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ORIGINAL ARTICLE

A cutting parameter energy-saving optimization method considering tool wear for multi-feature parts batch processing

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Abstract
Cutting parameters and tool wear both have significant influence on energy consumption in the processing. In a multi-feature parts batch processing, tool wear values are continuously increasing with the proceeding of processing, leading to a higher energy consumption. To reduce the wear speed, cutting parameters should be continuously adjusted according to different states of tool wear during batch processing. However, current cutting parameter optimization studies only focus on one specific workpiece and the tool wear is seldom considered in the batch processing. To fill this research gap, a cutting parameter energy-saving optimization method considering tool wear for multi-feature parts batch processing was proposed in this paper. First, the synergistic effect mechanism of cutting parameters and tool wear on energy consumption in the batch processing was analyzed. On this basis, a multi-objective cutting parameter optimization model for multi-feature parts batch processing was established. Then, the multi-objective cuckoo search (MOCS) algorithm was used to solve the optimization model. Finally, an experimental case was carried out to verify the effectiveness and practicability of the proposed method. Results show that energy consumption and machining time can be, respectively, decreased by 22.9% and 4.1%. Meanwhile, a conflict relationship exists between the energy consumption and machining time in the processing and the trade-off of them is analyzed in this paper.

Keywords Cutting parameters · Tool wear · Batch processing · Multi-objective optimization · Energy consumption

1 Introduction

Due to the increasing demand of production and productivity in the modern society, mass fossil fuels are burned to generate electricity in manufacturing industries, which causes huge amounts of energy consumption [1]. According to a report from U.S. Energy Information Administration, more than 33% of global energy is consumed by industrial manufacturing sectors, and demands for industrial energy consumption will increase by 50% in 2050 compared with 2018, predictably [2]. As the main carrier of machining activities, computer numerical control (CNC) machine tools consume about 60% of machinery tool sections energy [3, 4], which have become dominant energy consumers [5]. However, the energy efficiency of CNC machine tools is below 15% during machining activities according to the work presented by Gutowski et al. [6]. Therefore, numerous attempts should be implemented to improve energy efficiency of machine tools and relieve the impact of energy consumption [7].

Proper cutting parameters selection affects energy consumption significantly in a processing process [8, 9]. According to the study by Li et al. [10], the reduction in energy consumption can reach a maximum of 40% by selecting proper cutting parameters. Thus, many scholars have conducted research on relationships between cutting parameters and energy consumption, where studies can be divided into two groups. The first group of studies investigated contributions of cutting parameters affecting energy consumption through experimental methods. For instance, Bhushan [11] designed a CNC turning experiment to analyze effects of cutting parameters on energy consumption. The response surface methodology (RSM) results showed that cutting speed was the most significant parameter, followed by cutting depth and feed rate, as well as the energy consumption could be reduced by 13.55% by selecting optimum

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cutting parameters. Cui ang Guo [12] explored most optimal cutting parameters on energy saving in intermittent turning by an orthogonal experiment. Experimental results showed that lowest energy consumption could be achieved when feed rate was within 0.2–0.25 mm/r and cutting speed was within 110–125 m/min. The second group of studies conducted cutting parameter energy-saving optimization by modeling. For example, Chen et al. [13] established a cutting parameter optimization model to reduce energy footprint in face milling process. They found that energy footprint could be decreased by 10.97% through the proposed model. Similar work can be found in Moreira et al. [14] where a multi-objective cutting parameter optimization model was established and solved. The optimal solution achieved a 19.28% machining energy consumption reduction. The above two groups of studies point out several important cutting parameters which affect energy consumption and indicate that the energy-saving potential of cutting parameter optimization on CNC machining is tremendous.

Tool wear is inevitable in CNC machining and can affect energy consumption significantly [15]. Several studies proved that cutting energy consumption would increase continuously along the aggravation of tool wear [16], with a maximal rise of 44% approximately [17]. Hereby, optimizations should be adopted to reduce the impact of tool wear on energy consumption, especially in the cutting parameter optimization since cutting parameter selections are affected by tool wear [18]. Along with the deepening of research on this area, taking tool wear into consideration in cutting parameter optimization models has become a research focus in recent years. For example, Bagaber and Yusoff [19] took tool wear as an optimization parameter in the multi-objective optimization model. Results showed that energy consumption could be reduced by 14.94% under the optimized cutting parameters considering tool wear compared with initial cutting parameters. Xie et al. [20] studied turning parameter cooperative optimization for minimal energy consumption under different tool wear conditions. The cutting energy consumption could finally be decreased by 13.58% through the proposed model compared with the empirical setting parameters without tool wear values. Zhang et al. [21] integrated random tool wear processes into the proposed cutting parameter optimization energy-saving model, and results implied that the energy consumption could be reduced by 7.89% considering tool wear compared with results not considering tool wear in machining. In summary, it can be known by the perusal of literature that integrating tool wear into the cutting parameter optimization model can make a huge improvement on energy consumption and thus needs to be comprehensively considered.

In a batch processing, there are mass workpieces to be processed continuously and the tool wear of cutting tools will increase with the progress of processing [22]. A study by Shi et al. [23] showed that different tool wear states in processing would lead to a full difference in final energy consumption. Accordingly, the energy consumption of a batch processing process is much higher because of increasing tool wear values. As mentioned earlier, cutting parameters are significant in machining and there is also a close mixing relationship between cutting parameters and the tool wear [24]. Generally, the setting of cutting parameters will affect the process of tool wear and current tool wear state will also affect the selection of cutting parameters [25]. In actual production, cutting parameters are set in advance and constant during machining. However, with tool wear values increasing in a batch processing process, current cutting parameters are not guaranteed to be the most optimal for energy saving. Consequently, it is necessary to continuously adjust cutting parameters to adapt ever-changed tool wear state during batch processing [26]. Meanwhile, the optimal combination of cutting parameters and tool wear can contribute more for energy saving [27]. Therefore, comprehensively considering cutting parameter adjustment and tool wear state in the energy optimization during batch processing is meaningful. However, existed research focused more on cutting parameter optimization for one specific workpiece, which cannot be applied to the batch processing for energy saving. What's more, there are few studies utilizing the strategy of continuous cutting parameters adjustment according to tool wear states to reduce energy consumption.

Motivated by above remarks, this paper takes the CNC milling batch processing as an example to study the cutting parameter optimization for energy saving under different tool wear states. The gap can be filled in this research on following two areas:

1. A novel energy consumption model comprehensively considering cutting tools adjustment, cutting parameters adjustment and tool wear for multi-feature parts batch processing is established. This model indicates the synergistic effect between cutting parameters and tool wear on energy consumption.
2. A multi-objective cutting parameter optimization model considering tool wear is proposed and instantly solved through MOCS algorithm, where cutting parameters are continuously adjusted based on wear values. The validity of this model is proved via a case study and the trade-off between energy consumption and machining time is analyzed.

The rest of the paper is organized as follows: Sect. 2 gives the problem description for the multi-feature parts batch processing with definitions and assumptions. Section 3 analyzes the energy characteristics of multi-feature parts batch processing and establishes the energy consumption model. Section 4 presents the multi-objective optimization model and adopts the MOCS algorithm to solve the model. Section 5 gives the case study together with main results and discussions, while in Sect. 6, we present the conclusion of our work and point out a future research issue.

2 Problem description

In a batch processing, workpieces to be processed are generally multi-feature and each workpiece needs to be processed in accordance with the machining sequence of features. To ensure machining sequences of each feature for one workpiece, the corresponding cutting tools and cutting parameters for each feature should be selected in advance according to process flows, machining requirements and experience. There are following machining characteristics for the multi-feature parts batch processing:

1. The one-to-one correspondence between feature and cutting tool is not fixed. Due to the universal applicability of cutting tools, one specific feature can be processed by different cutting tools in a batch processing;
2. Before each feature processing, one cutting tool can be selected from the available tool set for this feature and corresponding cutting parameters will vary with different selected cutting tools;
3. During the batch processing, tool wear values are increasingly intensified. Even if using the same cutting tool to process the same feature, cutting parameters should be adjusted according to different tool wear states to reduce wear speed.

To sum up, the setting of cutting parameters is affected by cutting tools and tool wear states, as well as cutting tool and cutting parameter adjustments can be applied in the batch processing. The detailed flow diagram of this multi-feature parts batch processing problem is shown specifically in Fig. 1. To simplify this problem, several specific definitions related to this multi-feature parts batch processing process are given in Table 1.

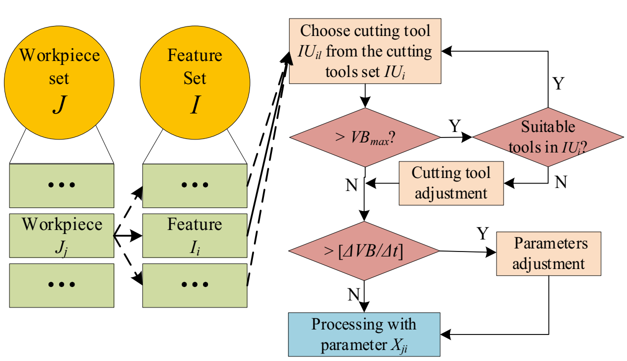


Fig. 1 Flow diagram of the multi-feature parts batch processing

Among them, batch processing task T is composed of N workpiece processing task T_j and each workpiece task T_j is composed of w feature processing task T_{ji}. In addition, when cutting tool IU_{il} reaches cutting tool adjustment standard VB^{il}_{max}, this cutting tool should be changed. And when cutting tool IU_{il} reaches cutting parameter adjustment standard $[\Delta VB/\Delta t]_{il}$, this set of cutting parameters should be adjusted.

