze Yuan[1] · Qi Lu[1] · Xiaoping Xiao[3]

Received: 8 January 2018 / Accepted: 4 June 2018 / Published online: 14 June 2018

Abstract

Nowadays, the accurate calculation and evaluation of processing carbon emissions (which refer to the total carbon emissions emitted by CNC consuming electrical energy during machining process) have become a hot topic owning to their great role on optimizing cutting processes, and thus reducing the global carbon dioxide emissions. However, the existing carbon emission calculation models for machining process do not pay much attention to the effect of tool wear on processing carbon emissions, which leads to the inaccurate evaluation. So in this paper, a practical carbon emission model for machining process is carried out. The model consists of two parts: (1) a relationship between processing carbon emissions and cutting power (which is the power only caused by removing materials from workpiece) and (2) a novel cutting power model considering tool wear condition. Afterwards, orthogonal experiments are performed on three different CNC machine tools in order to fit cutting power model's constants and coefficients. Experiment results and related data analysis indicate that the presented cutting power model and the experimental evaluation method are accurate, and the flank wear length (VB), which is the index of evaluating tool wear condition, is necessary to be introduced as an independent variable. Compared with other models which do not consider the tool wear condition, this model succeeds to improve the calculation precision of processing carbon emissions, and provides more accurate data supporting the cutting parameter optimization.

Keywords Processing carbon emissions · Tool wear · Predictive model · Orthogonal experiment

1 Introduction

With the rapid increase of global carbon dioxide emissions, a series of environmental problems, including global warming and sea level rising, have become the global problems. According to the research of International Energy Agency (IEA), nearly one third of worlds' total energy consumption and 36% of total carbon emissions were generated by manufacturing industry [1]. Besides, CO_2 and SO_2 emitted by a CNC machine tool with the spindle power 22 kW consuming electrical energy each year amounts to the emissions of 61 cars and 248 sport utility vehicles (SUVs) [2]. If machine's processing carbon emissions can be calculated accurately, the processing carbon emissions will be reduced as much as possible by optimizing cutting parameters, and thus, global carbon dioxide emissions could be reduced [3, 4]. Moreover, some researches [5–7] confirm that, in the machining process, the cutting power accounts for 15–70% of the processing power under different machining methods like turning or milling, which means that 15–70% of the total CO_2 emitted by CNC machine consuming electrical energy

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

✉ Guanghui Zhou
ghzhou@mail.xjtu.edu.cn

Shengze Yuan
roy8035@stu.xjtu.edu.cn

Qi Lu
luqi1234@stu.xjtu.edu.cn

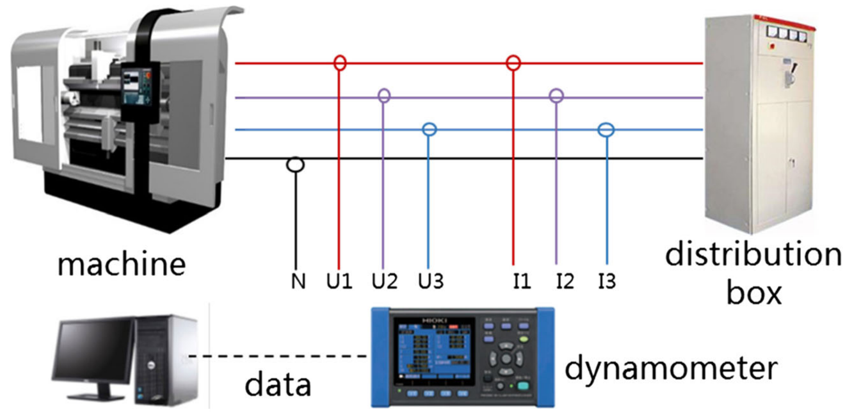
Xiaoping Xiao
124765365@qq.com

1 School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, People's Republic of China

2 State Key Laboratory of Manufacturing Systems Engineering, Xi'an Jiaotong University, Xi'an, Shaanxi 710049, People's Republic of China

3 Hunan Institute of Metrology and Test, Changsha, Hunan 410014, People's Republic of China

Fig. 1 Experiment setup



are caused by workpiece material removal. Therefore, accurate calculation of cutting power is of great significance to determine processing carbon emissions.

Different selections of calculation methods and model variables are the main factors affecting the cutting power calculation's accuracy and feasibility. However, there are certain constraints in the current research considering these two factors' selection.

For the selection of calculation methods, there are two common methods to calculate the cutting power during the process of feature machining, while both of them have some disadvantages.

1) One way of calculating cutting power is to use the product of the specific energy consumption (SEC) and the total volume of material removed in feature processing. In the beginning, the scholars associate SEC with the material removal rate (MRR), and then analyze their functional relationships. Draganescu et al. [8] illustrated the relationship between SEC, MRR, and cutting power, and described the effect of cutting parameters on SEC through response surface methodology as well. Gutowski et al. [9] established the functional relationship between SEC and MRR by using a heat balance method, and regarded the MRR as the most important variable affecting SEC. But further research finds that these models have two disadvantages. First, these models are not accurate. For example, Zhong et al. [10] summarized the experimental and empirical formula including SEC and MRR, and found that the accuracy was only 68%. Second, even under the same MRR, it is still difficult for researchers to determine how to choose the specific cutting parameters. Thus, these formulas cannot be reasonably applied to the actual processing. Therefore, scholars have established a series of functions between SEC and cutting parameters subsequently. A function between SEC, cutting parameters, and workpiece diameter was established by Guo et al. [11], and a further cutting parameter optimization were accomplished, which acquired precise surface finish with minimum energy consumption. Xie et al. [12] proposed the functional relationship between SEC, cutting tools, workpiece materials, and cutting parameters, the function of which was verified through a series of experiments. But the value of SEC between different references varies greatly, so it is difficult to provide an accurate and effective estimate according to the diverse processing conditions.
2) The other way is to use the product of the cutting force and the cutting speed to represent cutting power. Liu et al. [13] obtained cutting power at the tool tip by using an established cutting force model, and thus proposed a model for energy consumption prediction in machining processes. He et al. [14] calculated cutting power by the cutting force, and proposed a method to estimate the energy consumption of numerical control machining. However, calculating cutting power by cutting force is not a conducive practical application because cutting force could only be measured by using cutting force dynamometers. Furthermore, the dynamometer is expensive, complex in installation, and inconvenient in maintenance. In contrast, the power measurement of machine tools is much easier.

