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ORIGINAL ARTICLE

An energy consumption optimization strategy for CNC milling

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Abstract Energy saving is a problem of growing importance due to the low-energy utilization and increasing environmental awareness. However, the challenge of energy optimization is to assure the accuracy of the energy forecast model. As a full understanding of material-cutting energy is a key aspect of machining process, energy modeling is essential for its optimization. This study proposes a specific energy calculation model and an optimization model to predict and optimize the electrical energy consumed by a three-axis milling machine. In this model, the impacts of cutting parameters on energy are fully considered and the MATLAB optimization toolbox is used for the solution. To assess the usefulness and practicality of the proposed method, an experimental study with a CNC milling machine is presented. The results demonstrate the effectiveness of energy improvement of this method based on optimizing the spindle speed in milling process. Additionally, the predictive accuracy of the energy model is above 90 %, which offers a viable approach for achieving higher machining efficiency.

Keywords Energy consumption · Optimization strategy · Milling · Cutting process

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1 Introduction

With significant growths in global manufacturing, its power demand and consumption continue to increase. This growth brings about accelerated utilization of natural resources and energy, which lead to increasing burden of the environment [1]. Motivated by adverse environment situation and customer's growing concern of environmental issues, energy consumption has become a major of research in manufacturing.

The manufacturing industry sector accounts for about one half of the world's total energy consumption, and this has been doubled over the past 60 years [2]. While machining is the main part of the manufacturing industry, its efficiency is generally below 30 % [3]. Most of the environmental impacts related to CNC machine tools are due to their energy consumption [4, 5]. Low-energy utilization leads to serious environmental problems as a result of discharging more toxic gases into the atmosphere [6–8], as well as soil, air, and water pollution. From this perspective, energy saving results in higher environmental performance and productivity [9]. Towards this aim, this study presents an optimization strategy for the electrical energy consumed in CNC milling with the purpose of reducing its environmental impact.

As described by Liu et al. [10], the power demand of a machine tool is comprised of three stages, i.e., start stage, air cutting stage, and cutting stage. Besides, the auxiliary power (start stage, air cutting stage) demand dominates the total energy consumption, and the cutting power is the additional power drawn for the removal of material [3]. Considerations of several factors like spindle speed, feed rate, cutting depth, and chip load are required for the analysis of milling process energy consumption. These factors affect significantly the extent to which milling energy is optimized and the workpiece quality [11].

Energy optimization technologies for machining can be divided into two categories. The first category mainly focuses on machine improvement and new cutting technologies, such as high-speed cutting and minimum quantity lubrication machining. The second category is concerned with the relationship between process parameters and energy consumption, which leads to the development of energy consumption models and parameter optimization methods for energy saving. It is apparent that the first category is not appropriate for existing CNC machine tools, because CNC machine tools are generally too expensive to renew or replace. Consequently, the second approach is more relevant for industrial users. Therefore, machining parameter selection plays an important role in reducing energy consumption in manufacturing [12, 13].

Numerous algorithms such as genetic algorithm and ant colony algorithm or other methods like robust design have been used to optimize processing parameters to reduce energy consumption. Camposeco et al. [14] presents an experimental study for optimization cutting parameters in order to minimize the energy consumed of the machining process, by selecting the material removal rate as a constant value and using robust design to determine the cutting parameters. Mori et al. [15] selected the optimal cutting parameters, including cutting speed, feed rate, and cutting depth, based on several given sets of cutting conditions considering energy minimization. Xiao et al. [16] proposed an optimization approach for blank dimension design, by considering energy consumption, machining cost, and process time. Quintana et al. [17] constructed an artificial neural network to predict the CNC machine tool-processing power demand. Experiments on machining energy consumption were reported in the search for the optimal cutting parameters [18]. Summarizing the above efforts for machining energy reduction through process optimization, it seems that current studies tend to apply algorithm and simulation methods to find optimal cutting parameters. Relatively, the use of spindle speed and the workpiece material removal rate is much less reported.

Presently, the general approach to analyze machining energy consumption is based on computational model. An integrated framework for achieving the optimization of cost and energy consumption of manufacturing systems was proposed by Tolio et al. [19]. The analysis of variance model was adopted by Camposeco et al. [20] to analyze optimization cutting parameters during turning of AISI 6061 T6 under roughing conditions in order to get the minimum energy consumption. Zhang et al. [21] proposed a new process planning strategy from the point of view of machining features to reduce energy consumption. Cai et al. [22] optimized the machining parameters for micro-machining nozzle considering the characteristics of surface roughness. Mativenga et al. [23] calculated the optimum tool life for minimum energy footprint for the turning of EN8 (AISI 1040) steel. Zulaika et al. [24] also proposed an integrated approach for the design of productive and light-weighting milling machines in order to save energy. Energy consumption for machine tools was found to be primarily dependent on the processing time of the part, which is affected directly by the part geometry, tool path, and material removal rate [25].