Meanwhile, the following assumptions in the problem are given:

1. One batch is continuously processed until the end on the same machine tool, and cutting tools do not process other types of workpieces;
2. Ignore size errors and manufacturing errors between each workpiece;
3. Ignore errors caused by manufacturing technologies, processing environment, workers' operations and others on the machining process and tool wear law;
4. After finishing the previous task, it does not affect the tool wear law if the same cutting tool U_u is used for processing again after a short time;
5. All cutting tools are new when starting a batch machining task in the cutting tool set U;
6. The cutting tool adjustment standard and cutting parameter adjustment standard of the cutting tool IU_{il} are only related to the type of the cutting tool itself;
7. Features of workpiece J_j in the workpieces set J are processed sequentially from I_1 to I_w;
8. There is at least one optional cutting tool for each feature I_i to be processed.

Table 1 Problem definitions

Definitions	
J	workpiece set $J=\{J_j \mid j=1, 2, \ldots, N\}$
I	feature set $I=\{I_i \mid i=1, 2, \ldots, w\}$
U	cutting tool set $U=\{U_u \mid u=1, 2, \ldots, V\}$
IU_i	optional cutting tool set for feature I_i $IU_i=\{IU_{il} \mid l=1, 2, \ldots, N_i\}$ and $IU_1 \cup IU_2 \cup IU_3 \cup \ldots\ldots \cup IU_w = U$
T	batch processing task
T_j	j-th workpiece processing task
T_{ji}	i-th feature processing task of j-th workpiece
IU_{il}	cutting tool used to complete T_{ji} $IU_{il} \in IU_i$
VB^{ji}_{il}	tool wear value for IU_{il}
X_{ji}	cutting parameter for T_{ji}
VB^{il}_{max}	cutting tool adjustment standard for IU_{il}
$[\Delta VB/\Delta t]_{il}$	cutting parameter adjustment standard for IU_{il}

3 Energy consumption of multi-feature parts batch processing

The energy consumption model of the multi-feature parts batch processing is established in this section. According to the problem description, there are altogether N T_j in T. Besides, workpiece $J_{(j-1)}$needs to be removed and workpiece J_j needs to be set before T_j. Thus, energy consumption E_{total} of task T includes energy consumption of each workpiece processing task E_j and workpiece setting and removal E_{wsr}:

$$E_{total} = \sum_{j=1}^{N} \left(E_j + E_{wsr}\right) \tag{1}$$

Between each T_j, the machine tool is standby to change workpieces, so workpiece setting and removal energy consumption is related to standby power P_{st} and corresponding workpiece setting and removal time t_{wsr}:

$$E_{wsr} = P_{st} \cdot t_{wsr} \tag{2}$$

In each T_j, there are altogether w T_{ji}. Take one feature cutting of one workpiece in the CNC milling as an example, and Fig. 2 shows real-time power of one feature cutting process.

As shown in Fig. 2, there are five parts in one feature cutting process: startup, standby, spindle acceleration, air cutting and cutting. Among them, standby state, air cutting state and cutting state are the most significant with more energy consumption produced. In the standby state, the machine tool is standby and only some basic systems operate such as CNC system, lubricating system and lighting system. Before cutting, an air cutting distance is set to avoid violent collisions between cutting tools and workpieces. During this air cutting state, the spindle system, feed system and auxiliary system (cooling pump, etc.) are operating. In the cutting state, features are processed where cutting tools touch workpieces to remove extra material and all systems are operating to consume energy. During the multi-feature parts batch processing, the startup and spindle acceleration energy consumption can be ignored since the time is short. Moreover, the cutting tool and cutting parameters need to be adjusted because of tool wear according to Sect. 2, which also produce energy consumption. Therefore, energy consumption of one T_j can be calculated by:

$$E_j = \sum_{i=1}^{w} \left(E_{ji}^{st} + E_{ji}^{air} + E_{ji}^{c} + E_{adtool} + E_{adpar}\right) \tag{3}$$

where E_{ji}^{st}, E_{ji}^{air}, E_{ji}^{c}, E_{adtool}, and E_{adpar} are energy consumption in each T_{ji} of standby, air cutting, cutting, cutting tool adjustment and cutting parameter adjustment, respectively.

1. Standby energy consumption

   Standby energy consumption of each T_{ji} is related to standby power P_{ji}^{st} that drives basic systems and corresponding standby time t_{ji}^{st}.

   $$E_{ji}^{st} = P_{ji}^{st} \bullet t_{ji}^{st} \tag{4}$$

2. Air cutting energy consumption

   Air cutting energy consumption is related to air cutting power P_{ji}^{air} and corresponding air cutting time t_{ji}^{air}. And P_{ji}^{air} is composed of standby power P_{ji}^{st}, unload power P_{ji}^{u} which drives the spindle and feed system and auxiliary power P_{ji}^{aux} which drives auxiliary systems. Air

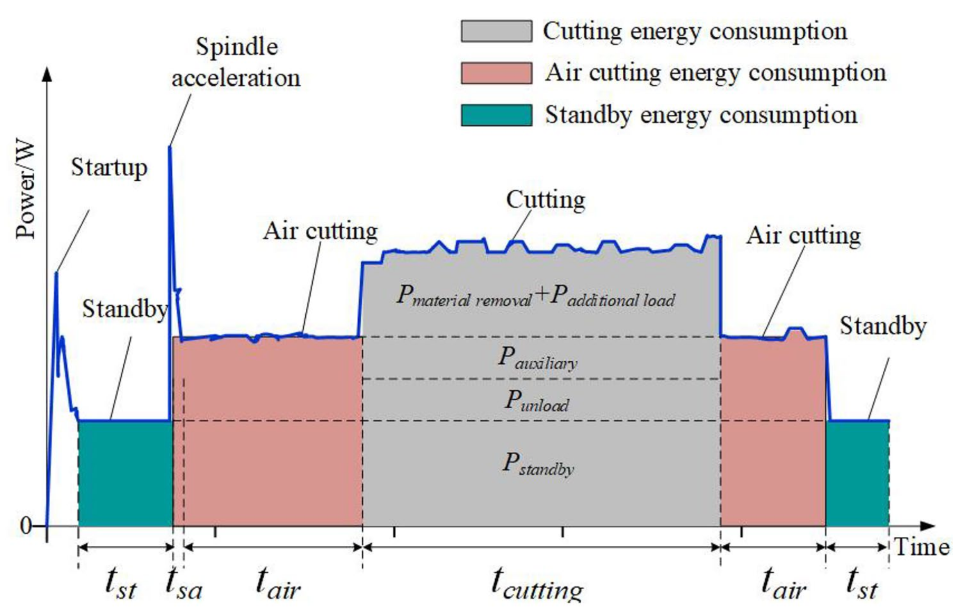


Fig. 2 Real-time power of one feature cutting process

cutting time is related to cutting tool diameter D, air cutting distance l_{ji}^{air}, cutting speed v_c^{ji} and feed rate f^{ji}.

$$E_{ji}^{air} = P_{ji}^{air} \bullet t_{ji}^{air} = \left(P_{ji}^{st} + P_{ji}^{u} + P_{ji}^{aux}\right) \bullet t_{ji}^{air} \tag{5}$$

$$t_{ji}^{air} = \frac{60\pi D l_{ji}^{air}}{v_c^{ji} f^{ji} \times 10^3} \tag{6}$$

3. Cutting energy consumption

Cutting energy consumption of each T_{ji} is related to cutting power P_{ji}^c and corresponding cutting time t_{ji}^c. During cutting, P_{ji}^c can be divided into five parts: standby power P_{ji}^{st}, unload power P_{ji}^u, auxiliary power P_{ji}^{aux}, material removal power P_{ji}^{mr} which removes workpiece material and additional load power P_{ji}^a which is generated accompanied with cutting loads. Cutting time is the function of cutting distance L, teeth number z, feed per tooth f_z^{ji} and spindle rotational speed n_{ji}.

$$E_{ji}^c = P_{ji}^c \bullet t_{ji}^c = \left(P_{ji}^{st} + P_{ji}^{u} + P_{ji}^{aux} + P_{ji}^{mr} + P_{ji}^{a}\right) \bullet t_{ji}^c \tag{7}$$

$$t_{ji}^c = \frac{60L}{z f_z^{ji} n_{ji}} \tag{8}$$

According to Sect. 2, cutting tool IU_{il} is selected to process feature I_i in each T_{ji} and cutting parameter set X_{ji} is selected based on cutting tools and tool wear state. Thus, P_{ji}^{mr} in this problem is the function of cutting parameters, cutting tools and wear values, as shown in Eq. (9):

$$P_{ji}^{mr} = F\left(X_{ji}\right) = F\left(v_c^{ji}, f^{ji}, a_p^{ji}, a_e^{ji} \middle| IU_{il} \Theta VB_{il}^{ji}\right) \tag{9}$$

where a_p^{ji} and a_e^{ji} are, respectively, the cutting depth and cutting width.

4. Cutting tool adjustment energy consumption

In a batch processing, cutting tool adjustment should be executed when cutting tool IU_{il} reaches cutting tool adjustment standard VB_{max}^{il}, which is accompanied with energy consumption. According to machining experience, cutting tool adjustment includes automatic adjustment and manual adjustment. Therefore, cutting tool adjustment energy consumption can be described as:

$$E_{adtool} = E_{adtool}^{aut} + E_{adtool}^{man} \tag{10}$$

where E_{adtool}^{aut} and E_{adtool}^{man} are energy consumption of automatic adjustment and manual adjustment, respectively.