Table 1 Parameter details of the machine tools using in the experiments

Machine tool	Spindle speed range (r/min)	Fastest feed rate (m/min)	Main motor power (kW)
FTC20	45–4500	24	18.5
VDL850	60–8000	10	11
VDL1000	60–8000	10	11

So, in this paper, a function illustrating the relationship between cutting power and cutting parameters is presented. This function is synthesized by an exponential function and a linear function. In detail, the exponential function is the formula illustrating the relationship between cutting force and cutting parameters, and the linear function is the formula

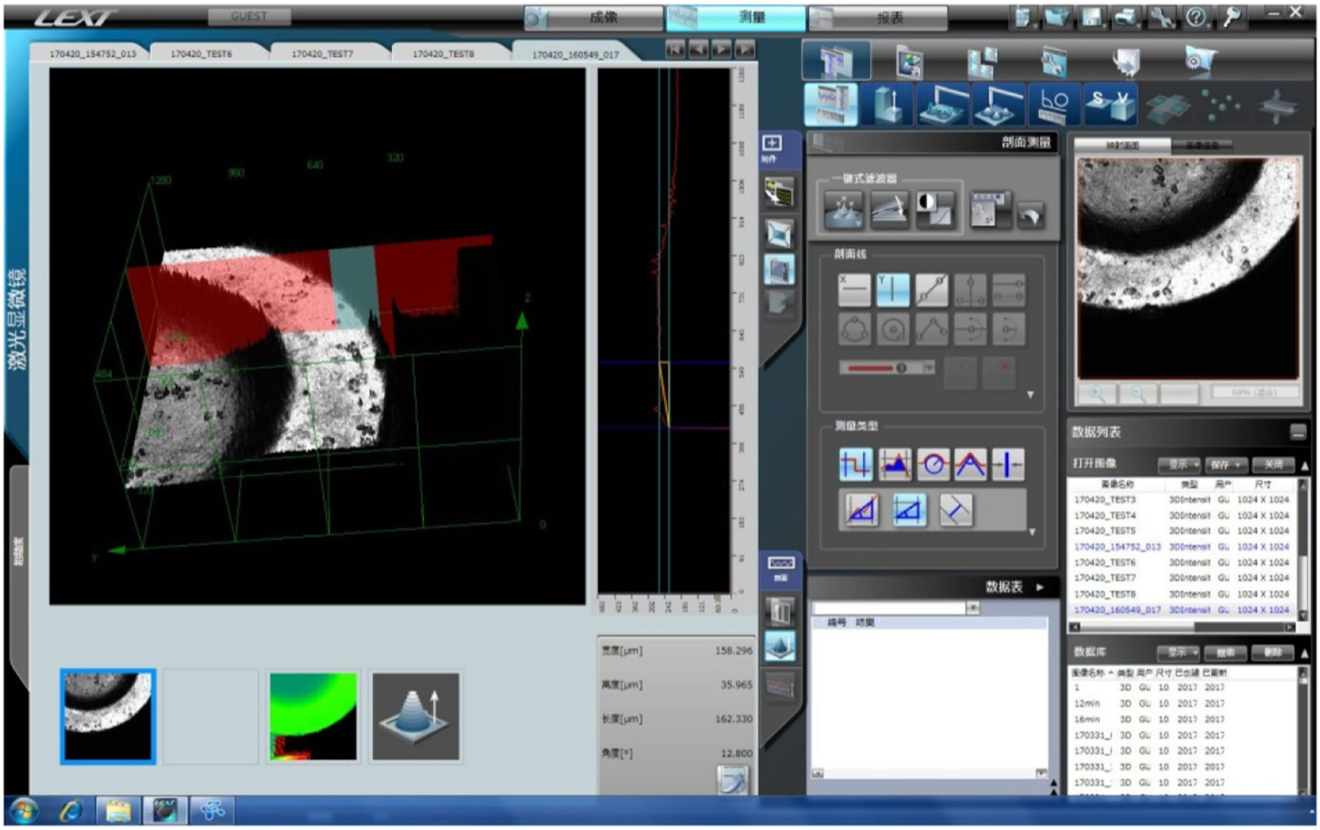


Fig. 2 Measurement of flank wear length by confocal microscope

illustrating the relationship between cutting force and cutting power. Compared with the old methods, this model is more practical and economical for commercial applications.

For the selection of model variables, many researchers only select cutting parameters to calculate cutting power. However, tool wear should also be taken into consideration since it is an important factor.

1) On the one hand, some researchers have already noticed the trend of the relationship between tool wear condition and machine power or energy consumption. Liu et al. [15] investigated the effect of process parameters and tool wear progression on energy consumption. The result indicated that tool wear progression indeed had a predominant influence on energy consumption. Grzesik et al. [16] revealed the variation trends of tool nose wear (VB_C) and the corresponding element changes which included component force, specific cutting energy, and specific ploughing energy. However, in terms of quantitative calculation, there are only a few researchers considering the power changes caused by tool wear when they compute machine tool power. Even though some researchers have considered the influence of tool wear, they only take the VB, which expresses the tool wear severity, as a part of undetermined coefficient in computational formula [17–19].
2) On the other hand, many studies have shown that variation of tool wear condition will lead to a significant change in cutting force. Petr et al. [20] established the model of cutting force coefficient by linear regression, and found that the tangential cutting force coefficient (in

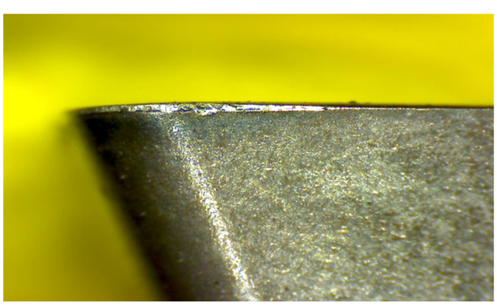


Fig. 3 Measurement of flank wear length by electronic microscope

Table 2 Levels of cutting parameters in experiment of the machine FTC20

Item	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
v (m/min)	94.2	188.4	282.6			
f (m/min)	0.1	0.15	0.2			
a_p (mm)	0.2	0.4	0.6			
VB (mm)	0	0.043	0.072	0.104	0.166	0.205

Table 3 Levels of cutting parameters in experiment of the machine VDL850

Item	Level 1	Level 2	Level 3	Level 4
n (r/min)	400	600	800	
f (m/min)	0.04	0.08	0.12	
a_e (mm)	30	40	50	
a_p (mm)	0.25	0.5	0.75	
VB (mm)	0	0.042	0. 086	0.137

positive proportion to the cutting force) increased by approximately 42% during the whole life time of all tested tools. Zhang et al. [21] developed a function with VB and cutting parameters as independent variables and cutting force as dependent variable. The function indicated that when VB increased from 0 to 0.3 mm, cutting force would increase by 25.97%. Rizal et al. [22] examined the effect of the tool wear for the main cutting force and feed force by turning processing experiment. According to the experimental data, when VB increased from 0.1 to 0.3 mm, the total cutting force increased by 31.29%. As mentioned above, the cutting power of the machine tool is proportional to the cutting force. Therefore, when cutting parameters are constant, a 30% increase in cutting force would correspondingly lead to a 30% increase in cutting power.

So, it is clear that the tool wear condition can significantly affect the cutting power of machine tools, and it is vital to induce VB as one of the independent variables of the cutting power computational model, which could improve the calculation accuracy of cutting power.

To solve problems mentioned above, this paper proposes a practical cutting power model considering tool wear effect. This model bridges cutting power and cutting parameters, which also avoids the problems of practicability caused by using cutting force dynamometer. Besides, by inducing VB as an independent variable, this model directly shows the influence of tool wear on cutting power. Combined with the relationship between processing carbon emissions and cutting power, a carbon emission quantitation model for machining process is established, which provides support for accurate calculation and further optimization of processing carbon emissions.

