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Feature-based sequencing optimization method for minimizing non-cutting energy consumption for CNC machine tools

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Abstract

There is variety scheme when a part with multiple features is processed in CNC machines, and hence, different feature sequencing during processing affects not only productivity but also energy consumption. This paper concentrates on the energy-saving strategy by optimizing the feature processing sequence in the part processing stage through reducing the energy consumption of the non-cutting process. The detailed energy model is established considering rapid feed and general feed path in the X, Y, Z+, Z- directions for analyzing the impact of processing feature sorting on reducing the energy consumption of parts processing. The feature sequencing optimization is carried out under the condition of fixed cutting parameters for specific machining features to better reveal the sequence influence on energy consumption and non-cutting time. Meanwhile, the energy consumption of the non-cutting of parts specifically includes the empty pass and an automatic tool change model, while the normal feed and the rapid feed are established in different moving axis, respectively. Based on the developed model, the genetic algorithm is used to solve the optimal processing sequence and the lowest processing energy consumption. Finally, a cutting orthogonal experiment is executed to collect energy consumption data, analyze the data and fit the data to establish a specific energy consumption model for each processing stage. A case study of a part with nine features is used to optimize sequencing, which shows the effectiveness and validity of the proposed method.

Keywords: energy-efficient machining; non-cutting energy consumption; feature sequencing; genetic algorithm; tool path optimization

1. Introduction

With the continuous improvement of global environmental laws and regulations, green manufacturing has become the theme of the manufacturing industry in the new era. There are many machine tools and a wide range of applications in industrial development, so the total energy consumption is large [1]. According to US Energy Intelligence, the power consumption of machine tools accounts for more than 50% of the entire US manufacturing industry [2]. Many studies have shown that the energy utilization rate of machine tools is generally less than 30%, so there is a lot of energy-saving space [3]. Most of the electric energy consumed is from thermal power generation, so it consumes many fossil energy, including coal. Hence, reducing the energy consumption of machine tools usage stage not only protects the environment but also saves precious fossil energy.

Reducing the energy consumption of machine tools mainly considers the three factors of structure design of machine tools, usage of parts processing, and production organization. The structural design of the machine tools itself reduces energy consumption mainly by using of lightweight design for the machine bed, high-quality parts, reducing the energy consumption of the ineffective work of machine tools, and the streamlined design [4]. In the stage of part processing, the energy consumption can be reduced by optimizing processing parameters, including feature processing methods, tool types, cutting parameters, and feature processing sequence. In the production organization stage, the energy consumption of machine standby and empty cutting can be reduced by optimizing the

production parameters of the parts, including the production scheduling plan and tool trajectory planning. Among them, how to optimize the ranking of processing features to reduce the energy consumption of parts machining is the focus of this article.

Many researchers focus on energy efficiency improvement of machine tools and energy consumption reduction in the manufacturing process of parts, which are divided into different levels based on optimization goals. The highest level is about the process planning on workshop scheduling [5], while the lowest level is from the perspective of cutting energy consumption and reducing energy consumption by optimizing processing parameters [6]. The optimization of cutting parameters mainly focus on cutting material process, which up to one level is the middle level—non-cutting energy consumption used in the change process of a different feature on the same workpiece [7]. For CNC machine tools, because of their degree of automatically or semi-automatically, programming capabilities can be realized by computers. Therefore, it is easier to achieve optimal energy efficiency in the machining process by using process optimization of CNC machine tools.

The machining process of machine tools can be divided into the cutting process and the non-cutting process. The process of removing part material is defined as the cutting process. The process in which the tool does not remove material is defined as the non-cutting process, including the non-cutting process and the automatic tool change process [8]. According to the literature [9], standby energy consumption and energy consumption during machine tool processing account for more than 50% of the total energy consumption of machine tools. In terms of cutting energy consumption modeling, Sheng et al. [10] studied a part with three processing features, analyzed the influence of the change of the feature sequence of the processed parts on the energy consumption of the parts, and established a cutting energy consumption model. Newman et al. [11] further designed an energy-saving model for the experimental study of part feature processing, and calculated in the experiment that the energy consumption of empty cutting accounts for about 35% of the total processing energy. Srinivasan et al. [12] improved the energy-saving model to improve the adaptability of the model, and process constraints are added. In addition, Lv et al. [13] analyzed and measured the cutting power of 7 machine tools, and established a material removal power model for cutting parameters.