Automatic adjustment refers that there is another cutting tool on the machine tool can be used when the last one is broken, and the specified cutting tool will be automatically adjusted by machine tool according to the program setting. At this state, machine tool is operating and E_{adtool}^{aut} is related to automatic adjustment power P_{adtool}^{aut} and corresponding time t_{adtool}^{aut}:

$$E_{adtool}^{aut} = P_{adtool}^{aut} \bullet t_{adtool}^{aut} k_{il}, \text{ where } k_{il} = \begin{cases} 1 & \text{Automatic adjustment} \\ 0 & \text{No automatic adjustment} \end{cases} \tag{11}$$

Manual adjustment refers that when all cutting tools on machine tool need to be changed, the specified cutting tool should be manually adjusted by workers. At this state, the machine tool is standby and the reference point should be set again after changing new cutting tools. E_{adtool}^{man} is related to standby power and corresponding time t_{adtool}^{man}:

$$E_{adtool}^{man} = P_{st} \bullet t_{adtool}^{man} r_{il}, \text{ where } r_{il} = \begin{cases} 1 & \text{Manual adjustment} \\ 0 & \text{No manual adjustment} \end{cases} \tag{12}$$

5. Cutting parameter adjustment energy consumption

Cutting parameter adjustment refers that when cutting parameters cannot meet processing requirement, this set of cutting parameters needs to be adjusted along cutting parameter adjustment time t_{adpar} by workers before processing feature I_i. Cutting parameter adjustment energy consumption E_{adpar} is shown in Eq. (13):

$$E_{adpar} = P_{st} \bullet t_{adpar} u_{il}, \text{ where } u_{il} = \begin{cases} 1 & \text{Parameter adjustment} \\ 0 & \text{No parameter adjustment} \end{cases} \tag{13}$$

4 Multi-objective optimization model of multi-feature parts batch processing

4.1 Variables

In this problem of the multi-feature parts batch processing, there is a close crossing influence between cutting tools and cutting parameters. Cutting tools selection and cutting parameters setting both can determine total energy consumption and machining time in the batch processing [28]. Based on this, cutting tools and cutting parameters under different tool wear are taken as the optimization variables in this integrated optimization model, which are shown as:

$$X = \left\{ X_{ji}\left(IU_{il}, v_c^{ji}, f^{ji}, a_p^{ji}, a_e^{ji} \middle| VB_{il}^{ji}\right) | j \in (1, N), i \in (1, w), j, i \in Z^+ \right\} \tag{14}$$

4.2 Objectives

To achieve high efficiency and energy conservation in the processing process, the energy consumption and machining time are chosen as optimization objectives in this optimization model. According to the analysis in Sect. 3, the energy consumption and machining time can be described as:

$$E_{total} = \sum_{j=1}^{N}\left(\sum_{i=1}^{w}\left(P_{ji}^{st}\bullet t_{ji}^{st}+P_{ji}^{air}\bullet t_{ji}^{air}+P_{ji}^{c}\bullet t_{ji}^{c}+P_{adtool}^{aut}\bullet t_{adtool}^{aut}k_{il}+P_{st}\bullet t_{adtool}^{man}r_{il}+P_{st}\bullet t_{adpar}u_{il}\right)+P_{st}\bullet t_{wsr}\right)$$
$$= \sum_{j=1}^{N}\left(\sum_{i=1}^{w}\left(\begin{array}{c}P_{ji}^{st}\bullet t_{ji}^{st}+\left(P_{ji}^{st}+P_{ji}^{u}+P_{ji}^{aux}\right)\bullet\frac{60\pi Dl_{ji}^{air}}{v_c^{ji}f^{ji}\times10^3}+\left(P_{ji}^{st}+P_{ji}^{u}+P_{ji}^{aux}+P_{ji}^{mr}+P_{ji}^{a}\right)\bullet\frac{60L}{zf_z^{ji}n_{ji}}\\+P_{adtool}^{aut}\bullet t_{adtool}^{aut}k_{il}+P_{st}\bullet t_{adtool}^{man}r_{il}+P_{st}\bullet t_{adpar}u_{il}\end{array}\right)+P_{st}\bullet t_{wsr}\right) \tag{15}$$

$$t_{total} = \sum_{j=1}^{N}\left(\sum_{i=1}^{w}\left(t_{ji}^{st}+t_{ji}^{air}+t_{ji}^{c}+t_{adtool}^{aut}k_{il}+t_{adtool}^{man}r_{il}+t_{adpar}u_{il}\right)+t_{wsr}\right)$$
$$= \sum_{j=1}^{N}\left(\sum_{i=1}^{w}\left(t_{ji}^{st}+\frac{60\pi Dl_{ji}^{air}}{v_c^{ji}f^{ji}\times10^3}+\frac{60L}{zf_z^{ji}n_{ji}}+t_{adtool}^{aut}k_{il}+t_{adtool}^{man}r_{il}+t_{adpar}u_{il}\right)+t_{wsr}\right) \tag{16}$$

4.3 Optimization model

Based on the above analysis, the cutting parameter optimization model considering tool wear for multi-feature parts batch processing is as follows:

$$\min F\left(IU_{il}, v_c^{ji}, f^{ji}, a_p^{ji}, a_e^{ji}\middle| VB_{il}^{ji}\right) = \min\left(E_{total}, t_{total}\right) \tag{17}$$

$$v_{c-\min}^{U_u} \le v_c^{U_u} \le v_{c-\max}^{U_u} \tag{18}$$

$$f_{z-\min}^{U_u} \le f_z^{U_u} \le f_{z-\max}^{U_u} \tag{19}$$

$$a_{p-\min}^{U_u} \le a_p^{U_u} \le a_{p-\max}^{U_u}, 0 \le a_e^{U_u} \le kd^{U_u} \tag{20}$$

$$n_{min} \le n \le n_{max} \tag{21}$$

$$P_c \le \eta P_{\max} \tag{22}$$

$$K_a C_a a_p^{X_a} f_z^{Y_a} a_e^{U_a} / d^{Q_a} n^{Z_a} \le F_{c-\max} \tag{23}$$

$$318 f_Z / \left[tg\left(L_a\right) + ctg\left(T_a\right)\right] \le \left[R_a\right] \tag{24}$$

$$VB^{U_u} \le VB_{\max}^{U_u} \tag{25}$$

$$\Delta VB_{U_u}/\Delta t \le \left[\Delta VB/\Delta t\right]_{U_u} \tag{26}$$

$$IU_{il} \in U \tag{27}$$

$$I_1 < I_2 < \cdots < I_w \tag{28}$$

To ensure the rationality and accuracy of the established multi-feature parts batch processing optimization model, constraints should be made on cutting parameters, feature cutting, machine tool characteristics and other aspects. Constraints (18)-(21) ensure v_c^{Uu}, f_z^{Uu}, a_p^{Uu}, a_e^{Uu} and rotational speed n are within the feasible range, where $v_{c-\min}^{Uu}/v_{c-\max}^{Uu}$, $f_{z-\min}^{Uu}/f_{z-\max}^{Uu}$, $a_{p-\min}^{Uu}/a_{p-\max}^{Uu}$ and $n_{\min}/n_{\max}$ are maximum and minimum cutting speed, feed, cutting depth and rotation speed, k is the tool path spacing coefficient and d^{Uu} is the cutting tool diameter. Constraints (22)–(24) ensure P_c, cutting force and roughness should not, respectively, exceed the permitted maximum power $P_{\max}$, maximum cutting force $F_{c\text{-max}}$ and roughness requirement, where η is the effective coefficient, K_a, C_a, X_a, Y_a, U_a, Q_a, Z_a are the corresponding influence indexes of the cutting forces [29], L_a and T_a are the front angle and the back angle of the milling cutter. Constraints (25) and (26) indicate that cutting tools and cutting parameters should be adjusted when reaching the adjustment standard. Constraint (27) ensures that all IU_{il} used are within U in the batch processing. Constraint (28) ensures that all features are processed sequentially.

4.4 Multi-objective cuckoo search algorithm

Cuckoo search (CS) algorithm is a bionic swarm intelligent optimization algorithm proposed by simulating cuckoo nesting behavior, which is mainly based on the natural law of cuckoo breeding by means of other birds' nests and Levy Flight [30]. CS algorithm is widely used in the engineering practice due to fewer parameters, unique optimization mechanism and strong convergence [31].

In this paper, cutting tools, cutting parameters and tool wear are taken as variables and there exists mutual restricting and influencing relationships between them. Therefore, the cutting parameter optimization considering tool wear of multi-feature parts batch processing is a typical nonlinear, multi-constrained and high-dimensional problem. To this end, the MOCS algorithm is used to solve the optimization problem. The specific flow chart is shown in Fig. 3.

According to actual requirements of this problem, algorithm mechanism is adjusted to improve search efficiency as follows:

1. Initial solution generation

   Initialize *Archive* = 0, *Archive* length as *Amax*, the maximum number of iterations as *Iter*, and the current number of iterations as $r=0$. When $r<R_{max}$, cutting tools and cutting parameters are randomly selected according to cutting tool and cutting parameter set K, as shown in Eq. (29). Calculate the fitness function value corresponding to the generated solution, then save the solution and delete the dominated solution in *Archive* in real time. Then, let $r=r+1$. When $r=R_{max}$, K should be output corresponding to each Pareto solution in *Archive*.

$$K=\sum_{j=1}^{N}\sum_{i=1}^{w}X_{ji}\left(IU_{il},v_c^{ji},f^{ji},a_p^{ji},a_e^{ji}\middle|VB_{il}^{ji}\right) \tag{29}$$

2. Neighborhood solutions generation

   According to the analysis of the multi-feature parts batch processing in this paper, two methods are used to generate neighborhood solutions. Cutting tool diameter and cutting parameter a are updated by crossover and mutation operations, where a is the cutting parameter that affect wear speed most. Cutting parameters b, c and d are updated with Levy Flight.