Table 4 Levels of cutting parameters in experiment of the machine VDL1000

Item	Level 1	Level 2	Level 3	Level 4
n (r/min)	400	600	800	
f (m/min)	0.04	0.08	0.12	
a_e (mm)	30	40	50	
a_p (mm)	0.25	0.5	0.75	
VB (mm)	0	0.055	0. 090	0.125

The rest of this paper is organized as follows. In Sect. 2, a practical carbon emission model for machining process has been put forward by formula deduction. Experimental setup has been introduced in great detail in Sect. 3. Experiment results and discussion are provided in Sect. 4, including the constants' and coefficients' calculation and model's verification. The conclusions are drawn in Sect. 5.

2 Carbon emission model for machining process considering tool wear condition

In this section, a carbon emission model for machining process based on tool wear condition will be presented. To achieve this goal, a relationship between processing carbon emissions and cutting power is going to be introduced, and then, a practical cutting power model considering tool wear condition will be built.

Based on the existing research of the same group [23, 24], the processing carbon emissions of machine tools belong to energy carbon emissions. The carbon emission factor method is often adopted to calculate this part of carbon emissions. This method uses the product of the carbon emission factor and the total energy consumption of machine tools. Among them, the carbon emission factor is obtained based on life cycle assessment and authoritative statistics at home and abroad (such as Ecoinvent 3.4, ELCD 3.0 core database, CLCD China life cycle data). And the machine tools' total energy consumption is calculated by the product of the machine power and the processing time, as shown in Eq. (1)

$$CE_{elec} = CEF_{elec} \times t_c \times P_{total} \tag{1}$$

where CE_{elec} (kg) is the processing carbon emissions of machines, CEF_{elec} (kgCO$_2$/kWh) is the carbon emission factor, t_c (s) is the processing time, and P_{total} (W) is the electrical consumption for machining process.

The processing power of machine tools should be divided into seven parts: lighting power, standby power, spindle power, feed power, cutting fluid power, tool tip cutting power, and load loss power, which is presented as Eq. (2)

$$P_{total} = P_{tooltip} + P_{sprindle} + P_{feed} + P_{extra} + P_{stand} + P_{fluid} + P_{light} \tag{2}$$

where $P_{tooltip}$ (W) is the tool tip cutting power, $P_{sprindle}$ (W) is the spindle power, P_{feed} (W) is the feed power, P_{extra} (W) is the load loss power, P_{stand} (W) is the standby power, P_{fluid} (W) is the fluid power, and P_{light} (W) is the lighting power.

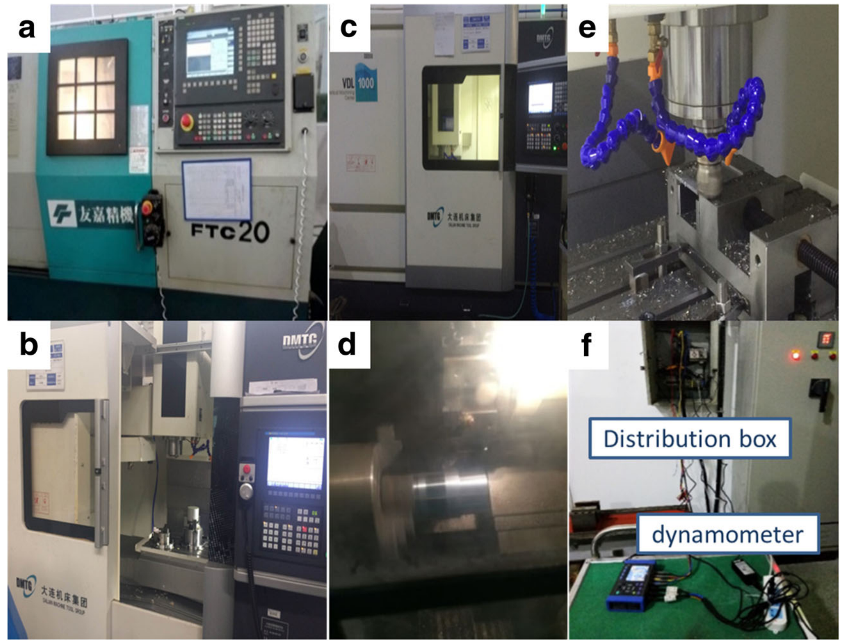


Fig. 4 **a** CNC lathe FTC20. **b** CNC milling machine VDL850. **c** Machining center VDL1000. **d** Turning processing. **e** Plain milling processing. **f** Dynamometer connection

Among them, the standby power, lighting power, and fluid power are constant; their values can be measured by a power meter directly. The spindle power can be indicated as Eq. (3), where n (r/min) is the rotational speed, f_b (Hz) is the basis frequency, and f_1 (Hz) is the corresponding frequency which is the change of power from decreasing or slightly increasing to linearly increasing. The other parameters are the coefficients to be fitted.

$$P_{sprindle} = \begin{cases} C_1 n^2 + C_2 n + C_3 & (f < f_b) \\ C_1{}' n^2 + C_2 n + C_3{}' + k\left(\frac{1}{n^2 + A}\right) & (f_b < f < f_1) \\ C_1{}' n^2 + C_2 n + C_3{}' & (f > f_1) \end{cases} \quad (3)$$

The way to calculate the machine tools' feed power is different according to the varies processing methods. Equation (4) reveals the way to calculate feed power for turning, and Eq. (5) is for the plane milling. Here, f (mm/r) is the feed rate per turn and f_z (mm/min) is the feed rate per tooth. The other parameters are the coefficients to be fitted.

$$P_{feed} = a_{cf_1}(nf)^2 + a_{cf_2}nf + c_{cf} \quad (4)$$

$$P_{feed} = a_{mf_1}(nzf_z)^2 + a_{mf_2}nzf_z + c_{mf} \quad (5)$$

The last two parts of processing power are related to material removal. Tool tip cutting power refers to the power loss caused by tooltip removing materials from workpiece, and the load loss power refers to the additional loss caused by cutting load applied to the spindle system and the feed system of machine tools. So, the combination of these two parts is called cutting power.