This paper is concerned with the effect of the material removal rate and spindle speed on energy consumption. The material removal rate for a three-axis CNC milling machine can be varied by changing the feed rate, width of cut, or depth of cut. Increasing the feed rate was found to have adverse effects on tool life and requires more power for the spindle motor and axis drives [26]. On the other hand, higher feed rate increases material removal rate and hence shorter machining times. Since the main interest is energy consumed during machining, the trade-off between power demand and machining time was analyzed to investigate the hypothesis that the increased loads due to higher material removal did not increase the total energy consumed.

The remainder of this paper is organized as follows: experimental planning between material removal rate (MRR) and energy is presented in the next section. Then, detailed discussions of the milling energy model and optimization model for MRR machining processes are given in Sect. 3. Experimental study performed on XK713 CNC milling machine was described in Sect. 4. Finally, the conclusions and future research directions are summarized in Sect. 5.

2 Experimental research between MRR and energy

Extensive experiments were conducted by Gutowski et al. [27, 28] and proposed linear function between cutting power and MRR. It was shown that the MRR is mainly related to width of cut, depth of cut, cutting speed, and chip load [29]. An improved energy consumption model was proposed by Balogun et al. [30]. Similarly, another improved power model was proposed to estimate the energy consumption of a CNC milling machine as function of MRR and spindle speed ($P = P_{\text{standby}} + b + k_1 n + k_0\text{MRR}$) [31]. However, most of existing improved models were based on the power demand and treating the air cutting power demand as a constant, which is not detailed discussion of the relationship between power and energy consumption. Actually, the air cutting power is mainly determined by the spindle speed and electric parameters, etc. [32]. This paper will more focus on the relationship between power and energy considering the air cutting power demand as a variable.

2.1 Energy property experiments of cutting width

Experiments of cutting width were conducted on a 1045 steel workpiece 80 mm in length. Firstly, the width of cutting was increased while machining with an uncoated carbide end mill. Peripheral cuts were made along the *y* axis at a depth of cut of 1 mm with a 10–mm-diameter end mill over a length of 80 mm in a 1045 steel workpiece. The width of cut was varied by 1-mm increments between 2 and 8 mm, in addition to a 9.5-mm width of cut. Table 1 summarizes the cutting experiment parameters. The chip load was maintained at approximately 0.05 mm/tooth to avoid tool excessive wear and breakage. The machining diagrammatic drawing is depicted in Fig. 1.

In each width of cut experiments, the total power and cutting power were measured at the same time, and that is because the instrument has six modules. So, the variable air cutting power could be extracted by subtracting the cutting power from the total power. Figure 2 shows the cutting power demand as a function of the MRR.

The cutting power demand for the 9.5-mm width of cut was ten times greater than the 2-mm width of cut, but the air cutting power increased only about 40 %. From Fig. 2, we also can find that with the increase of cutting width, the cutting power and air cutting power are also growing, but cutting efficiency is on the rise. Thus, in terms of this feature, the operator could find the optimal cutting width, under the condition of invariable in other processing parameters.

Figure 3 shows the relationship between the total average power demand and MRR of the XK713 milling machine; furthermore, the plot has a slightly parabolic trend with a point of inflection at approximately 1800 mm^3/min. Moreover, with the MRR increasing, the total power is also growing. And, the curve's growth trend is very evident.

2.2 Energy property experiments of cutting depth

Experiments of cutting depth were also conducted on a 1045 steel workpiece 80 mm in length. The depth of cutting was increased while machining with an uncoated carbide end mill.

Table 1 Experiment parameters of cutting width

Cutting width (mm)	Spindle speed (r/min)	Cutting speed (m/min)	Chip load (mm/tooth)	MRR (mm^3/min)
2	955	30	0.05	192.0
3	955	30	0.05	288.0
4	955	30	0.05	384.0
5	1270	40	0.05	716.3
6	1270	40	0.05	859.5
7	1270	40	0.05	1002.8
8	1430	45	0.05	1524.0
9	1430	45	0.05	1714.5
9.5	1430	45	0.05	1809.8

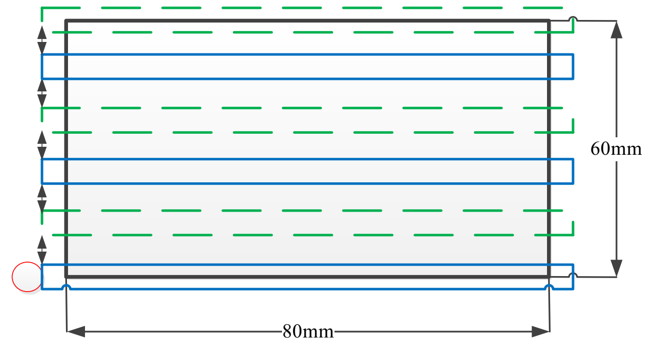


Fig. 1 The experiment machining diagrammatic drawing

Cuts were made along the *y* axis at a width of cut of 5 mm with a 10-mm diameter end mill over a length of 80 mm in a 1045 steel workpiece. And, the total cutting depth is 6 mm. Each cutting depths are 0.4, 0.6, 1.0, 1.2, and 1.5 mm, respectively. Table 2 summarizes the detailed parameters.