   (a) Crossover & mutation operation

   Figure 4 shows the flow chart of crossover and mutation operations. Known that crossover happens between current solution $K_{current}$ and Pareto solution

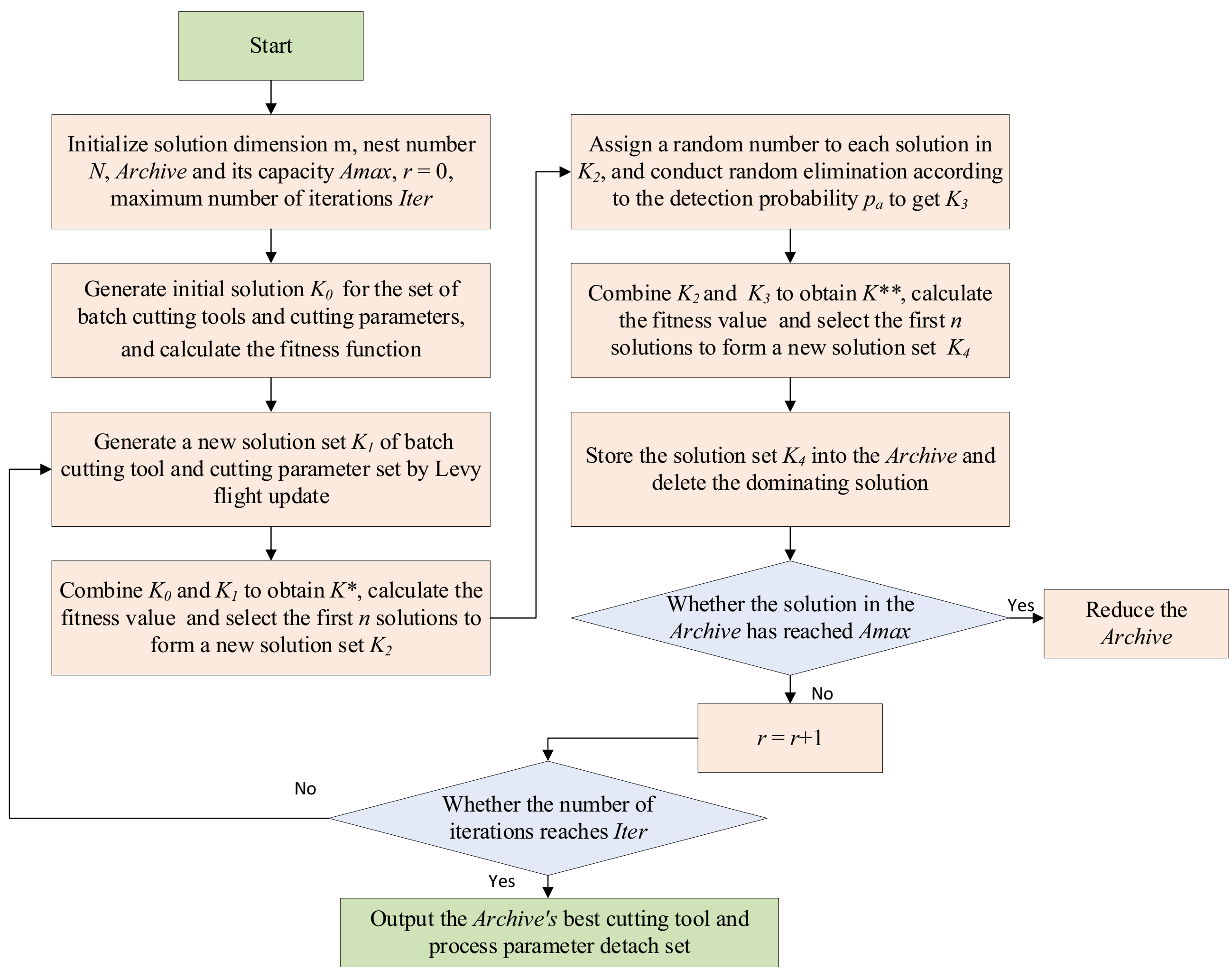


Fig. 3 Flow chart of the MOCS algorithm

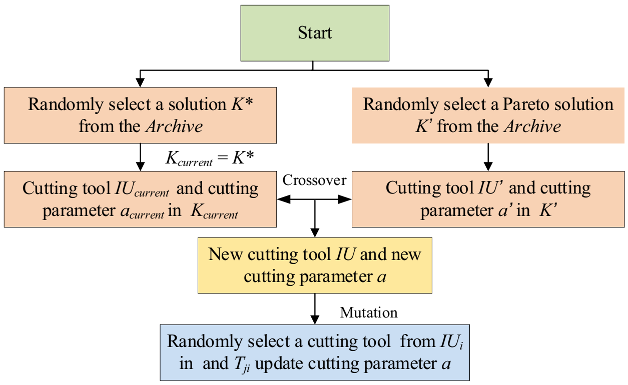


Fig. 4 Crossover and mutation operation

K' to generate a new cutting tool IU and new a. Then, a new cutting tool in IU_i is randomly selected again and a is updated according to the new cutting tool through the mutation.

(b) Levy flight

On the premise of the generated a and cutting tool IU, b, c and d are generated by Levy Flight [32] in Eq. (30) within the range of feasible cutting parameters. The search step size σ and the random step size obeying *Levy* distribution are shown in Eqs. (31) and (32), respectively.

$$K_i(r+1) = K_i(r) + \sigma \oplus Levy(\delta) \tag{30}$$

where $K_i(r+1)$ is the i-th optimal solution in generation $r+1$. $K_i(r)$ is i-th optimal solution in generation r. $\oplus$ is the point to point multiplication.

$$\sigma = \sigma_0\left[K_j(r) - K_i(r)\right] \tag{31}$$

$$Levy \sim \xi = t^{-1-\delta} \tag{32}$$

where σ_0 is the control value of the search step size. δ is constant. $K_j(r)$ and $K_i(r)$ are the optimal randomly selected solutions in generation r.

3. Cutting tool and parameter adjustment strategy

Cutting tool and parameter adjustments are not always happening in every T_{ji}. Several steps should be performed to judge whether there is a cutting tool adjustment or a cutting parameters adjustment before each T_{ji}. Figure 5 shows the strategy:

(a) If cutting tool IU_{il} is not the cutting tool of feature I_i of workpiece $J_{(j\text{-}1)}$, a set of cutting parameters can be directly selected within standard $[\Delta VB/\Delta t]_{il}$ and there is no cutting parameter adjustment;
(b) If cutting tool IU_{il} is the cutting tool of feature I_i of workpiece $J_{(j\text{-}1)}$ and reaches standard $[\Delta VB/\Delta t]_{il}$, cutting parameter adjustment should be performed;
(c) If all cutting tools IU_{il} in cutting tool set IU_i reach standard VB^{il}_{max}, manual cutting tool adjustment should be performed;
(d) If there exists cutting tool IU_{il} in cutting tool set IU_i not reaching standard VB^{il}_{max}, and IU_{il} is not the cutting tool of the feature $I_{(j\text{-}1)}$, automatic cutting tool adjustment should be performed. Otherwise, there is no cutting tool adjustment.

5 Case study

5.1 Experimental setup

To verify the effectiveness and practicability of the proposed model, the batch processing experiment is carried out by conducting CNC milling at an industrial enterprise in

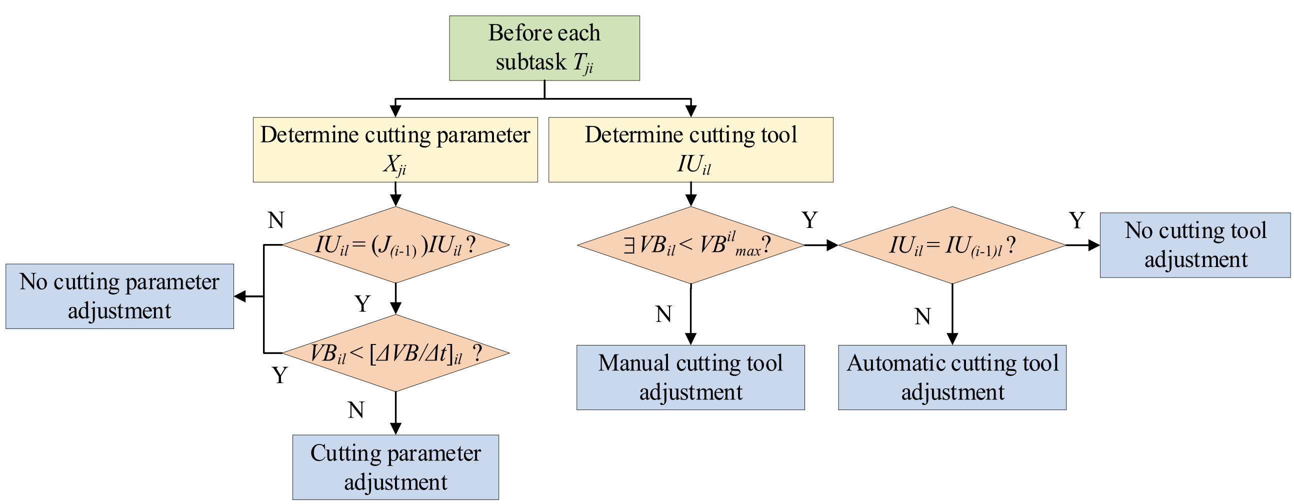


Fig. 5 Cutting tool and parameter adjustment strategy

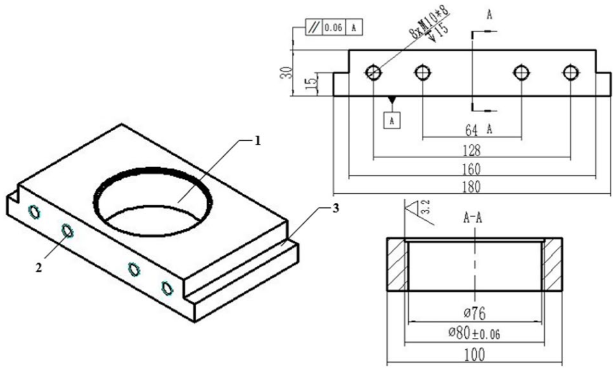


Fig. 6 Workpiece to be processed (1-hole#1, 2-hole#2, 3-slot)

Chongqing. The multi-feature z-axis cutter block is selected as the workpiece. There are three kinds of features on this workpiece which is one hole with the diameter of 80 mm, eight M10 threaded holes and two 100 mm × 20 mm × 15 mm slots, shown in Fig. 6. There is one machine tool and two kinds of cutting tools used in the experiment with 50 workpieces to be processed.

As shown in Fig. 7, VGC1500 vertical machining center is adopted to process workpieces and the efficiency monitoring system is used to monitor and collect power and time data in real time. Besides, tool wear states and values are measured using a super-depth three-dimensional microscope system. Details of machine tool, cutting tools, workpieces and relevant parameters are shown in Table 2.