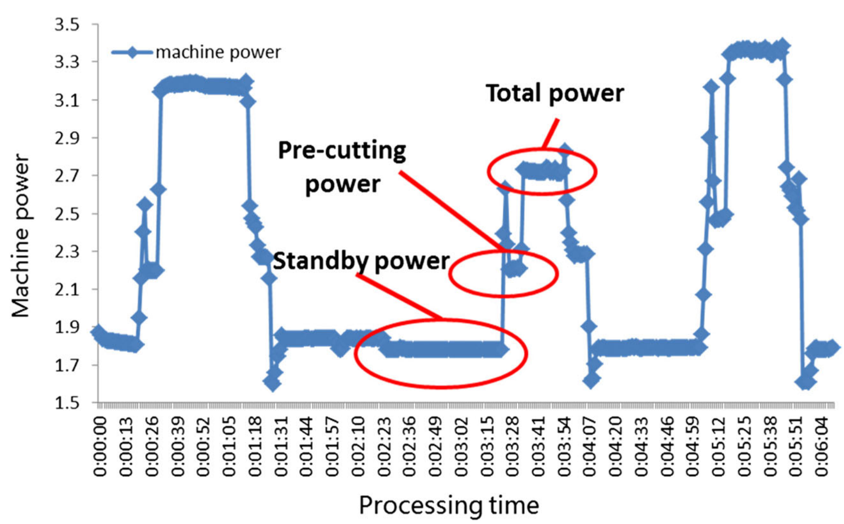


Fig. 5 Variation of total power in turning processing

Table 5 Experiment data of the machine FTC20

No.	VB (mm)	Cutting speed (m/min)	Cutting depth (mm)	Feeding rate (mm/r)	Cutting power (W)	Pre-cutting power (W)
1	0	92.8812	0.2	0.15	189.141	1687.933
2	0	185.762	0.4	0.2	771.604	2477.181
3	0	278.644	0.6	0.1	1002.51	3431.43
4	0.043	278.644	0.2	0.15	679.403	2758.649
5	0.043	92.8812	0.4	0.2	527.309	2057.477
6	0.043	185.762	0.6	0.1	917.194	3119.328
7	0.072	278.644	0.2	0.2	617.122	3053.649
8	0.072	185.762	0.6	0.15	1063.13	3160.986
9	0.072	92.8812	0.4	0.1	230.420	1761.45
10	0.104	185.762	0.2	0.2	511.898	2722.286
11	0.104	278.644	0.4	0.1	886.174	3357.481
12	0.104	92.8812	0.6	0.15	607.695	2156.13
13	0.166	278.644	0.4	0.15	1141.35	3178.222
14	0.166	92.8812	0.2	0.1	161.999	1701.287
15	0.166	185.762	0.2	0.1	368.999	2091.388
16	0.205	278.644	0.2	0.2	821.712	3184.929
17	0.205	92.8812	0.4	0.1	333.830	2093.357
18	0.205	185.762	0.6	0.15	1387.04	3115.964
19	0.072	92.8812	0.2	0.1	190.198	1583.898
20	0.072	185.762	0.4	0.15	798.426	2450.017
21	0.072	278.644	0.6	0.2	1456.59	3541.521
22	0.166	92.881	0.6	0.2	712.679	2631.773
23	0.166	278.644	0.6	0.2	1781.80	4197.253
24	0.166	185.762	0.4	0.15	842.002	2943.891

Then, the cutting power model based on tool wear condition should be established. The calculation method of tool tip cutting power is to obtain the product of the main cutting force and the cutting speed, which is shown as Eq. (6), where F_c(N) is the main cutting force and v (m/min) is the cutting speed.

$$P_{tooltip} = F_c \times v \tag{6}$$

Calculation of the main cutting force is modified based on the main cutting force model given by R. Uehara et al. [25]. VB, as an independent variable, has been added to the authors' equation, which is given as Eq. (7). VB (mm) is the flank wear length (the range of this parameter is 0 to 0.3 mm), a^p (mm) is the cutting depth, and others are the coefficients to be fitted.

Table 6 Experiment data of the machine VDL850

No.	VB (mm)	Cutting speed (m/min)	Cutting depth (mm)	Feeding rate (mm/r)	Cutting width (mm)	Cutting power (W)	Pre-cutting power (W)
1	0.086	56.5487	0.75	0.08	30	106.361	977
2	0.086	75.3982	0.5	0.08	30	86.9378	1048.643
3	0.086	62.8319	0.5	0.04	50	69.6280	944.7959
4	0.086	94.2478	0.25	0.04	50	50.8333	978.5
5	0.086	50.2655	0.75	0.12	40	191.676	949.8235
6	0.086	100.531	0.25	0.12	40	100.158	1048.429
7	0.042	37.6991	0.5	0.12	30	98.9433	937.2105
8	0.042	56.5487	0.25	0.12	30	64.794613	996.2963
9	0.042	125.664	0.25	0.08	50	93.0190	1067.381
10	0.042	62.8319	0.75	0.08	50	180.071	920
11	0.042	100.531	0.5	0.04	40	90.0143	1050.824
12	0.042	75.3982	0.75	0.04	40	98.0525	987.9302
13	0.137	56.5487	0.25	0.12	30	73.2708	1003.313
14	0.137	37.6991	0.5	0.12	30	111.638	948.6667
15	0.137	125.664	0.25	0.08	50	105.123	1074.15
16	0.137	62.8319	0.75	0.08	50	203.866	946.5789
17	0.137	100.531	0.5	0.04	40	102.018	1072.857
18	0.137	75.3982	0.75	0.04	40	109.692	1010.125
19	0	37.6991	0.25	0.04	30	22.7389	923.7292
20	0	75.3982	0.75	0.04	30	79.3009	1075.724
21	0	75.3982	0.5	0.08	40	90.2835	990.8276
22	0	50.2655	0.25	0.08	40	51.3834	925.7931
23	0	125.664	0.75	0.12	50	273.997	1032.037
24	0	94.2478	0.5	0.12	50	177.498	988.2353

Table 7 Experiment data of the machine VDL1000

No.	VB (mm)	Cutting speed (m/min)	Cutting depth (mm)	Feeding rate (mm/r)	Cutting width (mm)	Cutting power (W)	Pre-cutting power (W)
1	0.09	37.6991	0.5	0.12	30	81.1529	992.2
2	0.09	75.3982	0.75	0.04	40	89.6491	1119.091
3	0.09	125.664	0.25	0.08	50	71.2487	1162.714
4	0.09	56.5487	0.25	0.12	30	54.25	1055.4
5	0.09	100.531	0.5	0.04	40	80.0917	1124.2
6	0.09	62.8319	0.75	0.08	50	183.241	1012.826
7	0	37.6991	0.25	0.04	30	19.68	1012.397
8	0	75.3982	0.5	0.08	40	85.4331	1077.444
9	0	125.664	0.75	0.12	50	244.639	1120.571
10	0	75.3982	0.75	0.04	30	76.3442	1110.291
11	0	50.2655	0.25	0.08	40	55.67	1076.25
12	0	94.2478	0.5	0.12	50	165.216	1075.889
13	0.055	56.5487	0.75	0.08	30	119.548	1057.857
14	0.055	100.531	0.25	0.12	40	113.3	1138.167
15	0.055	62.8319	0.5	0.04	50	74.1383	1028.842
16	0.055	75.3982	0.5	0.08	30	87.9655	1108.034
17	0.055	50.2655	0.75	0.12	40	192.111	1069.889
18	0.055	94.2478	0.25	0.04	50	42.1808	1076.585
19	0.125	56.5487	0.25	0.12	30	63.781	1056.286
20	0.125	100.531	0.5	0.04	40	95.1786	1130.25
21	0.125	62.8319	0.75	0.08	50	187.228	1028.667
22	0.125	37.6991	0.5	0.12	30	104.981	1009.929
23	0.125	75.3985	0.75	0.04	40	103.583	1084.667
24	0.125	125.664	0.25	0.08	50	79.5529	1159.8

$$F_c = k(1+VB)^w a_p^x f^y v^{z'} \tag{7}$$

Combine Eqs. (6) and (7) to get the following Eq. (8).