Figure 4 summarizes the total power demanded by the XK713 and the energy consumed as a function of material removal rate. Although the power demand increases with load, the energy consumption still drops drastically with the increase in material removal rate. This shows that the decrease in processing time effectively dominates over the increase in power demand due to increased loads.

Since the power demand was shown to increase with load, the experimental results show that this increase in load was not enough to increase the overall energy consumption. So, to find the equilibrium relationship between power demand and processing time will help us reduce the energy consumption.

3 Energy characteristics of milling process based on MRR

The milling process electrical energy consumption is dependent on the power demand, *P*, and processing time, *T*. As was mentioned previously, the power demand is composed of cutting power, p_{cut}, and air cutting power, p_{air}; the processing time is composed of cutting time, t_{cut}, and air time, t_{air}. Consequently, the total energy consumption can be expanded as follows:

$$E = \int_0^T (P_{cut} + P_{air}) dt \tag{1}$$

Cutting power changes with time during the variable-MRR machining process due to the changing cutting parameters [29]. And, the air cutting power demand is also not a constant but associated with spindle speed as a quadratic function relationship approximately [33]. Conspicuously, the spindle speed

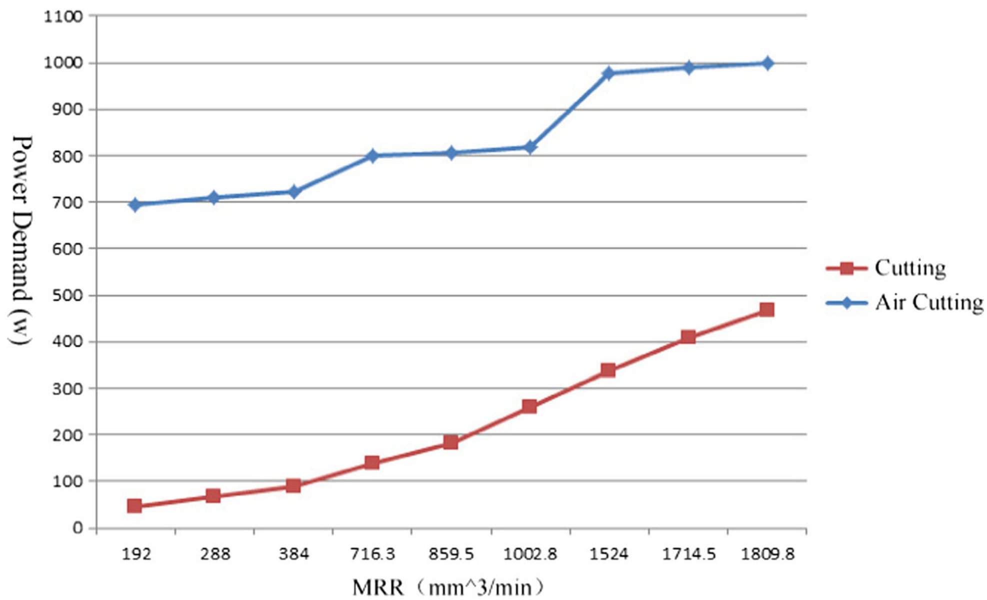


Fig. 2 The cutting and air cutting average power demand

and MRR are helpful to establish the milling energy model. The following section will make detailed discussion.

3.1 The energy consumption model for milling process

The material removal rate of various manufacturing processes was previously summarized by Gutowski et al. [34]. But for many given case study, the power associated with the material removal process always be extracted by the average total power demand subtracting the average air cutting power demand. This method is not accurate of obtaining the material removal process energy consumption, which includes a lot of auxiliary power consumption (such as cutting fluid system and the energy dissipations of the hydraulic system). This study will directly obtain the air cutting energy and the material removal process energy through YOKOGAWA experiment instrument WT1800, in order to make the experimental data more closer to the real value, thus more accurate to prove the theoretical model more effective.

3.1.1 Material removal power model

Based on references [33, 35], the relationship model between material-cutting power and MRR can be established as follows:

$$E_m = \lambda \times \text{MRR} \times T_m \tag{2}$$

$$\lambda = (1 + \partial) \times \text{SCE} \tag{3}$$

where E_m is the material removal energy, J; T_m is the duration of material removal machining process, s; MRR is the average material removal rate, cm^3/s; SCE is the specific cutting energy, J/cm^3; and ∂ is the coefficient of power loss.