5.2 Optimization model parameter configuration

The proposed optimization model involves several parameters such as power coefficients and tool wear values which are hard to obtain directly. In this paper, the experiment method is operated utilizing equipment in Sect. 5.1 to quantify the energy model. Firstly, the spindle idle experiment is conducted to fit unload power P_u. Then, the material removal power $Pmr\ ji$ and the additional load power $Pa\ ji$ are fitted since the relationship between them is complex and it is difficult to extract data separately. Finally, tool wear values VB are measured under different conditions.

1. Modeling P_u

   When the machine tool is idling, basic systems, spindle system and feed system are operating. As a result, idle power P_{idle} includes standby power P_{st} and unload power P_u. Also, P_u is the quadratic function of the spindle speed n_{ji}, as shown in Eq. (33). To obtain P_u, P_{idle} under different spindle speed n_{ji} need to be obtained through the idle experiment with n_{ji} (r/min) increasing from 2500 to 4500. Results are shown in Table 3 and the unload power expression can be obtained by fitting, as shown in Eq. (34). The variance analysis of the obtained unload power function model is carried out and results are shown in Table 4. It can be seen from the table that R-Sq = 98.91%, and R-Sq(adj) = 98.62%, indicating that the model is reliable.

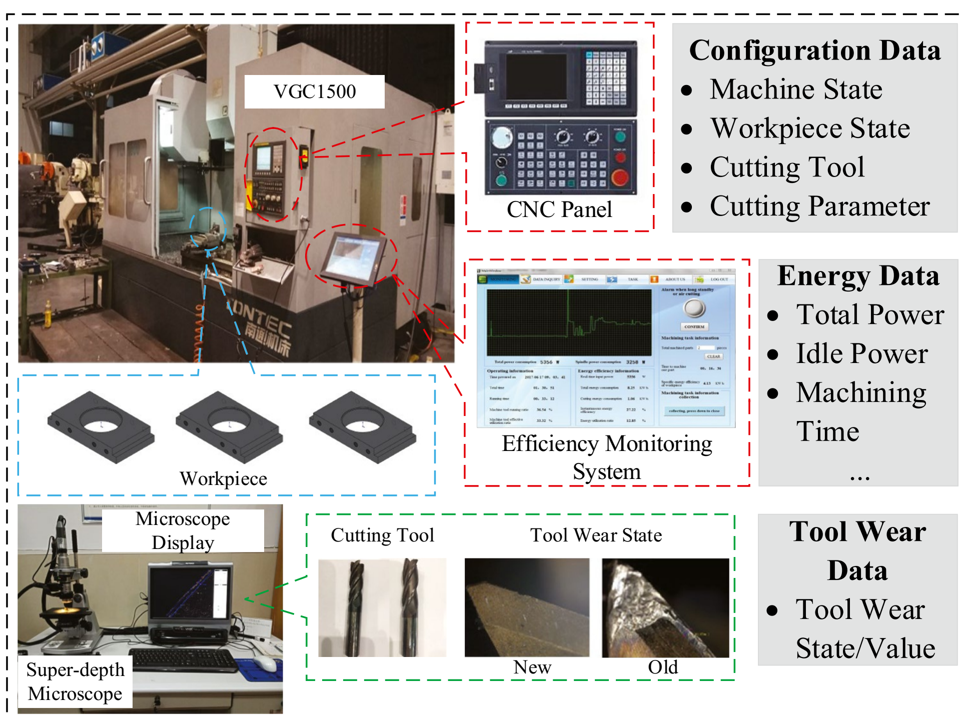


Fig. 7 Data acquisition platform

Table 2 Machining configuration

Item	Notation	Unit	Value
Machine tool	VGC1500	-	-
Max power	P_{max}	W	18,500
Spindle speed	n	r/min	0–6000
Feed speed	f	mm/min	0–5000
Power factor	PF	-	0.8
Cutting tool	-	-	-
Diameter	D	mm	15, 20
Teeth	f_z	-	4
Material	-	-	Cemented carbide
Processing	-	-	End milling
Feeding	-	-	Single
Workpiece	Cutter block	-	-
Feature	-	-	Hole, slot
Material	-	-	45 steel
Number	-	-	50
Coolant condition	-	-	Dry cutting
Parameters			
Standby power	P_{st}	W	1569
Auxiliary power	P_{aux}	W	213
Cutting distance	L	mm	180
Air cutting distance	l_{ji}^{air}	mm	10
Manual tool adjustment time	t_{adtool}^{man}	s	98
Automatic tool adjustment time	t_{adtool}^{aut}	s	7
Workpiece setting and removal time	t_{wsr}	s	49
Parameter adjustment time	t_{adpar}	s	17

$$P_{idle} - P_{st} = P_u = a_0 + a_1 n_{ji} + a_2 \left(n_{ji}\right)^2 \tag{33}$$

$$P_{ji}^{u}\left(n_{ji}\right) = 647.46 - 0.39 n_{ji} + 9.01 \times 10^{-5} n_{ji}^2 \tag{34}$$

where a_0, a_1 and a_2 are relevant coefficients of unload power.

Table 3 Unload power experiment results

No	n_{ji} (r/min)	P_{idle} (W)	P_{st} (W)	$P_u = P_{idle} - P_{st}$ (W)
1	2500	1801	1569	232
2	2750	1824	1570	254
3	3000	1856	1570	286
4	3250	1895	1569	326
5	3500	1952	1568	384
6	3750	2014	1569	445
7	4000	2097	1569	528
8	4250	2179	1570	609
9	4500	2281	1568	713

2. Modeling P_{ji}^{mr} and P_{ji}^{a}

There is a quadratic relationship between P_{ji}^{a} and P_{ji}^{mr}. According to formulas (5) and (7), the sum of P_{ji}^{mr} and P_{ji}^{a} is the difference of P_{ji}^{c} and P_{ji}^{air}, as shown in Eq. (35). Meanwhile, P_{ji}^{mr} considering tool wear can be expressed in Eq. (36) from the literature [18]. To obtain the sum of P_{ji}^{mr} and P_{ji}^{a}, the orthogonal experiment with three levels of cutting parameters and tool wear values shown in Table 5 is carried out. Experimental results are shown in Table 6 and the final expression of the sum of P_{ji}^{mr} and P_{ji}^{a} is shown in Eq. (37). The variance analysis of the obtained $P_{ji}^{mr} - P_{ji}^{a}$ model is carried out and results are shown in Table 7, where R-Sq = 96.16%, R-Sq(adj) = 95.01%, indicating that the model is reliable.

$$P_{ji}^{mr} + P_{ji}^{a} = \left(c_0 + 1\right) P_{ji}^{mr} + c_1 \left(P_{ji}^{mr}\right)^2 = P_{ji}^{c} - P_{ji}^{air} \tag{35}$$

$$P_{ji}^{mr} = k\left(1 + VB_{il}\right)^{w} v_c^{a} f_z^{b} a_p^{c} a_e^{d} \tag{36}$$

Table 4 Variance analysis of the unload power model

Source of variance	Degree of freedom	Mean square	F value
Regression model	2	11,240.6	15,779.9
Error	6	7.12	–
Total	8	–	–
$S = 41.43$	$R\text{-}Sq = 98.91\%$	$R\text{-}Sq(adj) = 98.62\%$	–

$$P_{ji}^{mr} + P_{ji}^{a} = 56.4 \times \left(1 + VB_{il}\right)^{1.28} v_c^{0.97} f_z^{0.83} a_p^{0.46} a_e^{0.29} - 0.79 \times \left(1 + VB_{il}\right)^{2.56} v_c^{1.94} f_z^{1.66} a_p^{0.92} a_e^{0.58} \tag{37}$$

where k, c_0, c_1 and c_2 are relevant coefficients of material removal power and additional load power.

At last, the energy consumption model in Eq. (15) can be finally translated in Eq. (38) according to Eqs. (34) and (37):

$$E_{total} = \sum_{j=1}^{N} \left(\sum_{i=1}^{w} \left(\begin{array}{l} P_{ji}^{st} \cdot t_{ji}^{st} + \left(P_{ji}^{st} + 647.46 - 0.39 n_{ji} + 9.01 \times 10^{-5} n_{ji}^2 + P_{ji}^{aux} \right) \cdot \frac{60 \pi D l_{ji}^{air}}{v_c^{ji} f^{ji} \times 10^3} \\ + \left(\begin{array}{l} P_{ji}^{st} + 647.46 - 0.39 n_{ji} + 9.01 \times 10^{-5} n_{ji}^2 + P_{ji}^{aux} \\ +56.4 \times \left(1 + VB_{il}\right)^{1.28} v_c^{0.97} f_z^{0.83} a_p^{0.46} a_e^{0.29} \\ -0.79 \times \left(1 + VB_{il}\right)^{2.56} v_c^{1.94} f_z^{1.66} a_p^{0.92} a_e^{0.58} \end{array} \right) \bullet \frac{60L}{z f_z^{ji} n_{ji}} + P_{adtool}^{aut} \bullet t_{adtool}^{aut} k_{il} \\ + P_{st} \bullet t_{adtool}^{man} r_{il} + P_{st} \bullet t_{adpar} u_{il} \end{array} \right) + P_{st} \bullet t_{wsr} \right) \tag{38}$$

3. Tool wear acquisition

According to the analysis in Sect. 2, tool wear values VB vary with respect to cutting parameters. To find out how cutting parameters (v_c, f_z, a_p, a_e) affect tool wear values, the sensitivity analysis is carried out. Two cutting parameters are set fixed successively, and the influence of the remaining two cutting parameters on tool wear is analyzed. Figure 8 shows the sensitivity analysis results. Figure 8a shows that at the condition of $f_z = 0.12$ mm/r, $a_p = 1.0$ mm, VB increases with the increasing of v_c and a_e. The steepness in the direction a_e-axis is lower than of v_c-axis, so the effect of v_c is higher than a_e. Figure 8b shows that at the condition of $f_z = 0.12$ mm/r, $a_e = 10$ mm, with the rise of v_c and a_p, VB continuously increases. The rate of v_c-VB curve is higher than a_p-VB, which means that v_c influences wear value VB more than a_p. In Fig. 8c, VB also increases with the growing of v_c and f_z. And v_c has more effects than f_z observing that v_c rises faster than f_z. Therefore, cutting speed has the greatest impact on tool wear values among these four cutting parameters. In this paper, tool wear values are measured under seven sets of cutting speeds ($v_c = 70$, 80, 90, 100, 110, 120, 130, unit m/min). Time and tool wear values corresponding to reference points at each set of v_c are shown in Table 8.