$$\begin{aligned} P_{tooltip} &= k(1+VB)^w a_p^x f^y v^{z'} \times v \\ &= k(1+VB)^w a_p^x f^y v^z \end{aligned} \tag{8}$$

The tool tip cutting power for milling can be obtained similarly, shown as Eq. (9).

$$\begin{aligned} P_{tooltip} &= k(1+VB)^v a_e^w a_p^x f^y v^{z'} \times v \\ &= k(1+VB)^v a_e^w a_p^x f^y v^z \end{aligned} \tag{9}$$

Calculation of load loss power is shown as Eq. (10).

$$P_{extra} = k' P_{tooltip} \tag{10}$$

The cutting power model of turning and plane milling can be obtained by combining the models of tool tip cutting power and the models of load loss power, shown as Eqs. (11) and (12).

$$\begin{aligned} P_{cutting} &= \left(1+k'\right) k(1+VB)^w a_p^x f^y v^z \\ &= K(1+VB)^w a_p^x f^y v^z \end{aligned} \tag{11}$$

$$\begin{aligned} P_{cutting} &= \left(1+k'\right) k(1+VB)^v a_e^w a_p^x f^y v^z \\ &= K(1+VB)^v a_e^w a_p^x f^y v^z \end{aligned} \tag{12}$$

The linear regression method is used to get the constants and coefficients of these equations above. In order to facilitate the use of linear regression to get the unknown coefficients, both sides of Eqs. (11) and (12) are taken the logarithm, which are shown as Eqs. (13) and (14).

$$\ln P = \ln K + w\ln(1+VB) + x\ln a_p + y\ln f + z\ln v \tag{13}$$

$$\ln P = \ln K + v\ln(1+VB) + w\ln a_e + x\ln a_p + y\ln f + z\ln v \tag{14}$$

3 Experimental setup and details

To fit the coefficients and verify the model mentioned above, orthogonal experiments of two machining methods (turning and plane milling) should be carried out. Experimental setup and details will be explained in this section.

Table 8 Linear regression coefficient table of the machine FTC20

Model	Unstandardized coefficients		Standardized coefficients	t	Significance
	B	Standard error	Beta		
Constant	3.724	0.440		8.457	0.000
VB	1.387	0.471	0.144	2.943	0.011
Cutting speed	0.961	0.066	0.711	14.665	0.000
Cutting depth	0.925	0.067	0.687	13.751	0.000
Feeding rate	0.724	0.109	0.335	6.620	0.000

The experimental setup is given in Fig. 1. During processing, the power data of the lathe is acquired by a clamp dynamometer, which connects with power distribution boxes, and the data is stored in a laptop connected with the dynamometer. Three different machine tools are adopted in this experiment, which include CNC lathe FTC20 from Taiwan Fair Friend Group (for turning process), CNC milling machine VDL850, and machining center VDL1000 from Dalian Machine Tools Group (for plane milling process), respectively. The parameter details of these machine tools are shown as Table 1. An ASTM 080M46 bar with dimensions of $\varphi 100 \times 80$ mm and a same material plate with dimensions of $155 \times 90 \times 10$ mm are selected as the workpiece for turning and milling, respectively. The workpiece material is hardened to 45 ± 2 HRC. Various wear levels of coated carbide inserts WNMG080412 (made by Golden Egret Co., Ltd., Xiamen, China) and APMT1604PDER (made by Aken Co., Ltd.) are employed in machining experiments. Upmilling is adopted in the milling process.

The flank wear length is measured by confocal microscope OLS4000 (Fig. 2) and digital microscope ISM-PM200

Table 9 Linear regression coefficient table of the machine VDL850

Model	Unstandardized coefficients		Standardized coefficients	T	Significance
	B	Standard error	Beta		
Constant	2.653	0.414		6.411	0.000
Cutting speed	0.429	0.107	0.431	4.016	0.002
Feeding rate	0.721	0.069	0.933	10.425	0.000
Cutting depth	0.829	0.067	1.072	12.290	0.000
Cutting width	0.696	0.141	0.415	4.929	0.000
VB	1.440	0.633	0.146	2.274	0.042

Table 10 Linear regression coefficient table of the machine VDL1000

Model	Unstandardized coefficients		Standardized coefficients	t	Significance
	B	Standard error	Beta		
Constant	2.767	0.591		4.681	0.001
Cutting speed	0.289	0.106	0.205	2.714	0.019
Feeding rate	0.634	0.067	0.520	9.464	0.000
Cutting depth	0.903	0.066	0.741	13.609	0.000
Cutting width	0.753	0.203	0.285	3.708	0.003
VB	1.516	0.560	0.136	2.709	0.019

(Fig. 3). The power measurement is based on the HIOKI clamp dynamometer PW3360.

The orthogonal table L18 (6×3^7) is selected in this experiment. Meanwhile, six more groups of experiments are added as a validation group to verify the rationality of the fitting model. The details of the orthogonal test are shown in Tables 2, 3, and 4, respectively.

Under the same set of test parameters, every 10 components of power data recorded by the dynamometer determines one average value of the cutting power components in the cutting, which can limit the experimental error at minimum. The actual machining is presented in Fig. 4.

4 Experiment results and discussion

Experiment results and discussion are provided in this section. Before coefficients' calculation and model's verification, how to acquire cutting power should be explained firstly. Taking the turning process as an example, the data of machine total power variation with time is shown in Fig. 5. The standby power corresponds to the machine standby power. The pre-cutting power refers to the machine tool's power in the state of pre-cutting, which means the state of spindle rotation, tool feed but without material removing. The total power refers to the processing power of the machine tools. Therefore, the cutting power is obtained by subtracting average pre-cutting power from average total power.

The original data obtained in the experiments is shown in Tables 5, 6, and 7, respectively.

Linear regression of the experiment data is used to obtain the coefficients to be fitted in the model by IBM SPSS Statistics (version 19). The fitting result and linear regression coefficient table are shown as Eqs. (15)–(17) and Tables 8, 9, and 10.

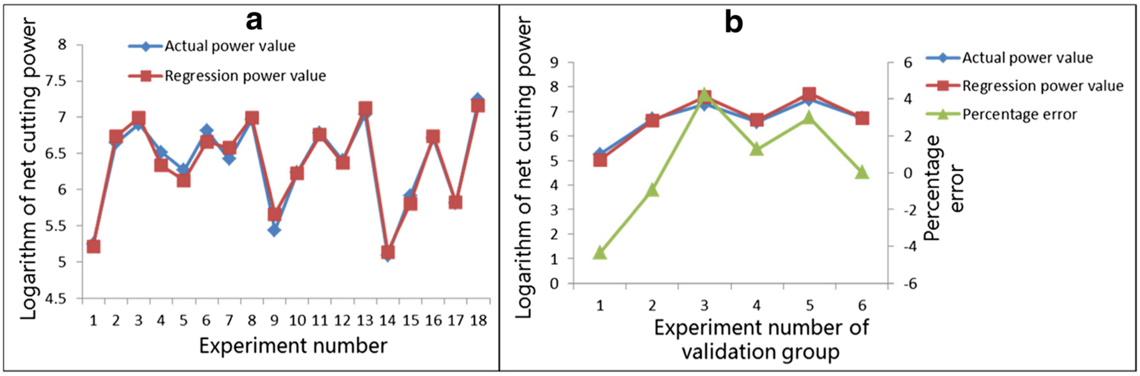


Fig. 6 Fitting effect and percentage error in verification group of the machine FTC20