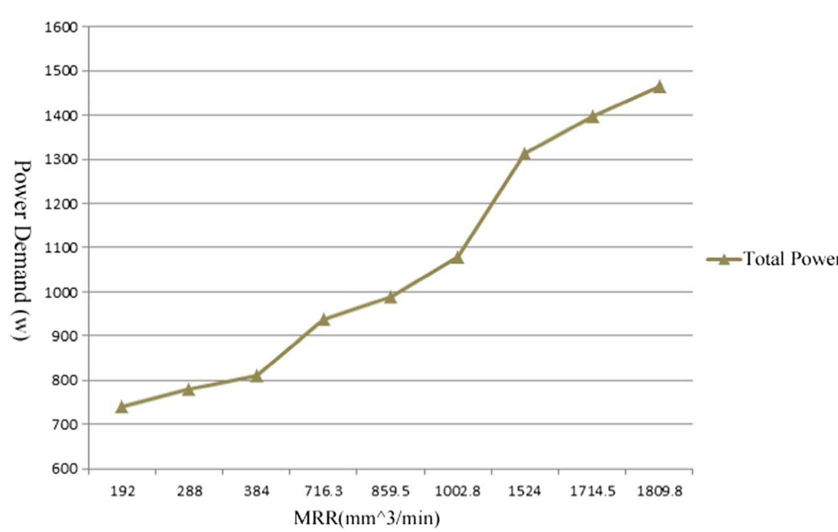


Fig. 3 The average total power demand

Table 2 Experiment parameters of cutting depth

Cutting depth (mm)	Spindle speed (r/min)	Cutting speed (m/min)	Chip load (mm/tooth)	MRR (mm^3/min)
0.4	2070	65	0.05	621.0
0.6	1750	55	0.05	787.5
1.0	1430	45	0.05	1072.5
1.2	1270	40	0.05	1143.0
1.5	1110	35	0.05	1248.8

The specific energy, which accounts for cutting and air-cutting power demand, was indeed found to have an inverse relationship with the MRR discovered from Fig. 2. So, the SCE can be represented as follows:

$$\mathrm{SCE} \quad = \quad k \times \frac{1}{\mathrm{MRR}} + a \tag{4}$$

where the constant k essentially has unit of power and a represents no unit. Then, Eq. 2 can be expanded as follows:

$$E_m = (1+\partial)(k + \partial \times \mathrm{MRR}) \times T_m \tag{5}$$

MRR is essentially determined by the cutting parameters (such as $v_c, v_f, a_e, a_p, \ and \ n$), so it is dynamic changing along with the machining process. Followed by the MRR (mm/s) is calculated as follows:

$$\mathrm{MRR} \quad = \quad 0.01 \times a_e \times a_p \times f_z \times n \times z \tag{6}$$

where the constants a_e and a_p are the cutting width and cutting depth, mm; f_z is the chip load, mm/tooth; n is the spindle speed, r/min; and z is the tooth.

The total material removal power model in cutting process can be expressed as follows:

$$E_m = \int_0^{T_m} (1+\partial)\left(k + 0.01 \times \partial \times a_e \times a_p \times f_z \times n \times z\right) dt \tag{7}$$

In the above model, the MRR is further broken down rather than be treated as a variable. While fully considering the impact of each cutting parameter on the material-cutting power, the model will be more consistent with the material-cutting energy consumption behavior of actual machining.

3.1.2 Air-cutting power model

The air-cutting power demand is not a constant but associated with spindle speed as a quadratic function relationship approximately [33], and it can be established as follows:

$$E_u = \sum_{i=1}^{N} \int_0^{T_u} \left(x_1\omega^2 + x_2\omega + x_3\right) dt \tag{8}$$

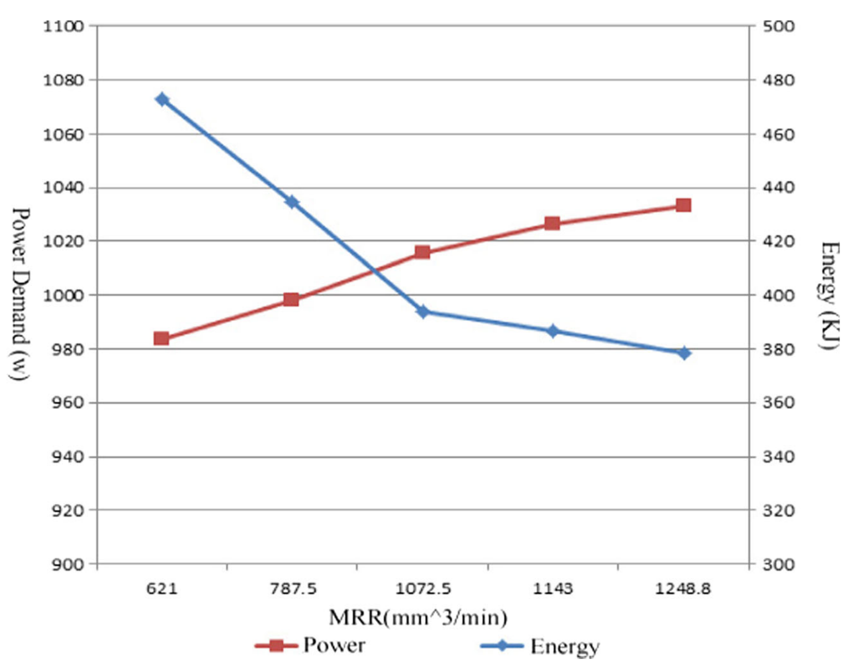
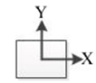
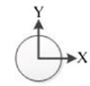
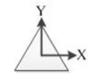
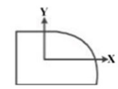
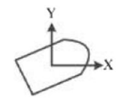
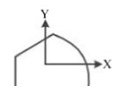