In regard to energy consumption modeling for non-cutting, Lv et al. [14] designed experiments to establish a normal feed power model about the feed rate on the X, Y, and Z axes of the machine tool, and the accuracy of the model was as high as 90% or more. Li et al. [15] further studied the rapid traverse power of the machine tool through experiments, and proposed that the rapid traverse power is determined by the characteristics of the machine tool itself and is a fixed value that can be measured by experiments. Aiming at the energy consumption modeling of machine tool change, Balogun et al. [16] measured the power of automatic tool change of the machine tool to account for about 20% of the total power through experimental measurement. Gara et al. [17] analyzed the relationship between the number of tool positions rotated by the tool post and the tool change time, and established a machine tool tool change time model. He et al. [18] proposed that the tool change energy consumption can be calculated by the product of the tool change time and the tool change power.

A certain number of processing features are involved in the processing of a part. These features include steps, grooves, planes, and drill holes [19]. Assuming a part is composed of n different features, there are $n!$ sort of processing features. Different sorting methods have different processing energy consumption. Therefore, choosing a

reasonable processing feature sorting method in the actual processing process plays an important role in reducing the energy consumption of the machine tools. With the reduction of energy consumption, the operating cost of the enterprise is also reduced. In terms of optimizing the sorting of parts processing features to reduce energy consumption of machine tools, Sheng et al. [10] used enumeration method to enumerate 6 sorting methods of part feature processing, and respectively calculated the processing energy consumption corresponding to the 6 sorting methods and got the optimal processing ordering method and the lowest processing energy consumption. Wiener et al. [20] pointed out that when the number of parts processed is too large, the enumeration method is still adopted and the calculation time and workload increase. Therefore, when the number of features in the part is large, a more effective method is needed to solve the problem. Some scholars have used deterministic algorithms and heuristic algorithms to solve the optimal machining feature ranking problem in the process of parts processing [21]. Deterministic algorithms include dynamic programming and other mathematical methods, which have been used to solve the problem of the shortest part processing time [22]. But the deterministic algorithm is only suitable for parts with a small number of features. When the number of features is greater than 20, the calculation time is too long [23], and the heuristic algorithm has almost the same calculation time when the number of features increases [24]. In the actual production process, the number of features of the part is often large. Due to the high efficiency of the heuristic algorithm, it is widely used in various large-scale solving problems [25]. Although the heuristic algorithm is efficient, it is easy to fall into the local optimal solution, so more effective heuristic algorithm is needed. Bhaskara et al. [26] used genetic algorithm to solve the shortest part processing time problem, which proved the high efficiency of proposed method.

For obtaining more precise energy consumption of non-cutting process, this paper establish a mathematical model of machine tool energy consumption for processing feature sorting. Meanwhile, heuristic algorithm genetic algorithm is used to optimize energy consumption during parts processing. Additionally, orthogonal experiments is designed to collect energy consumption data of machine tools to establish a model of machined parts for case studies.

2. Energy consumption mathematical model of feature-based sequencing

2.1 Description of problem

The energy consumption of parts processing is mainly composed of cutting energy consumption and empty cutting energy consumption. Cutting energy consumption is mainly determined by the set cutting parameters (cutting speed, feed rate, measured knife amount, back knife amount), which result in different cutting energy per unit volume for each machining feature. Due to the goal of this paper is the optimization of the processing feature sequencing, the cutting energy consumption is regarded as a fixed value determined by the cutting parameters. Therefore, no matter how the processing sequence changes, the volume of the material that needs to be cut does not change, and the cutting energy consumption does not change. The difference of feature sequencing affect the energy consumption of non-cutting process composing of tool change energy consumption and empty tool energy consumption. It not only depends on the set cutting parameters, but also is limited by the sorting method of processing features. When the order of processing features of a part is changed, the corresponding processing path will change. Meanwhile, the order and frequency of tool change will also change, which affect the energy consumption of empty pass and tool change.

For example, a part with only two features is processed including holes and cavity as shown in Fig. 1. The schematic diagram of the processing path is shown in Fig. 2. The initial tool point as the starting point and the tool change point is set as F0, and the processed tool end point is marked as F3. The cavity feature is marked as F1, and the hole feature is marked as F2. The cavity and the hole are processed with different tools, so the operation of tool changing is required after processing a feature. There are two processing sequencing methods. One process is the cavity first and then process the hole (F0→F1→F2→F3), and another process is the hole first and then process the cavity (F0→F2→F1→F3). These two sorting methods directly lead to different processing paths and directly affect the final machine tool processing energy consumption results.