1) The fitting formula of FTC20 cutting power.

$$P_{cutting} = e^{3.724}(1+VB)^{1.387}a_p^{0.925}f^{0.724}v^{0.961} \quad (15)$$

2) The fitting formula of VDL850 cutting power.

$$P_{cutting} = e^{2.653}(1+VB)^{1.440}a_e^{0.696}a_p^{0.829}f^{0.721}v^{0.429} \quad (16)$$

3) The fitting formula of VDL1000 cutting power.

$$P_{cutting} = e^{2.767}(1+VB)^{1.516}a_e^{0.753}a_p^{0.903}f^{0.634}v^{0.289} \quad (17)$$

According to the analysis results of the three models, R^2 are 0.970, 0.950, and 0.970, respectively, which are all greater than 0.85. The significance of each coefficient is less than 0.05. In the validation group, the maximum percentage error (MPE) of the fitting model is no more than 4.4, 4, and 5.4%, and the mean absolute percentage errors (MAPE) are only 2.31, 1.34, and 2.70% (Figs. 6, 7, and 8), respectively. All these results indicate that these models are fitted well.

According to the experimental validation, some conclusions can be drawn as follows:

1) Cutting power accounts for an important proportion in the processing power of the machine tool.

As shown in Fig. 9, in turning and milling process, the cutting power accounts for 9.5–44.5 and 2.2–21% of the machine's processing power, respectively. Besides, with the increase of the processing power, the proportion of the cutting power increases as well. The reason why the cutting power proportion of milling is significantly less than that of turning is the installation of milling cutter blades. Only one milling blade has been installed on the disk milling cutter in each milling experiment for ensuring the accuracy of milling blade's wear condition. However, four milling blades are installed on the disk milling cutter normally. In this way, experiment data errors caused by the different wear condition of blades could be avoided. Under this condition, the milling parameters should be appropriately reduced to ensure the machining stability. Therefore, the lower parameters finally lead to the lower cutting power proportion of milling.

2) Taking VB as one of the independent variables is necessary and significant.

According to the fitting formula obtained by linear regression, such as FTC20's formula shown in Eq. (15), under the same condition of machining material, cutting tool type, and cutting parameters (such as cutting speed is 150 m/min, cutting depth is 0.5 mm, and feed is 0.2 m/min), a new blade's (VB equals 0) cutting power calculation result is 839.52 W,

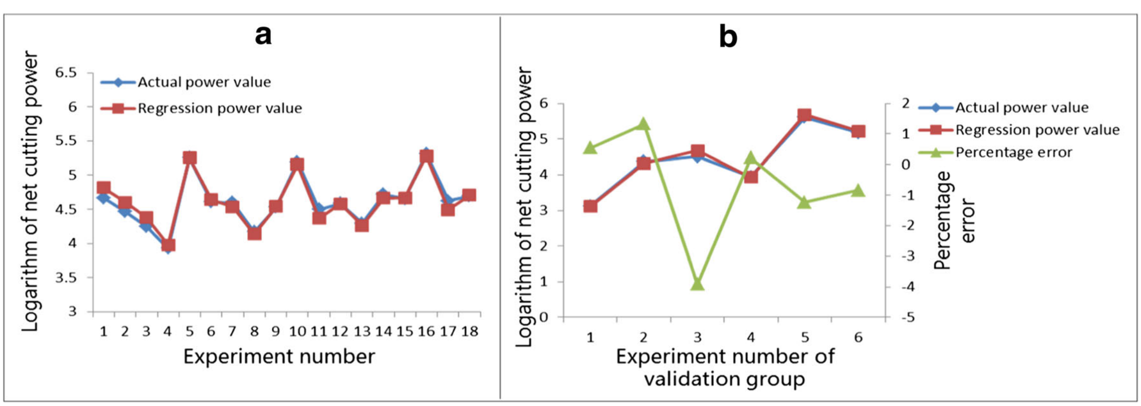


Fig. 7 Fitting effect and percentage error in verification group of the machine VDL850

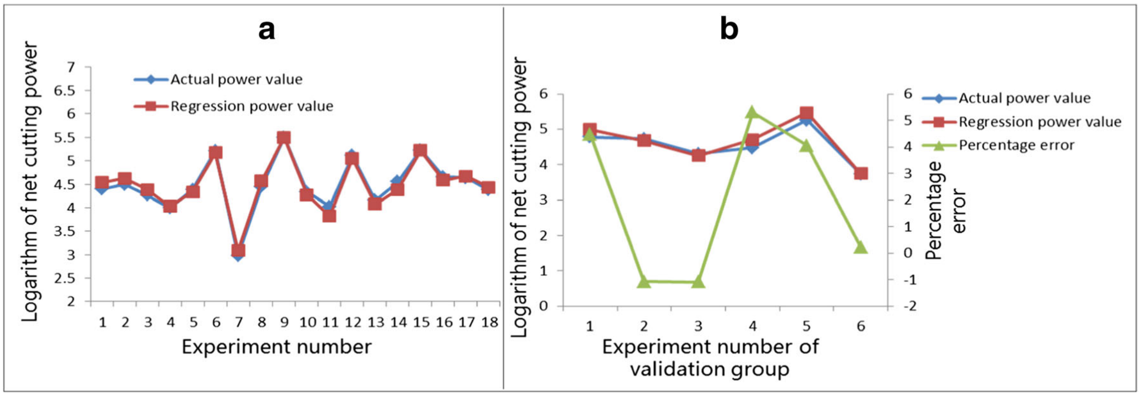


Fig. 8 Fitting effect and percentage error in verification group of the machine VDL1000

and a blunt blade's (VB equals 0.3 mm) cutting power calculation result is 1208.01 W, which has a 43.9% increase. Similarly, the cutting power growth caused by different tool wear states of VDL850 and VDL1000 are 45.91 and 48.85%, respectively. Besides, based on the equations shown in Eqs. (15)–(17) and experimental data shown in Tables 4, 5, and 6, when VB is increased to 0.3 with the same pre-cutting power, the change of maximum cutting power can reach 8.2% (VDL1000), 10.6% (VDL850), and 16.2% (FTC20) of the processing power, respectively. The average power variation can reach 2.67% (VDL1000), 3.23% (VDL850), and 6.89% (FTC20), respectively. Because processing carbon emissions is proportional to processing power, changes in tool wear can result in a same proportion increase in processing carbon emissions. It shows that tool wear can cause a certain range of changes in processing carbon emissions. So, taking VB as one of the independent variables is necessary and significant.

3) The form of the cutting power model is reasonable.