Fig. 4 The average total power demand and energy

Table 3 Classify the cutting paths

No.	Tool paths	Explanation	Diagram
1	Orthogonal	During processing, tool by orthogonal feeding	
	Slash	During processing, tool by slash feeding	
2	Curve	During processing, tool by curve feeding	
	Slash and Curve	During processing, tool by slash and curve feeding combined	
3	Orthogonal and Slash	During processing, tool by slash and orthogonal feeding combined	
4	Orthogonal and Curve	During processing, tool by curve and orthogonal feeding combined	
5	Orthogonal and Slash and Curve	During processing, tool by curve and slash, as well as, orthogonal combined	

where E_u is the air-cutting energy, J; T_u is the duration of air-cutting machining process, s; ω is the motor angular velocity, rad/s; x_1 , x_2 , *and* x_3 are the coefficients; and N is the number of air-cutting subintervals.

For the air-cutting model, the spindle speed and the number of subintervals are the key issues of public concern. The air-cutting intervals are not only including the before and after machining stage but also including the idle stage of machining. As you have known, it is difficult to obtain the air-cutting subintervals in machining process accurately. As these facts exist in real air-cutting model, this work is used CNC G code to break up the machining process, so as to extract the air-cutting process.

3.1.3 Time evaluation for air-cutting stage and material removal stage

The total time consists of processing time and idle time. It is easy to get the before machining stage's idle time T_{u1} and after machining stage's idle time T_{u3} by processing code or a stopwatch. So, this section will more focus on how to extract the air-cutting time from the machining process time.

The machining process can be divided into the following three steps: plunge cut (no load) → machining → retract (no load). The machining process's idle time can be calculated as follows:

$$T_{u2} = T_0 - T_m \tag{9}$$

where T_0 is the total processing time and T_m is the actual processing time.

The actual processing time is determined by tool paths and feeding speed. Different cutting paths lead to different actual processing time, so divide the cutting path into five categories (as shown in Table 3), in order to get the actual processing time accurately.

Accordingly, take different measures to calculate the actual machining time of different feeding path. The detailed discussions are given as follows:

Table 4 Values of coefficients in the optimization model

Parameters	Spindle speed range (r/min)	α	k	z	X_1	X_2	X_3
Values	900~2000	3.5	12.6	3	0.13	−25.8	1987.3

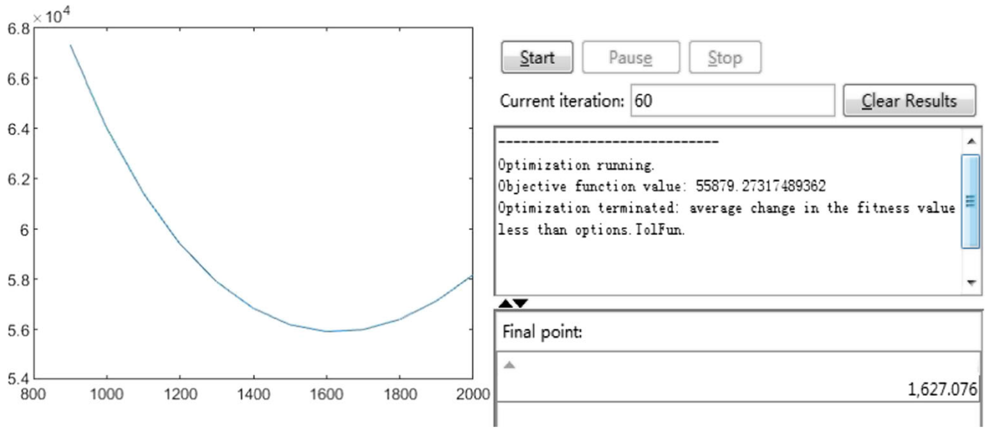


Fig. 5 The simulation result

a. Orthogonal. The actual machining time calculation as follows:

$$T_{m_a} = T_{m_{ax}} + T_{m_{ay}} + T_{m_{az}} \tag{10}$$

$$T_{m_{ax}} = \frac{\sum|X|}{f}, T_{m_{ay}} = \frac{\sum|Y|}{f}, T_{m_{az}} = \frac{\sum|Z|}{f} \tag{11}$$

where $\sum|X|, \sum|Y|, \sum|Z|$ is the sum of the absolute value, respectively, which is the coordinate of the practical processing route.

b. Slash, curve, and slash and curve. The X-Y axis is synchronized feeding in this processing mode, so the actual machining time calculation is as follows:

$$T_{m_b} = T_{m_{bx}} + T_{m_{by}} + T_{m_{bz}} \tag{12}$$

$$T_{m_{bx}} = T_{m_{by}} = \frac{1}{2}\left(T_0 - \frac{\sum|Z|}{f}\right) \tag{13}$$

where T_0 is the total processing time that can be obtained by processing code.