Table 5 Three cutting parameter factor levels

Factor level	v_c (m/min)	f_z (mm/r)	a_p (mm)	a_e (mm)	VB (mm)
1	80	0.08	1	15	0.05
2	120	0.10	1.8	25	0.20
3	160	0.12	2.6	35	0.35

5.3 Optimization results and discussions

1. Optimization results

To prove the effectiveness of the optimization model and algorithm, three optimization schemes are set: 1) Scheme 1: Separate optimization of E_{total}; 2) Scheme 2: Separate optimization of t_{total}; 3) Scheme 3: Comprehensive optimization of E_{total}&t_{total}. Main parameters of the MOCS algorithm are set as Table 9. Based on this, programming is conducted and optimization results of the above schemes are obtained in Tables 10, 11, and 12, where cutting tools, cutting parameters, tool wear values and their adjustments are given. According to tables, cutting parameters are continuously adjusted according to different cutting tool to reduce the wear speed and obtain optimal objectives.

Tables 10 and 11 show detailed optimization results of scheme 1 and 2. In scheme 1, cutting speeds are set at a higher level with five times of cutting tool automatic adjustment, three times of cutting tool manual adjustment and three times of cutting parameters adjustment. In scheme 2, cutting speeds are set at a lower level with

Table 6 Material removal power experimental results

No	VB(mm)	v_c(m/min)	f_z(mm)	a_p(mm/r)	a_e(mm)	P^{mr}-$P^a=P^c$-P^{air}(W)
1	0.05	80	0.08	1	15	228.1
2	0.2	80	0.08	1	15	281.3
3	0.35	80	0.08	1	15	332.4
4	0.05	120	0.1	1.8	15	753.5
5	0.2	120	0.1	1.8	15	802.3
6	0.35	120	0.1	1.8	15	865.9
7	0.05	160	0.12	2.6	15	1149.8
8	0.2	160	0.12	2.6	15	1203.1
9	0.35	160	0.12	2.6	15	1267.6
10	0.05	160	0.1	1	25	871.4
11	0.2	160	0.1	1	25	924.4
12	0.35	160	0.1	1	25	977.8
13	0.05	80	0.12	1.8	25	687.4
14	0.2	80	0.12	1.8	25	724.3
15	0.35	80	0.12	1.8	25	769.6
16	0.05	120	0.08	2.6	25	1081.8
17	0.2	120	0.08	2.6	25	1149.4
18	0.35	120	0.08	2.6	25	1181.2
19	0.05	120	0.12	1	35	1035.8
20	0.2	120	0.12	1	35	1099.2
21	0.35	120	0.12	1	35	1148.5
22	0.05	160	0.08	1.8	35	1169.7
23	0.2	160	0.08	1.8	35	1245.2
24	0.35	160	0.08	1.8	35	1290.8
25	0.05	80	0.1	2.6	35	979.6
26	0.2	80	0.1	2.6	35	1030.4
27	0.35	80	0.1	2.6	35	1089.2

three times of cutting tool automatic adjustment, four times of cutting parameters adjustment and no cutting tool manual adjustment. Compared with scheme 2, E_{total} of scheme 1 decreases by 3.8%, but t_{total} increases by 20%, as well as cutting tool and parameter adjustments of scheme 1 are more frequent.

Figure 9 shows the Pareto front of scheme 3, where there is an obvious conflict relationship between E_{total} and t_{total}. Thus, the separate optimization of E_{total} and t_{total} is inapplicable in the actual production and a trade-off between the reduction in E_{total} and t_{total} should be conducted to obtain the comprehensive optimization result [33, 34].

Table 12 shows optimization results of scheme 3, which is one set of Pareto solutions. There is one time of cutting tool manual adjustment, four times of cutting tool automatic adjustment and four times of cutting parameters adjustment. Compared with scheme 3, E_{total} of scheme 1 decreases by 16.3%, but t_{total} increases by 9.6%, and t_{total} of scheme 2 decreases by 8.7%, but

Table 7 Variance analysis of the material removal power model

Source of variance	Degree of freedom	Mean square	F value
Regression model	7	177.45	1741.11
Error	20	8152.77	–
Total	27	–	–
$S=41.43$	$R\text{-}Sq=96.16\%$	$R\text{-}Sq(adj)=95.01\%$	–

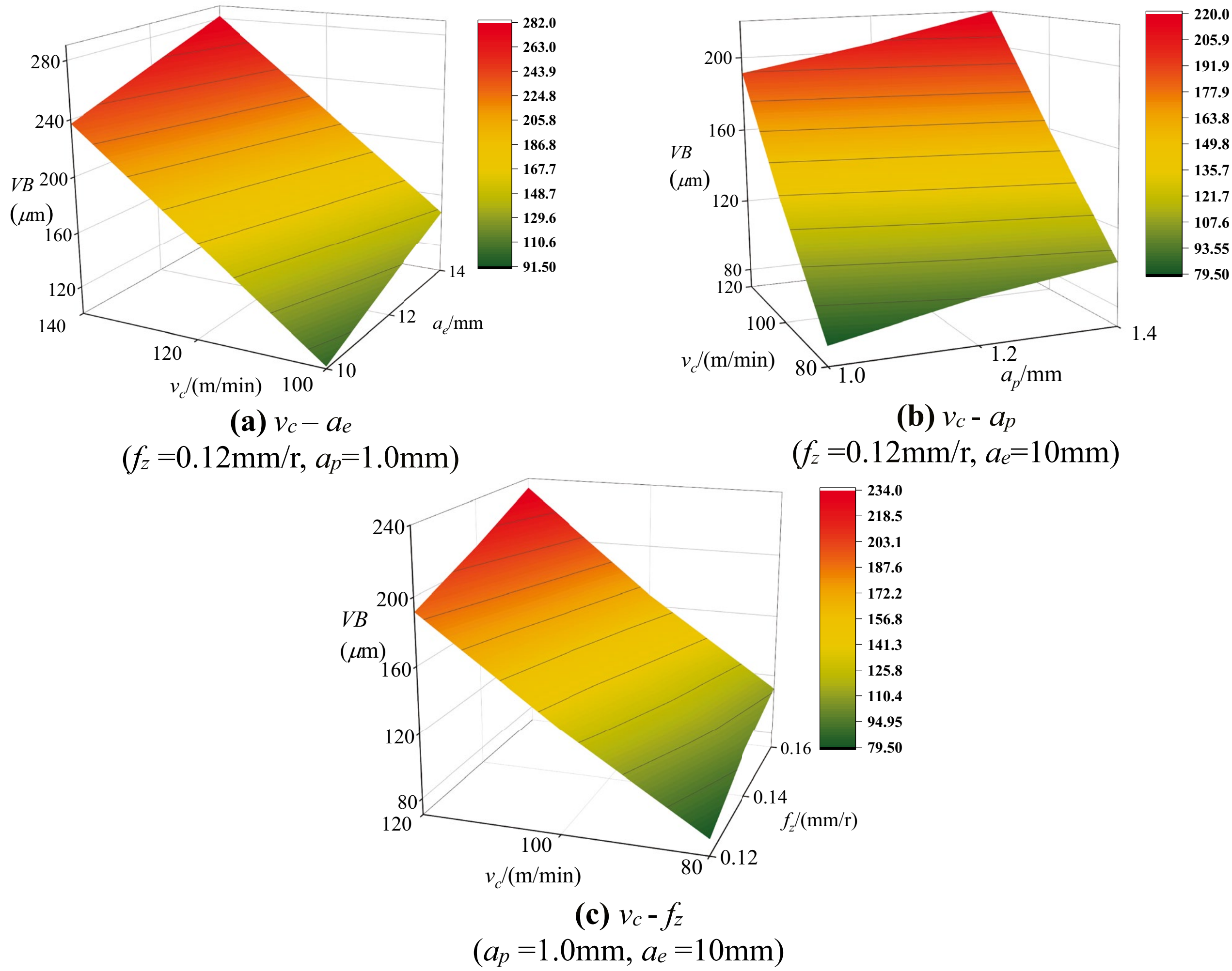


Fig. 8 Sensitivity analysis of cutting parameters on tool wear

E_{total} increases by 35.5%. Frequency of cutting tool and parameter adjustments in scheme 3 is compromise. Through the comparative result, although the multi-objective optimization cannot both reduce E_{total} and t_{total}, it can make a good trade-off between the conflict of E_{total} and t_{total} and realize the win–win between energy saving and production efficiency. This result can provide guidance for engineering practice with different production objectives, which verifies the effectiveness of proposed optimization model and algorithm.