The actual cutting power values of VDL850 (shown in red line of Fig. 10) and the fitting power values obtained by using the VDL850 independent variables and the VDL1000 fitting formula (shown in blue line of Fig. 10) are compared. The result finds that only one set's data error is more than 5% in the 24 sets of data, and the average absolute error is only 2.59%. It illustrates that although the specific machine parameters' differences lead to some errors, the

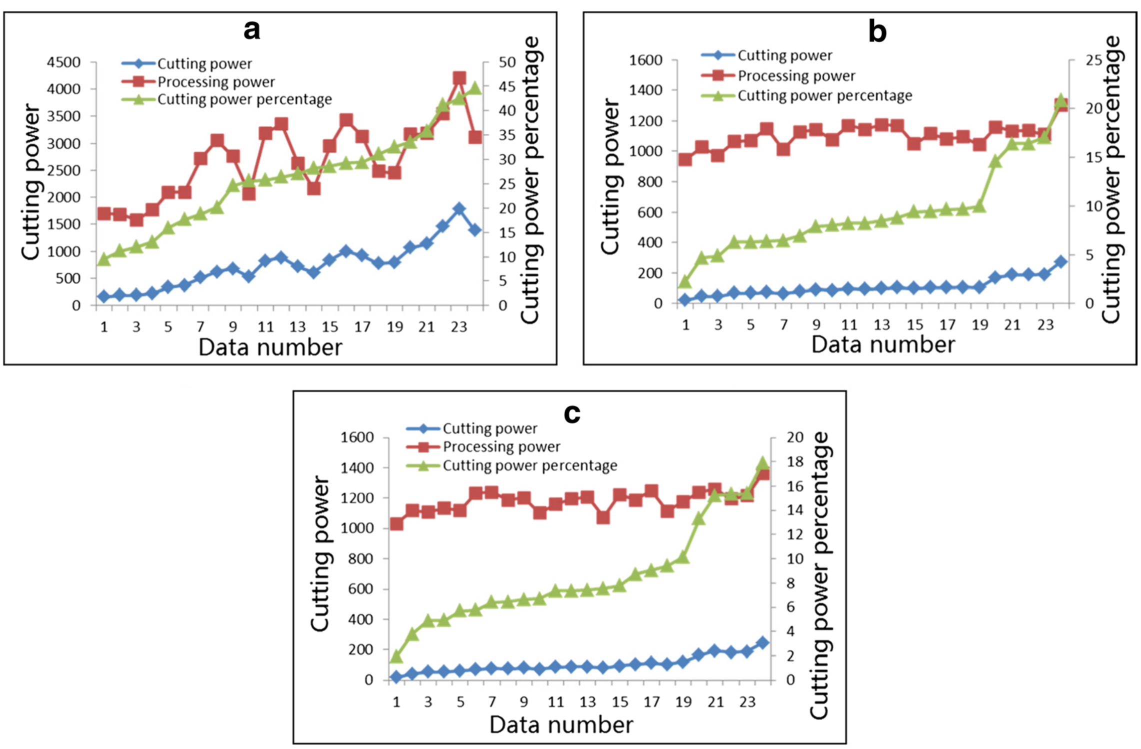


Fig. 9 Analyses of cutting power and cutting power percentage

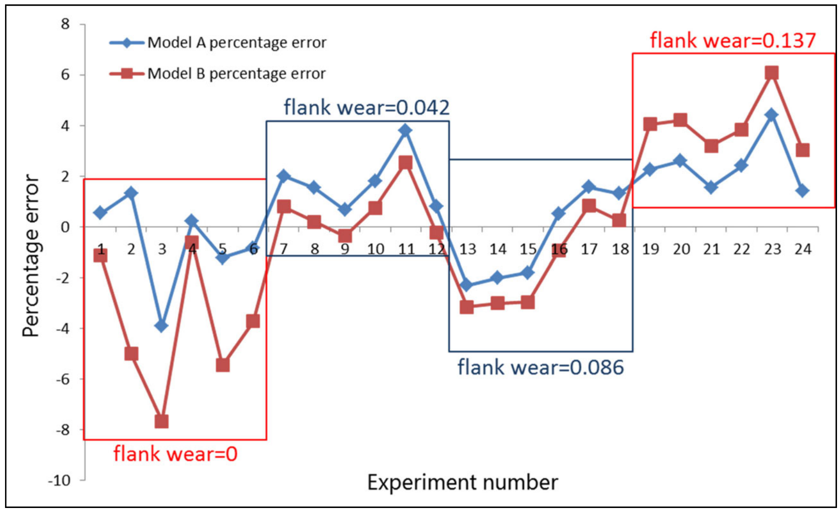


Fig. 10 Error analysis of fitting power values obtained using the VDL850 independent variables and the VDL1000 fitting formula and actual power values

fitted cutting power and the actual cutting power are in the same trend. As a result, the model is consistent with the actual processing characteristics, and the form of the cutting power model is reasonable.

4) The model which considers tool wear effect is more accurate comparing with the model which does not consider tool wear effect.

Take VDL850's data as an example, the fitting error comparative analysis between the model which contains tool wear (Eq. (12), model A) and the model which does not contain tool wear (Eq. (18), model B) has been carried out. The method of comparative analysis is as follows: take out six sets of data in VDL850 as a validation group (the VB of these six sets of data is consistent) and other 18 sets of data as fitting group which is used to fit the coefficients. After model's fitting, the error percentage of fitting results and actual measurement results of two models is compared. The results are shown as Table 11 and Fig. 11.

$$P_{cutting} = Ka_e^w a_p^x f^y v^z \tag{18}$$

The result indicates when VB = 0.042 or 0.086, the differences between two models' fitting error are not significant, and the fitting effect of model B sometimes is even better. However, when VB = 0 or 0.137, the differences are obvious and the model B indeed has bigger deviation. Besides, all data of the validation group which VB = 0 is smaller than the actual value. Meanwhile, all data of the validation group which VB = 0.137 is bigger than the actual value. So, it is clear that the model B has systematic defects, and the model which contains tool wear is more accurate comparing with the model which does not contain tool wear.

In summary, this cutting power model is accurate, practical, and reasonable. This model can reflect the effect of tool wear condition on cutting power as well. The carbon emission quantitation model for machining process, which combined with the cutting power model and the relationship between cutting power and processing carbon emissions, also has these advantages. Introduction of tool wear allows the model to calculate carbon emissions more accurately. Furthermore, this model directly builds the cutting parameters—cutting power—processing carbon emission calculation method, which also avoids the use of dynamometer and improves the practicality of the model. As a result, this carbon emission quantitation model can calculate processing carbon emissions accurately, provide support for low-carbon optimization of cutting parameters, and ultimately achieve the goal of reducing global carbon emissions.