c. Orthogonal and slash. The actual machining time calculation as follows:

$$T_{m_c} = T_{m_{cx}} + T_{m_{cy}} + T_{m_{cz}} \tag{14}$$

$$T_{m_{cx}} = T_{m_{cy}} = \frac{L}{f} + \frac{L'}{f}, T_{m_{cz}} = \frac{\sum|Z|}{f} \tag{15}$$

$$L = \sqrt{x^2 + y^2} \tag{16}$$

where L is the sum of the slash feeding route length and L' is the sum of the orthogonal feeding route length.

d. Orthogonal and curve. The actual machining time calculation as follows:

$$T_{m_d} = T_{m_{dx}} + T_{m_{dy}} + T_{m_{dz}} \tag{17}$$

$$T_{m_{dx}} = T_{m_{dy}} = \frac{S}{f} + \frac{S'}{f}, T_{m_{dz}} = \frac{\sum|Z|}{f} \tag{18}$$

$$S = \begin{cases} \arccos\left(\frac{2R^2 - (x^2 + y^2)}{2R^2}\right) \cdot R; & R > 0 \\ 2\pi R - \arccos\left(\frac{2R^2 - (x^2 + y^2)}{2R^2}\right) \cdot R; & R < 0 \end{cases} \tag{19}$$

Fig. 6 The experiment machining wiring drawing

Fig. 7 The experiment machining process

where x,y are the X and Y coordinate values of the arc portion, respectively; R indicates the arc radius; S is the sum of the curve feeding route length; and $S^{'}$ is the sum of the orthogonal feeding route length.

e. Orthogonal and slash and curve. The actual machining time calculation as follows:

$$T_{m_e} = T_{m_{ex}} + T_{m_{ey}} + T_{m_{ez}} \tag{20}$$

$$T_{m_{ex}} = T_{m_{ey}} = \frac{S}{f} + \frac{L}{f} + \frac{B}{f}, T_{m_{ez}} = \frac{\sum |Z|}{f} \tag{21}$$

where B is the sum of the orthogonal feeding route length.

In conclusion, it is straightforward using the above formulas to extract the air-cutting time from the machining process time exactly.

The total energy consumption model in milling process can be expressed as follows:

$$E_{\text{total}} = \int_0^{T_m} (1+\partial)\left(k + 0.01 \times \partial \times a_e \times a_p \times f_z \times n \times z\right) dt + \sum_{i=1}^{N} \int_0^{T_u} \left(x_1\omega^2 + x_2\omega + x_3\right) dt \tag{22}$$

$$T_u = T_{u1} + T_{u2} + T_{u3} \tag{23}$$

3.2 The energy optimization model for milling process

As was discussed previously, the energy consumption in milling process is closely related to the material removal rate and spindle speed. In characterizing the energy consumption of a milling tool, as the MRR approaches infinity, the machining energy is expected to reach a steady state of zero. But, given the work volume, spindle speed, and table feed constraints of a milling tool as well as the maximum loads that can be applied without deforming the main body frame or breaking the spindle motor, the operator will never reach a MRR anywhere near infinity. So, it is feasible to find out the optimal processing parameters.

When cutting width, cutting depth, and chip load are determined, the higher spindle speed and the higher MRR are, but the milling energy consumption is the other way around. However, with the increase of spindle speed, the air-cutting energy consumption will also increase. So, it is very essential to find the balance between milling energy consumption and air-cutting energy consumption, so as to optimize the total consumption. Absolutely, the spindle speed is related to the cutting tool and workpiece material, as well as the milling tool power rating and milling parameters. The energy utilization ratio of milling process can be expressed as

Table 5 The calculation results for test groups

Materials	Spindle speed (r/min)	Cutting speed (m/min)	MRR (mm^3/min)	$E_{\text{calculated}}$ (KJ)	$E_{\text{ave-measured}}$ (KJ)	Accuracy (%)
1045 steel	955	30	573	65.27	70.13	93.07
	1270	40	762	58.27	56.36	96.61
	1590	50	954	55.92	52.76	94.01
	1627	52	976	55.88	51.17	90.80
	1680	53	1008	55.93	52.78	94.03
	1910	60	1146	57.21	62.68	91.27

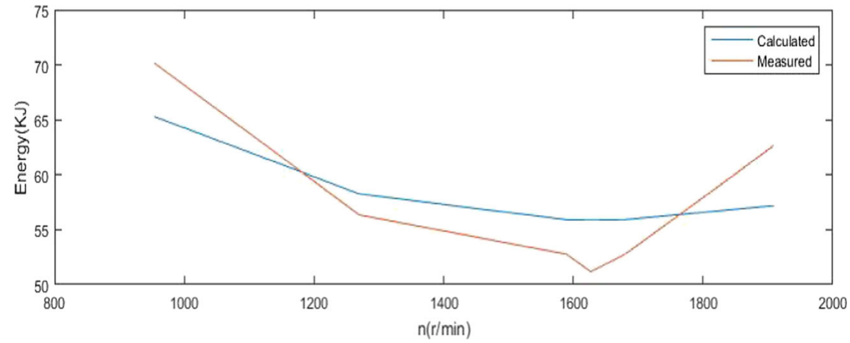


Fig. 8 The result fitting tendency diagram

material removal energy consumption and the ratio of the total energy consumption in milling process. The calculation formulae are as follows:

$$U=\frac{E_m}{E_m+E_u} \tag{24}$$

$$\delta=\frac{\Delta t_m}{\Delta t_u} \tag{25}$$

$$\beta=\frac{\Delta E_m}{\Delta E_u} \tag{26}$$

Equation 26 shows the relationship between ΔE_m and ΔE_u; the ΔE_m expressed the depressed material removal energy with the spindle speed increase, and ΔE_u expressed the increased air-cutting energy with the spindle speed increase. Where Δt_m expressed the depressed material removal time with the spindle speed increase, Δt_u expressed the increased air-cutting time with the spindle speed increase.

?>So if β is more than 1, this would be the case for milling machine tools, such that the depressed material removal energy is more than the increased air-cutting energy; continuing to increase the speed will achieve higher efficiency under allowable speed range. Through the above analysis, we can establish the following mathematical optimization model as follows:

1) Objective function, $f(x)=E_{\text{total}}\rightarrow \min$;
2) Constraint conditions;
3) $n\in[n_{\min}, n_{\max}]$;

$$v_c\in\left[\frac{\pi d_0 n_{\min}}{1000}\leq v_c\leq\frac{\pi d_0 n_{\max}}{1000}\right];$$

$$\beta=\frac{\Delta E_m}{\Delta E_u}\geq 1;$$

$$P\leq\eta P_{\max};$$

where $P_{\max}$ is the power rating and η is the transfer efficiency.

4) Optimization model

$$E_{\text{total}}=\int_0^{T_m}(1+\partial)(k+0.01\times\partial\times a_e\times a_p\times f_z\times n\times z)\,dt+\sum_{i=1}^{N}\int_0^{T_u}(x_1\omega^2+x_2\omega+x_3)\,dt \tag{27}$$

$$\omega=\frac{2\pi n}{60} \tag{28}$$

As a consequence, through the optimization of spindle speed can increase the material removal rate and improve the milling energy consumption, followed to achieve the energy efficiency improvement. The above energy optimization

Table 6 Energy calculation models

Energy component	Models	Source	Equation number
E_1	$E_{\text{total}}=\int_0^{T_m}(1+\partial)\,(k+0.01\times\partial\times a_e\times a_p\times f_z\times n\times z)dt+\sum_{i=1}^{N}\int_0^{T_u}(x_1\omega^2+x_2\omega+x_3)dt$	Sect. 3.2	(27)
E_2	$\text{SCE}=C_0+\frac{C_1}{\text{MRR}}\ E_{\text{total}}=\text{SCE}\times Q$	Kara and Li [37]	(29)
E_3	$\text{SCE}=k_0+k_1\frac{n}{\text{MRR}}+\frac{k_2}{\text{MRR}}\ E_{\text{total}}=\text{SCE}\times Q$	Li et al. [31]	(30)

Table 7 Values of coefficients in the models

Q	C_0	C_1	k_0	k_1	k_2
7632	5.14	861.41	2.96	1.77	297.78

method can be one of the research strategies which are used for manufacturing system efficiency mechanism. Further work can be conducted in which the assumption that the cutting speed and chip load does not stay constant to expand the applicability of the energy and speed trade-off analysis.

4 Experimental study

This section describes the energy optimization of machining process for a CNC milling machine. The milling machine, as a typical electromechanical product, is of great potential for energy optimization. The CNC milling machine's machining process may have an efficiency of below 30 % and have great space of energy saving. To illustrate the proposed method for energy optimization of machining process, the experimental study adopted the XK713 CNC milling machine.

4.1 Simulation result

A lot of software tools can be used to solve the optimization problems, among which MATLAB is widely applied. Hence, MATLAB 2014 was used to solve the problem. It is necessary to determine some parameters and data ahead of optimization. From the energy property experiments of cutting depth and width, which refer to the second part of this article, we can calculate the fitted coefficients (as shown in Table 4). In addition, this experiment processing type is orthogonal processing, so the machining time range can be obtained by Eqs. 10 and 11.

According to the parameters in Table 4 and the optimization model last chapter proposed, using the MATLAB function optimization toolbox can find out the optimal spindle speed. From the simulation, the plot has a parabolic trend with a point of inflection at approximately 1600 r/min. Furthermore, according to the MATLAB calculation results, the accurate optimal spindle speed was 1627 r/min, and the optimal total energy consumption was 55.88 KJ (the simulation results are shown in Fig. 5).

4.2 Model validation

The above section concludes that the optimal rotation speed and the optimal energy consumption are based on the optimization model the present paper proposed, so this section needs to put forward the model validation, in order to ensure the accuracy of the results.