2. Results verification

To verify the proposed optimization model, a set of fixed empirical cutting parameters is selected according to actual engineering experience to process work-

Table 8 Tool wear values and time corresponding to reference points

v_c (m/min)	VB (mm)	Time (s)
130	0.24	224
120	0.29	271
110	0.33	338
100	0.36	396
90	0.39	482
80	0.41	553
70	0.43	651

Table 9 Main parameters of MOCS

Parameter	Notation	Value
Solution dimension	m	5
Nest number	N	200
Maximum iteration number	I_{ter}	500
Archive length	A_{max}	100
Detection probability	p_a	0.6
Control value of the search step size	σ_0	0.2

Table 10 Optimization results of scheme 1

Total energy consumption E_{total} (J)	Total machining time t_{total} (s)	Cutting tools used number	No	Parameters					
				Cutting tool (mm)	v_c (m/min)	f_z (mm/z)	a_p (mm)	a_e (mm)	VB (mm)
15.86×10^6	3065	5	1	15	120	0.11	0.8	20	0.29
			2	20	130	0.1	2	2	0.24
			3	15	110	0.09	1.1	20	0.33
			4	20	120	0.1	2	2	0.29
			5	20	100	0.1	0.9	10	0.36
			6	20	90	0.1	2	2	0.39
			7	15	90	0.08	1	10	0.39
			New tool 1 manual adjustment						
			8	15	110	0.09	2	2	0.33
			9	15	90	0.1	1.1	12	0.39
			10	20	80	0.08	2	2	0.41
			New tool 2 manual adjustment						
			11	20	130	0.1	1.1	15	0.24
			New tool 1 manual adjustment						
			12	15	110	0.09	2	2	0.33

pieces under the same processing condition. Comparative results between scheme 3 and empirical scheme are shown in Table 13. Compared with empirical scheme, cutting tools number is less in scheme 3, and E_{total} decreases by 22.9% and t_{total} decreases by 4.1%. Main reason lies that 1) empirical scheme has no cutting parameters adjustment so that tool wear values increases rapidly, causing more cutting tools used in the processing and high E_c. Although no cutting parameter adjustment can reduce standby energy consumption, E_{total} increases at last. 2) In empirical scheme, more cutting tool adjustments result in high t^{man}_{adtool}. At the same time, due to the interference factors such as the inconsistency of workers' operation, time such as tool adjustment and workpiece clamping has certain deviation, eventually leading to an increase in t_{total}.

Based on comparative results and analysis, continuously adjusting cutting parameters based on tool wear states is an effective way to reduce wear speeds, and considering tool wear in cutting parameter optimization can

Table 11 Optimization results of scheme 2

Total energy consumption E_{total} (J)	Total machining time t_{total} (s)	Cutting tools used number	No	Parameters					
				Cutting tool (mm)	v_c (m/min)	f_z (mm/z)	a_p (mm)	a_e (mm)	VB (mm)
25.67×10^6	2552	2	1	15	110	0.11	0.8	15	0.33
			2	15	100	0.11	2	2	0.36
			3	20	120	0.08	1	15	0.29
			4	20	100	0.11	2	2	0.36
			5	20	90	0.1	0.8	12	0.39
			6	15	80	0.1	2	2	0.41
			7	20	80	0.11	1.1	20	0.41
			8	20	70	0.08	2	2	0.43

Table 12 Optimization results of scheme 3

Total energy consumption E_{total} (J)	Total machining time t_{total} (s)	Cutting tools used number	Parameters						
			No	Cutting tool (mm)	v_c (m/min)	f_z (mm/z)	a_p (mm)	a_e (mm)	VB (mm)
18.94×10^6	2796	3	1	15	110	0.1	0.9	20	0.33
			2	20	110	0.09	2	2	0.33
			3	15	90	0.11	0.9	12	0.39
			4	15	80	0.08	2	2	0.41
				New tool 1 manual adjustment					
			5	15	130	0.11	1.1	15	0.24
			6	15	120	0.1	2	2	0.29
			7	15	110	0.1	1.1	12	0.33
			8	20	100	0.09	2	2	0.36
			9	15	90	0.11	1	10	0.39
			10	15	70	0.09	2	2	0.43

reduce energy consumption and machining time significantly. The validation of proposed optimization model is verified.

3. Decomposition analysis

To further explain optimization results and summarize energy-saving rules that can be used to guide engineering practice, the energy consumption and machining time composition diagrams of different schemes are drawn, shown in Fig. 10. Figure 10a shows the energy consumption composition, where the greatest difference between three schemes is E_c, followed by E^{man}_{adtool} and E^{aut}_{adtool}. E_{st}, E_{air}, E_{adpar} and E_{wsr} are at the same level. Figure 10b shows he machining time composition, where t_{st}, t_{air}, t_c and t_{wsr} are at the same level. Differences between t^{man}_{adtool}, t^{aut}_{adtool} and t_{adpar} will mainly affect t_{total} in different schemes.

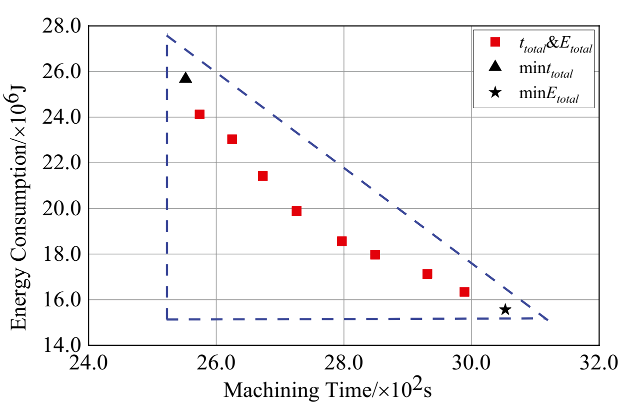


Fig. 9 Pareto front of scheme 3

The analysis is as follows: 1) In scheme 1, there are three cutting tool 1 and two cutting tool 2 used to complete the batch processing task and parameters are adjusted frequently during processing. As a result, t_{adpar} and *tman adtool* become longer, thus increasing t_{total}. On the other hand, the processing of scheme 1 starts at a high cutting speed, and the cutting parameters are constantly adjusted frequently to make the cutting tools act on the low tool wear state for a long time, ultimately resulting in a lower E_{total}. 2) In scheme 2, there is only one cutting tool 1 and one cutting tool 2 used to complete the batch processing task. The number of tools used is small, and there is no manual cutting tool adjustment. As a result, there is no t^{man}_{adtool} and t_{adpar} is also short, finally making t_{total} become shorter. On the other hand, the same cutting tool without cutting parameters adjustment is used for a long time so that the tool wear state is intensified, resulting in a higher E_{total}.

4. Influence of cutting parameters and tool wear on cutting power

As aforementioned study, cutting parameters and tool wear have synergistic effect on energy consumption, and cutting state consumes dominate energy known from the decomposition analysis. Thus, this section comprehensively analyzes the influence of cutting parameters and tool wear on cutting power to explore the detailed relationship and influence mechanism between them

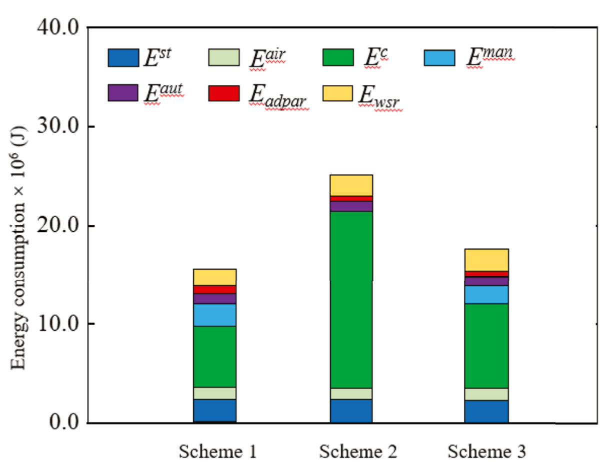
Table 13 Comparative results between scheme 3 and empirical scheme

Optimization type	Cutting tool used number	Cutting parameters adjustment	Total energy consumption E_{total} (J)	Total machining time t_{total} (s)
Scheme 3	3	Yes	18.94×10^6	2796
Empirical Scheme	5	No	24.58×10^6	2914

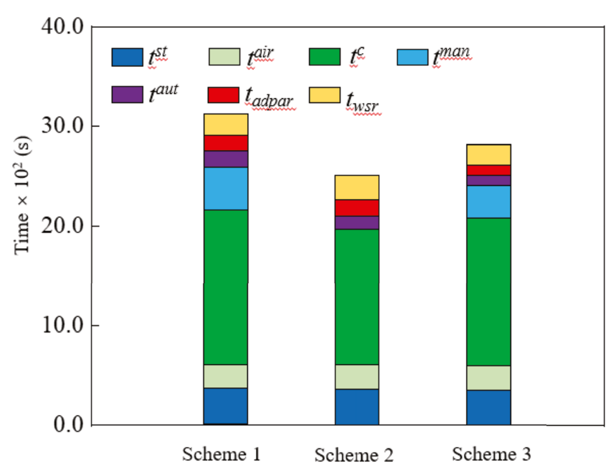
and prove the existence of the synergistic effect. Tool wear VB, cutting speed v_c, feed f_z and cutting depth a_p are selected as variables. Figure 11 shows different cutting powers P_c under different cutting parameters and wear values. From Fig. 11a to Fig. 11d, VB, v_c, f_z and a_p vary sequentially with other three parameters staying constant.

In Fig. 11, with the other three parameters fixed, P_c increases along another parameter. The analysis shows that 1) the friction between tool and workpiece increases with the increase in tool wear, causing the workpiece subjected to a greater cutting force, which is transmitted to the motor and increases the output power of the motor. 2) With cutting parameters increasing, more materials are removed in unit time, and the cutting force on the workpiece increases, leading to the increase in motor output power. 3) According to the actual processing experience, increasing v_c and f_z can improve the processing efficiency. Under the requirement of large cutting thickness, increasing a_p can reduce cutting steps to save time. Through the above analysis, cutting parameters and tool wear have significant indigenous effects on energy consumption and machining time. Therefore, in the actual processing, cutting parameters should be selected according to the comprehensive consideration of the propensity of enterprises to energy consumption and machining time.