Fig. 1 The shape of one part with double features

Fig. 2 Power profiles of two different sequence (a) (F0→F1→F2→F3); (b) (F0→F2→F1→F3)

The processing sequence mainly affects the energy consumption of empty cutting. The energy value of empty cutting is expressed respectively as :

$$E_1 = E_n^{(F0-F1)} + E_n^{(F1-F2)} + E_n^{(F2-F3)} \quad (1)$$

$$E_2 = E_n^{(F0-F2)} + E_n^{(F2-F1)} + E_n^{(F1-F3)} \quad (2)$$

Where $E_n^{(Fi-Fj)}$ is the energy consumption of empty cutting of the part from feature i to feature j , the energy consumption of the empty cutting is composed of the energy consumption of the tool change and the energy consumption of the empty pass, that is, the energy consumption of the empty cutting can be expressed as:

$$E_n^{(Fi-Fj)} = E_{ct}^{(Fi-Fj)} + E_{ep}^{(Fi-Fj)} \quad (3)$$

Where $E_{ct}^{(Fi-Fj)}$ is the energy consumption of tool change after machining feature i and then feature j . $E_{ep}^{(Fi-Fj)}$ is the energy consumption of the empty pass between the i feature and the j feature.

As shown in Fig. 2, the change of part feature processing sequence directly leads to the difference of the processing path and the difference of the tool change time, leading to the difference in the energy consumption of the empty cutting of the part processing. Therefore, it can be converted to solve the problem of the minimum energy consumption of the part machining empty cutting.

2.2 The energy consumption model of feature-based processing

It can be seen from the analysis in the section 2.1 that designers need to consider the energy consumption optimization of empty cutting in the process of parts processing. The previous section qualitatively analyzes the influence of the ordering of processing features on reducing the energy consumption of parts processing. However, it is necessary to further establish a model for quantitative calculation for comparing energy of different sequencing. Therefore, this section establishes a part empty cutting energy consumption processing model, which is mainly composed of an empty pass energy consumption model and an automatic tool change energy consumption model. According to this model, the empty cutting energy consumption part of the part processing process can be accurately calculated.

2.2.1 Energy consumption model of empty path

From cutting one feature to the next feature, the process of empty cutting is divided into several feed motions. The energy consumption of the empty pass between the two features is the sum of the energy consumption of these several feed activities. The model of the empty pass between two features can be established as:

$$E_{ep}^{(Fi,Fj)} = \sum_{a=1}^n E_a^{(Fi,Fj)} \quad (4)$$

Where $E_{ep}^{(Fi,Fj)}$ is the energy consumption of empty cutting between two features. $E_a^{(Fi,Fj)}$ is the energy consumption of the a -th feed activity.

There are two feed methods for the machine tool, which are divided into rapid feed and ordinary feed. The energy consumption of the machine tool is different for these two feed methods, so it is necessary to analyze and model separately.

(1) Energy consumption model of rapid feed

The speed of rapid feed is determined by the characteristics of the machine tools itself. The specific performance is that the feed system of the machine tool moves to the target position at the fastest speed on the X, Y, and Z axes. In addition to the energy consumed by the three motors in the feed direction, the power consumption of rapid traverse also includes the energy consumed by the spindle idling and the machine standby. Therefore, if there is a rapid feed activity between the two features, the following energy consumption model is established as:

$$E_a^{(Fi,Fj)} = P_{XF} \times t_{XF} + P_{YF} \times t_{YF} + P_{ZF} \times t_{ZF} + (P_{spindle} + P_a) \times t_{max} \quad (5)$$

Where $E_a^{(Fi,Fj)}$ is the energy consumption of the a -th feed activity between two features (rapid feed). P_{XF} , P_{YF} , P_{ZF} are the rapid traverse power in 3 moving directions, t_{XF} , t_{YF} , t_{ZF} are the rapid traverse time in 3 directions.

$P_{spindle}$ is the spindle idling power model, P_a is the standby power model of the machine tool, t_{max} is the maximum feed time in 3 directions, which is $t_{max} = \max(t_X, t_Y, t_Z)$.