Table 11 Percentage error comparison of two models

Item	VB = 0	VB = 0.042	VB = 0.086	VB = 0.137
Model A MPE	− 3.91542785	3.783083927	− 2.30560568	4.420221336
Model B MPE	− 7.66636211	2.546058864	− 3.15444451	6.073626986
Model A MAPE	1.344608098	1.760484658	1.582598497	2.437898573
Model B MAPE	3.934457089	0.808801418	1.858268031	4.065371014

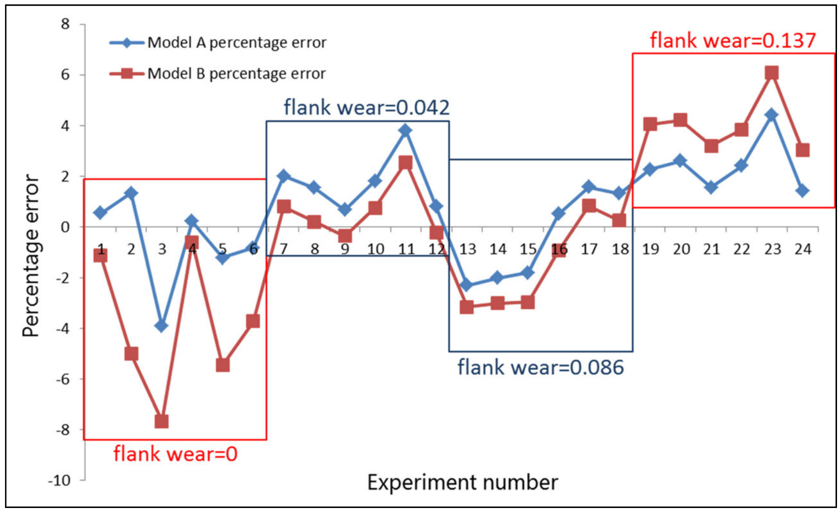


Fig. 11 Percentage error comparison of two models

5 Conclusions

Accurate calculation of processing carbon emissions is of great significance to optimize the cutting processes, and thus reducing the global carbon emissions. In this paper, a practical model for machine's processing carbon emissions has been presented by associating the carbon emission-cutting power relationship with a novel cutting power model. This model takes the influence of both the cutting parameters and tool wear into consideration. Besides, two machining methods' orthogonal experiments have been carried out in order to fit the coefficients and verify the model.

Specifically, two conclusions can be drawn. Firstly, the model for processing carbon emissions is reasonable and accurate. The results of verification show that the model fits well, and confirm that it is necessary to induce VB as an independent variable. Compared with the model which does not consider tool wear effect, this model is more accurate. Secondly, this model is really practical. This model bridges cutting power and cutting parameters, which avoid the problems of practicability caused by using cutting force dynamometer. So, this model is indeed useful for commercial applications.

In conclusion, the model has good prospect for providing support to promote cutting parameter optimization, to increase energy efficiency, and to reduce processing carbon emissions.

Acknowledgments This research is supported by the National Natural Science Foundation of China (grant no. 51575435).

References

1. Liu ZJ, Sun DP, Lin CX, Zhao XQ, Yang Y (2016) Multi-objective optimization of the operating conditions in a cutting process based on low carbon emission costs. J Clean Prod 124(Supplement C): 266–275
2. Zhou LR, Li JF, Li FY, Meng Q, Li J, Xu XS (2016) Energy consumption model and energy efficiency of machine tools: a comprehensive literature review. J Clean Prod 112(Part 5):3721–3734
3. Miranda J, Camposeco-Negrete C, Calderón J (2016) Optimization of cutting parameters to minimize energy consumption during turning of AISI 1018 steel at constant material removal rate using robust design. Int J Adv Manuf Technol 83:1341–1347
4. Li CB, Li LL, Tang Y, Zhu YT, Li L (2016) A comprehensive approach to parameters optimization of energy-aware CNC milling. J Intell Manuf 1–16
5. Peng T, Xu X (2017) An interoperable energy consumption analysis system for CNC machining. J Clean Prod 140(Part 3):1828–1841
6. Kordonowy DN (2002) A power assessment of machining tools. Massachusetts Institute of Technology, Cambridge
7. Dietmair A, Verl A (2009) Energy consumption forecasting and optimisation for tool machines. MM Sci J 3:62–67
8. Draganescu F, Gheorghe M, Doicin CV (2003) Models of machine tool efficiency and specific consumed energy. J Mater Process Technol 141(1):9–15
9. Gutowski T, Dahmus J, Thiriez A (2006) Electrical energy requirements for manufacturing processes. Proceedings of the 13th CIRP International Conference on Life Cycle Engineering, Leuven, Belgium, May 31–June 2, 2006
10. Zhong Q, Tang RZ, Lv JX, Jia S, Jin M (2016) Evaluation on models of calculating energy consumption in metal cutting processes: a case of external turning process. Int J Adv Manuf Technol 82(9):2087–2099
11. Guo Y, Loenders J, Duflou JR, Lauwers B (2012) Optimization of energy consumption and surface quality in finish turning. Procedia CIRP 1:512–517
12. Xie J, Liu F, Qiu H (2016) An integrated model for predicting the specific energy consumption of manufacturing processes. Int J Adv Manuf Technol 85(5):1339–1346

13. Liu N, Zhang YF, Lu WF (2015) A hybrid approach to energy consumption modelling based on cutting power: a milling case. J Clean Prod 104:264–272
14. He Y, Liu F, Wu T, Zhong FP, Peng B (2012) Analysis and estimation of energy consumption for numerical control machining. Proc Inst Mech Eng B J Eng Manuf 226(2):255–266
15. Liu ZY, Guo YB, Sealy MP, Liu ZQ (2016) Energy consumption and process sustainability of hard milling with tool wear progression. J Mater Process Technol 229(Supplement C): 305–312
16. Grzesik W, Denkena B, Żak K, Grove T, Bergman B (2015) Energy consumption characterization in precision hard machining using CBN cutting tools. Int J Adv Manuf Technol 85:2839–2845
17. Wang Q, Liu F, Wang X (2013) Multi-objective optimization of machining parameters considering energy consumption. Int J Adv Manuf Technol 71(5–8):1133–1142
18. Moradnazhad M, Ünver HÖ (2017) Energy consumption characteristics of turn-mill machining. Int J Adv Manuf Technol 91(5): 1991–2016
19. Altıntaş RS, Kahya M, Ünver HÖ (2016) Modelling and optimization of energy consumption for feature based milling. Int J Adv Manuf Technol 86(9):3345–3363
20. Kolar P, Fojtu P, Schmitz T (2015) On cutting force coefficient model with respect to tool geometry and tool wear. Procedia Manuf 1(Supplement C):708–720
21. Zhang BJ, Song SM, Chen M (2010) Study of cutting force model based on tool condition. Tool Eng. (02):27–30. (In Chinese)
22. Rizal M, Ghani JA, Nuawi M, Che Haron CH (2013) The application of I-kazTM-based method for tool wear monitoring using cutting force signal. MITC2013 68:461–468
23. Zhou GH, Zhou C, Lu Q, Tian C, Xiao Z (2017) Feature-based carbon emission quantitation strategy for the part machining process. Intl J Comput Integr Manuf 11:1–20
24. Zhou GH, Lu Q, Xiao ZD, Zhou C, Yuan SZ, Zhang C (2017) Ontology-based cutting tool configuration considering carbon emissions. Int J Precis Eng Manuf 18(11):1641–1657
25. Uehara K, Kiyosawa F, Takeshita H (1979) Automatic tool wear monitoring in NC turning. CIRP 28(1):38–42