On this basis, the sensitivity analysis of above four parameters (VB, v_c, f_z and a_p) on cutting power is conducted. Two of them are set fixed successively, and the influence of the remaining two is analyzed. Figure 12 shows the analysis result. In Fig. 12a, b, the steepness of v_c-axis is higher than f_z-axis and a_p-axis, and f_z-axis rises faster than a_p-axis in Fig. 12c, showing that v_c is the most influential parameter on cutting power among three cutting parameters under fixed wear value, followed by f_z and a_p. Figure 12d reveals that under fixed f_z and a_p, effects of v_c on cutting power is a little higher than that of VB, since the rate of v_c curve is higher than VB curve. In addition, it can be obtained that the energy consumption is different under different cutting parameters and tool wear values. Even under the same cutting parameters, the energy consumption is still different if tool wear values are different, which proves that there is a synergistic effect between cutting parameters and tool wear on the energy consumption.



(a) Energy consumption composition



(b) Machining time composition

Fig. 10 Composition of energy consumption and machining time

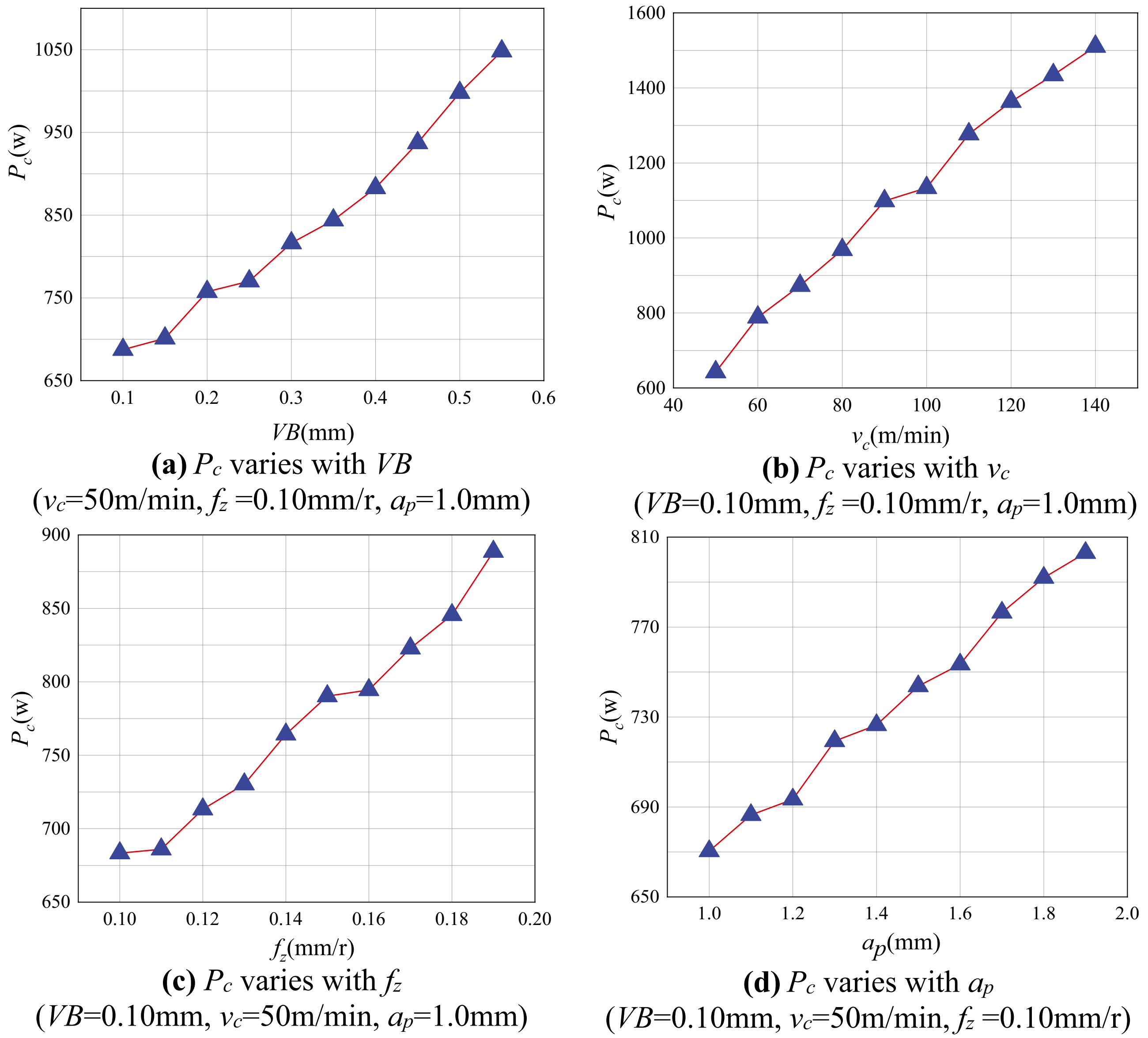


Fig. 11 Influence of cutting parameters and tool wear on cutting power

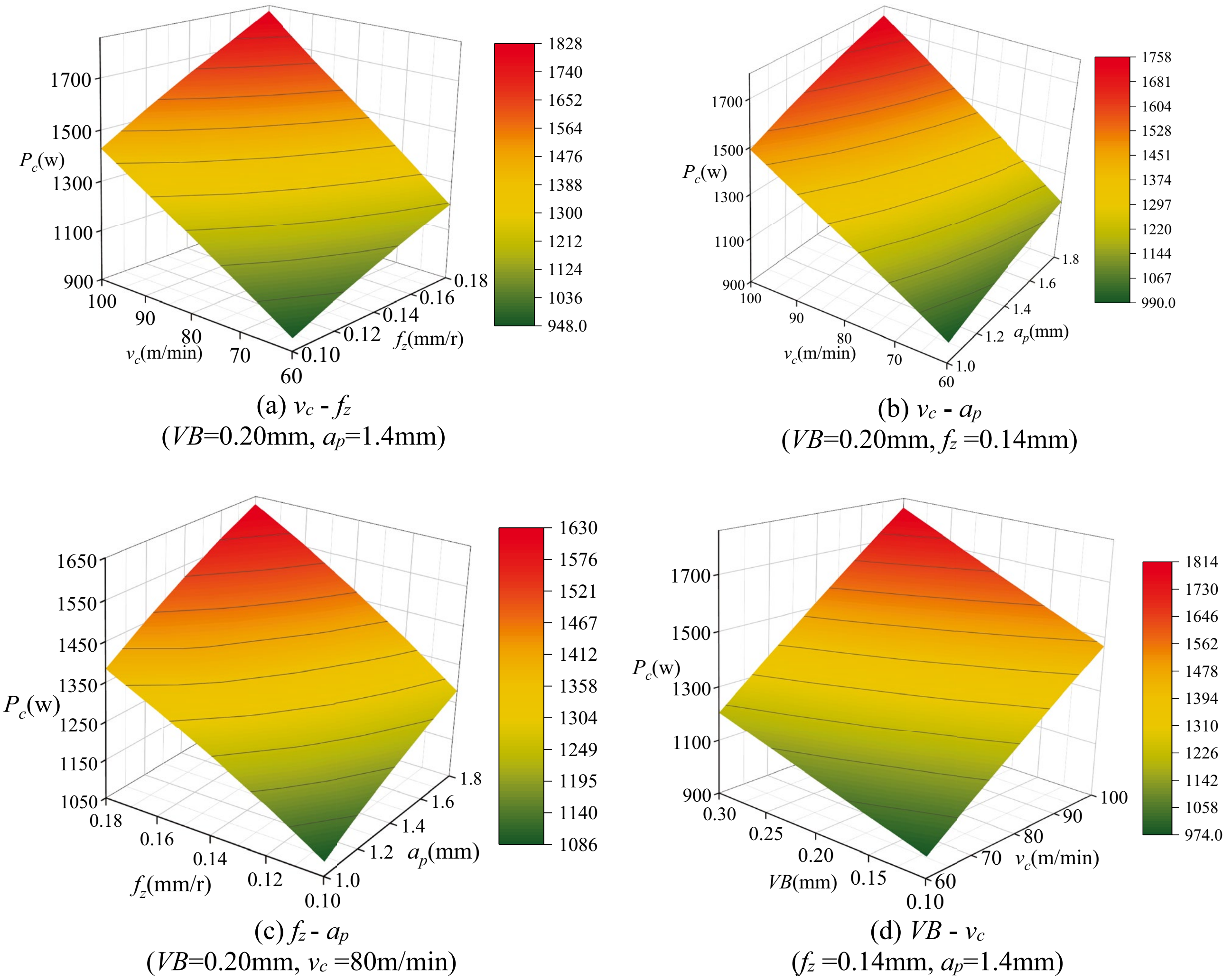


Fig. 12 Sensitivity analysis of cutting parameters and wear value on cutting power

6 Conclusion

In the cutting parameter optimization of the multi-feature parts batch processing problem, the comprehensive influence of cutting parameters, cutting tools and too wear states on the energy consumption and machining time are less included in previous researches. A cutting parameter optimization model considering tool wear for multi-feature parts batch processing is proposed for energy and machining time saving in this paper. Firstly, the energy consumption analysis for the multi-feature parts batch processing considering tool wear and adjustment of cutting tools and cutting parameters is conducted. Secondly, a multi-objective optimization model is proposed. In this model, the influence of the synergistic effect between the tool wear and cutting parameters is comprehensively considered. Finally, the MOCS algorithm is combined in this problem to solve the model and a case study is carried out to verify the effectiveness and practicability of the proposed model. The optimization results show that the trade-off between energy consumption and machining time is achieved. The verification results show that the continuous adjustment of cutting parameters can further reduce tool wear speeds, thus reducing energy consumption and machining time.

In the actual production, to complete a batch processing tasks may require multiple machine tools and multiple processing technologies cooperating to complete the task. Therefore, under the premise of considering the tool wear state, comprehensively considering the influence of the coordination of multiple machine tools and multiple processing technologies on the whole batch processing will be the research focus of the next step.

Author contribution Congbo Li and Shaoqing Wu designed the work, performed the research and analyzed the data. Congbo Li, Shaoqing Wu and Qian Yi discussed the results and wrote the manuscript. All authors contributed to conducting experiment, drafting and revising the manuscript.

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Availability of data and material The data needed to evaluate the conclusions in the study are included in this article.

Code availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

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