Additionally, the feed time is obtained by the joint solution of the feed distance and the feed speed, and the calculation of the feed time is solved as:

$$t_{XF} = \frac{L_{XF}}{V_{XF}}, \quad t_{YF} = \frac{L_{YF}}{V_{YF}}, \quad t_{ZF} = \frac{L_{ZF}}{V_{ZF}} \quad (6)$$

Where L_{XF} , L_{YF} , L_{ZF} are the feed distances in the three directions of X, Y, and Z, V_{XF} , V_{YF} , V_{ZF} are the feed rates in the three directions of X, Y, and Z. Spindle idling model can be established as:

$$P_{spindle} = k_1 \times n + b_2 \quad (7)$$

Where n is the spindle speed, k_1 , b_2 are constants.

The above content completes the establishment of the energy consumption model of rapid traverse.

(2) Energy consumption model of general feed

The rapid feed rate is determined by the machines' performance, but the normal feed can be controlled by artificially setting the feed rate. Similar to rapid traverse, the power consumption of ordinary feed includes the energy consumed by the three motors in the feed direction, as well as the energy consumed by the spindle idling and the machine standby. The difference is that the feeding time in the ordinary feeding process is the entire time of the entire feeding activity. Because the ordinary feeding system needs to overcome gravity when it moves upward in the Z direction. Therefore, modeling in the Z direction needs to be divided into vertical upward modeling as Z+ direction, and vertical downward modeling as Z-direction. If there is a normal feed activity between the two features, the following energy consumption model is established as:

$$E_a^{(Fi,Fj)} = P_{XO} \times t_{XO} + P_{YO} \times t_{YO} + P_{ZO}^+ \times t_{ZO}^+ + P_{ZO}^- \times t_{ZO}^- + (P_{spindle} + P_a) \times t_{sum} \quad (8)$$

Where $E_a^{(Fi,Fj)}$ is the energy consumption of the a -th feed activity between the two features (normal feed), P_{XO} , P_{YO} , P_{ZO}^+ , P_{ZO}^- are the normal feed power in X, Y, Z+ and Z- directions, t_{XO} , t_{YO} , t_{ZO}^+ , t_{ZO}^- are the normal feed time in X, Y, Z+ and Z- directions, $P_{spindle}$ is the spindle idling power model, P_a is the machine standby power model, t_{sum} is the sum of time for the entire feed activity, which is $t_{sum} = t_{XO} + t_{YO} + t_{ZO}^+ + t_{ZO}^-$.

The feed time is obtained by the joint solution of the feed distance and the feed speed, and the calculation of the feed time is solved as:

$$t_{XO} = \frac{L_{XO}}{V_{XO}}, \quad t_{YO} = \frac{L_{YO}}{V_{YO}}, \quad t_{ZO}^+ = \frac{L_{ZO}^+}{V_{ZO}^+}, \quad t_{ZO}^- = \frac{L_{ZO}^-}{V_{ZO}^-} \quad (9)$$

The spindle idling energy consumption model has been established in the rapid traverse energy consumption model. The general feed power model is established respectively in the X, Y, Z+ and Z- directions as:

$$P_{XO} = k_1 \times V_{XO} + b_1 \quad (10)$$

$$P_{YO} = k_2 \times V_{YO} + b_2 \quad (11)$$

$$P_{ZO}^+ = k_3 \times V_{ZO}^+ + b_3 \quad (12)$$

$$P_{ZO}^- = k_4 \times V_{ZO}^- + b_4 \quad (13)$$

Where k_1 , b_1 , k_2 , b_2 , k_3 , b_3 , k_4 , b_4 are constants.

The above content establishes the energy consumption model of the empty pass.

2.2.2 Energy consumption model of automatic tool change

When the next feature needs to be processed after processing last feature, different features require different tools for processing. The CNC machining center has an automatic tool change function, and hence, the energy consumption of automatic tool change can be calculated by multiplying the tool change time and the corresponding machine power during the tool change. When the machine tool is automatically changing tools, the machine tool is still running. So the automatic tool change power includes the standby power of the machine tool and the tool change power, where the tool change power is mainly the power of the tool change motor and the air pump motor. Therefore, the automatic tool change model can be built as:

$$E_{ct}^{(Fi,Fj)} = (P_a + P_{ct}^{(Fi,Fj)}) \times T_{ct}^{(Fi,Fj)} \quad (14)$$

Where $E_{ct}^{(Fi,Fj)}$ is the tool change energy consumption after processing the i feature and then processing the j feature, P_a is the standby energy consumption of the machine tool, $P_{ct}^{(Fi,Fj)}$ is the tool change power to process the j feature after machining the i feature, $T_{ct}^{(Fi,Fj)}$ is the tool change time after machining feature i and then feature j . $P_{ct}^{(Fi,Fj)}$ and $T_{ct}^{(Fi,Fj)}$ are determined by the number of tool holder positions the tool rotates.