In order to examine the validity of the improved energy consumption model and the energy optimization model, six test experiments were conducted. The material of the blank selected for the tests was #45 steel (ASTM 1045 steel). The six tests were conducted on the XK713 CNC milling machine and using Yokogawa WT1806 to measure the energy consumption; moreover, each test was repeated three times to improve the reliability of the observed data. Depth of cut and width of cut of 0.8 and 5 mm, respectively, were used. The chip load of 0.05 mm/tooth was maintained constant across the experiments to allow for the comparison of the results. The experiment process is shown in Figs. 6 and 7.

According to the improved energy consumption model in section 3, the total energy consumption can be calculated. Following the same calculation processes, the test 2~test 5 can also be obtained. The calculation results and the average measured values are listed in Table 5.

Referring to the experimental results shown in Table 5, the predictive accuracy of the energy calculation model is above 90 %, so the results verified the effectiveness of the energy consumption model. With the increase of spindle speed, the energy consumption decreased first and then increased (as shown in Fig. 8); from the MATLAB fitting tendency diagram, it can be seen that it also has a parabolic trend and can find the optimal spindle speed very intuitive. In addition, the optimal energy consumption reduces to more than 14 % of its maximum value.

The energy consumption decreased first mainly because the processing time that decreased effectively dominates over the increase in power demand due to the increased loads. Namely, the depressed cutting energy is greater than

Table 8 Validation results of SEC models

Equation	Cutting parameters				MRR (mm^3/min)	E_{cal} (KJ)	E_{mes} (KJ)	Accuracy (%)
	Cutting speed v (m/min)	Feed rate f (mm/r)	Depth of cut a_p (mm)	Spindle speed n (r/min)				
Eq. 27	50	0.05	0.8	1590	954	55.92	52.76	94.01
Eq. 29						46.10	52.76	81.70
Eq. 30						47.41	52.76	89.86

Table 9 Comparison of SEC models

Evaluation criteria	Models		
	Eq. 27	Eq. 29	Eq. 30
Applicability	No limitation		
Accuracy (%)	94.01	81.70	89.86
Computational efforts	Two steps	Three steps	
	Step 1 obtaining coefficients Step 2 time computation	Step 1 obtaining coefficients Step 2 MRR computation Step 3 SEC computation	
Complexity of fitting coefficients	Statistical regression for a set of coefficients		
Ease of data collection	Medium	Easy	
Priority	√	—	—

the increased air-cutting energy, so the total energy consumption continues to reduce. With the spindle speed continuing to increase, the depressed cutting energy is less than the increased air-cutting energy; as a result, the total energy increased. In conclusion, the proposed energy calculation model and optimization model are significant in reducing the energy consumption and improving the energy efficiency.

4.3 Model evaluation

Section 4.2 verified the validity of the proposed model, and this section is comparing to the existing energy consumption model, in order to ensure that the proposed model is more suitable than others. Zhong et al. [36] proposed five evaluation criteria, applicability, accuracy, computational efforts, complexity of fitting coefficients, and ease of data collection, to assist practitioners in evaluating models to calculate energy consumption. Therefore, this paper uses these criteria to evaluate the proposed energy consumption model. As shown in Table 6, three calculation models of energy consumption based on material removal rate are expressed as functions of independent process variables. The process variables primarily refer to spindle speed, feed rate, depth of cut, MRR, and processing time.
where Q is the cutting volume (mm^3) and $C_0, C_1, k_0, k_1,$ *and* k_2 are the coefficients whose values may be determined through experiments, as shown in Table 7.

The models can be used to calculate the energy and has an accuracy of over 80 %, as shown in Table 8.

The comparison between the three models is summarized in Table 9. Based on the five evaluation criteria, the evaluation criterion of accuracy is most important, followed by computational efforts and complexity of fitting coefficients, and applicability and ease of data collection appear less. They are used as a whole, avoiding a biased evaluation to a certain extent.

As noted from Table 9, with the higher accuracy, Eq. 27 outperforms Eqs. 29 and 30 in calculating the energy consumption of a machine tool in a material removal process. Compared to the other four criteria, the three models all need to obtain the coefficients by experiment, and the difference in Eq. 27 is a bit more complex than Eqs. 29 and 30. Although either of them is convenient to be used for the estimation of the energy consumption, Eq. 27 is more accurate than Eqs. 29 and 30. In conclusion, Eq. 27 is more reliable for calculating the energy consumption.

5 Conclusions

This investigation proposes an energy calculation model and an optimization model to maximize the efficiency and minimize the energy consumption of CNC milling. The research includes an experimental study to demonstrate the feasibility of the energy optimization model. The results show that this method is effective for improving energy consumption and energy efficiency through optimizing the spindle speed in milling process. Additionally, it provides a viable method for characterizing the material removal rate as a function of energy consumption, and this approach can be extended to other types of machining processes.

This research also provides a reliable approach for air-cutting energy prediction. From a holistic point of view, this is helpful for the selection of appropriate processing parameters that result in higher machining efficiency. Finally, future study could focus on a multi-objective optimization model integrating environmental issues in the manufacturing process optimization.

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