3. Genetic algorithm-based optimization problem

In actual processing, the number of features of parts is often large. At this time, it is no longer suitable to use traditional methods such as enumeration or permutation and combination to select the optimal solution. However, compared with traditional methods, heuristic algorithms have certain advantages in solving large-scale industrial problems and problems with high computational complexity. The genetic algorithm is a kind of algorithm with higher solving efficiency in this kind of algorithm, so this paper uses genetic algorithm to solve the energy consumption optimization problem in the process of parts processing (processing feature ranking).

The genetic algorithm uses the principle of biological evolution and borrows the principle of Darwin's theory of evolution to continuously produce new offspring and eliminate the inferior offspring through an iterative method, so that the final offspring is the optimal offspring of the problem. For the energy consumption optimization problem of the part machining process, the optimal descendant is the machining special ordering scheme corresponding to the lowest energy consumption of the machine tool for empty cutting. As shown in Fig. 3, the steps are shown as follows:

Step one: Encoding. Integer coding is used to encode the part processing and sorting scheme into a certain number of chromosomes composed of genes. For example, one of the sorting schemes F0-F3-F1-F2-F4 can be encoded as a chromosome composed of 5 genes [03124], where gene 1 represents feature F3.

Step 2: Generate the initial population. Randomly generate an initial population with A chromosomes. As the first generation population, the value range of A is usually in the range of [10,800]. If the sequence of genes in the chromosome does not match the constraints, the chromosome is illegal. The order of genes in illegal chromosomes needs to be adjusted to make the chromosomes legal.

Step 3: Calculate the fitness value. In the iterative process, a fitness function is established to facilitate the calculation of the fitness value corresponding to each chromosome, and the chromosome is selected according to this value for the next generation. The fitness function is a tool for evaluating the quality of chromosomes. If the fitness value corresponding to the chromosome is larger, the probability of being selected is higher, and vice versa. Aiming at the problem of energy consumption optimization for parts processing, the fitness function is $\text{Fitness} = 1/E_n$.

Step 4: Choose an operation. Selection is also called replication. The specific process is to use a method of selecting individuals in which part of the chromosomes are selected as the parent chromosomes for the next generation of populations. There are many ways to select individuals, and this article uses roulette to select methods. When using this method, the lower the energy consumption of the machine's empty cutting, the higher the probability that the chromosome corresponding to the processing special order will be selected.

Step 5: Cross operation. The crossover operation is also called gene recombination, and the specific operation is: swapping the gene fragments corresponding to the processing features in the chromosome, and inheriting the fragments to the offspring. This article uses partial crossover operations. If the crossover operation violates the constraint relationship, the gene order is changed until the condition is met.

Step 6: Mutation operation. The mutation operation is to change the genes in the chromosome, and the ordering of processing features becomes diversified. In this paper, the method of crossover mutation is used to select genes at any two positions on the same chromosome for exchange. Similarly, if the mutation operation violates the constraint relationship, the gene order is changed until the condition is met.

Step 7: The algorithm terminates. And the algorithm stops, and an output is made to the final result in order to obtain the optimal solution. The machining special certificate sorting scheme corresponding to the lowest energy consumption of the machine's empty cutting and the corresponding minimum value.

Fig. 3 The flow chart of genetic algorithm

4. Case study

4.1 Orthogonal experiment design and energy consumption data collection

The VMC580E CNC machining center is used for orthogonal experiment design, whose detailed information has been pressed in the article [27]. The CNC machining energy consumption collection system is established, and the cutting orthogonal experiment is designed. The cutting parameters and level numbers are shown in Table 1. The

above-established empty cutting energy consumption model is used to provide data support for the sequencing problem. The basic composition of the energy collection system is shown in Fig. 4, and the sensor wiring diagram is shown in Fig. 5, including: ① CNC machining center, ② WB-9128 three-phase power sensor, ③ NI-9201 voltage acquisition module, ④ NI-cDAQ-9188 acquisition Chassis, ⑤ computer, ⑥ CNC acquisition program.

Table 1 Processing parameter setting table

Cutting parameters	Level 1	Level 2	Level 3
$n(r/min)$	1000	1500	2000
$v_f(m/min)$	100	150	200
$a_p(mm)$	0.2	0.3	0.4
$a_e(mm)$	4	6	8

Fig. 4 Diagram of energy consumption collection equipment

Fig. 5 Wiring diagram of actual machine tool sensor

Data processing is performed on the energy consumption collected in the CNC machining process. Table 2 includes standby power, rapid traverse power and rapid traverse speed in X, Y, and Z directions. Table 3 contains the normal feed power model and spindle idling model in the X, Y, Z+ and Z- directions. Table 4 contains the tool change power and tool change time corresponding to different tool positions of the tool post.

Table 2 Basic energy consumption collection

Collect energy consumption	power(w)
Standby energy consumption (P_a)	342
Rapid feed in X direction (32m/min)	35
Rapid feed in Y direction (32m/min)	47
Rapid feed in Z direction (32m/min)	28

Table 3 Common feed and spindle idling power model

Energy consumption	Energy consumption model (w)
Feed power in the X-axis direction	$P_{XO} = 0.22 \times V_{XO} - 15$
Feed power in the Y-axis direction	$P_{YO} = 0.38 \times V_{YO} - 22.67$
Feed power in the positive direction of Z axis	$P_{ZO}^+ = 0.04 \times V_{ZO}^+ + 8$
Feed power in the negative direction of Z axis	$P_{ZO}^- = 0.08 \times V_{ZO}^- - 5$
Spindle idling ($P_{spindle}$)	$P_{spindle} = \begin{cases} 111.6 + 0.2704 \times n, & 500 < n \ll 1500 \\ 1117 - 0.6184 \times n + 0.000129 \times n^2, & 1500 < n \ll 2400 \\ 338.61 + 0.01493 \times n, & 2400 < n \ll 3300 \\ 0.12963 \times n - 34, & 3300 < n \ll 5100 \end{cases}$

Table 4 Tool change time and tool change power

Tool change time and tool change power (w)				
Number of tool changes	0	1	2	3
Power	0	85.2	91.2	94.3
Time	0	18.5	19.5	20.4

4.2 Part design and algorithm solution

As shown in Fig. 6, a part with 8 processing features is designed. Figs. 7 and 8 are the top and front views of the part respectively. The specific feature information is shown in Table 5, which includes one step feature, two hole features, two u-shaped groove features, one arc groove feature, and two 2.5D cavity features. The defined tool starting point and tool change point are both feature F1, which is a virtual feature that is artificially defined. We define the ordinary feed speed of 480mm/min and the speed of 1500n/min, then bring the ordinary feed power model to solve the X, Y, Z+, Z- direction power respectively (unit: w): $P_{XO}=949.4$, $p_{YO}=1018.53$, $p_{ZO}^+=892.2$, $p_{ZO}^-=886.2$.

Table 5 Basic information of parts

Feature name	Feature number
Tool starting point and automatic tool change point	F1
Steps	F2
Drilling ($D = 8$)	F3, F4
U-groove	F5, F6
Arc groove	F7
2.5D cavity	F8, F9

Fig. 6 Parts diagram

Fig. 7 Top view of parts

Fig. 8 Front view of parts

Fig. 9 Trajectory diagram of feature processing

Fig. 9 shows the designed machining trajectory of each feature. According to the trajectory, the energy consumption of the empty cutting between the two features is calculated. Firstly, the empty path between the two

features is calculated, and the empty path and feed rate are used to solve for the empty path time. Multiplying the calculated value of the empty tool power and the empty tool time in the X, Y, Z+, Z- directions calculates the empty tool energy consumption. Secondly, it is need to determine whether or not a tool change operation between these two features. If a tool change operation is required, it adds the tool change energy consumption value shown in Table 5. This value is the empty cutting energy consumption between the two features as shown in Table 6. According to this method, the characteristics are established respectively. Table 7 shows the energy consumption of empty cutting during the period. The process of genetic algorithm searching for the optimal solution is shown in Fig.10.

Table 5 Tool change time

	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	0	0	18.5	18.5	18.5	18.5	19.5	19.5	19.5
F2	0	0	18.5	18.5	18.5	18.5	19.5	19.5	19.5
F3	0	18.5	0	0	0	0	18.5	18.5	18.5
F4	0	18.5	0	0	0	0	18.5	18.5	18.5
F5	0	18.5	0	0	0	0	18.5	18.5	18.5
F6	0	18.5	0	0	0	0	18.5	18.5	18.5
F7	0	19.5	18.5	18.5	18.5	18.5	0	0	0
F8	0	19.5	18.5	18.5	18.5	18.5	0	0	0
F9	0	19.5	18.5	18.5	18.5	18.5	0	0	0

Table 7 Energy consumption of empty cutting between features

	F1	F2	F3	F4	F5	F6	F7	F8	F9
F1	/	11862.5	28960.75	26415.75	33242	26879.5	32621.38	40903.5	34541
F2	19332.5	/	15660.75	18205.75	16124.5	22487	21866.38	23786	30148.5
F3	22168.75	18205.75	/	3652.5	5388.75	7933.75	14668.63	20405.75	22950.75
F4	19623.75	15660.75	3652.5	/	7933.75	5388.75	14668.63	22950.75	20405.75
F5	23987.5	20024.5	2926.25	26913.75	/	5007.5	11742.38	17479.5	20024.5
F6	21442.5	17479.5	5471.25	26913.75	44393.25	/	11742.38	20024.5	17479.5
F7	24731.63	21312.63	14114.88	38846.5	60159.13	74274	/	8835.875	8835.875
F8	37126.25	33707.25	23964.5	61090.75	94798	118762.5	179853.3	/	11028.75
F9	30763.75	27344.75	26509.5	57273.25	84618	111127.5	168400.8	11028.75	/

Fig. 10 The process of genetic algorithm searching for the optimal solution

The import data using the genetic algorithm to solve the optimal value is shown in Table 8. The input parameters of genetic algorithm as follows: Set the population size to 100, the number of iterations to 200, the crossover probability to 0.9, and the mutation rate to 0.05. After multiple iterations of the algorithm, the minimum energy consumption for empty cutting is 102020J, and the optimal feature processing sequence is: F1→F2→F5→F3→F4→F6→F9→F8→F7.

Table 8 The energy of different feature sequence

Feature processing sequence	Energy consumption
F1→F2→F4→F3→F5→F6→F7→F8→F9	103940J
F1→F2→F5→F3→F4→F6→F7→F8→F9	106100J
F1→F2→F5→F3→F4→F6→F9→F8→F7	102020J
F1→F2→F5→F7→F8→F9→F6→F3→F4	105821J
F1→F2→F7→F9→F8→F5→F3→F4→F6	104483J

5. Conclusions and future work

This paper mainly studies the energy-saving optimization problem of part machining feature sorting on the premise of the fixed cutting parameters in the part processing stage. Firstly, we analyze the influence of processing feature sorting on reducing energy consumption of parts processing. Part processing energy consumption is mainly composed of cutting energy consumption and empty cutting energy consumption. Since the cutting parameters are determined, it is only necessary to analyze the order of processing features to reduce the energy consumption of empty cutting. Therefore, the energy consumption model of empty cutting for parts processing is established combining energy consumption model of empty pass and the model of automatic tool change. Meanwhile, a normal feed energy consumption model and a rapid feed energy consumption model are established respectively. Secondly, the genetic algorithm is used to optimize the energy consumption in the process of parts processing, and then the definition of the genetic algorithm and the steps of the genetic algorithm to solve the optimization problem. Finally, a case study of part processing feature optimization is carried out, and a genetic algorithm is used to solve a part with nine features. Through calculating the empty cutting energy consumption between the two features, and the empty cutting energy consumption table between the features are obtained. The result of case study shows that the necessity of optimizing non-cutting process, which could save energy consumption and non-cutting time.

In future, energy-saving optimization strategy of parts processing features still need to be studied deeply in industrial application. The intelligent method need to be used to integrate energy-saving optimization method into process formulation and G nodes for promoting the application of the high energy efficiency methods.

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Conflicts of interest/Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Authors' contributions

Chunhua Feng: Conceptualization, Methodology, Software, Validation, Writing-Original Draft, Funding acquisition. **Yugui Huang:** Investigation, Data Curation, Software. **Yilong Wu:** Investigation, Data Curation, Resources. **Jingyang Zhang:** Investigation, Data Curation, Resources.

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