ENERGY EFFICIENCY OPTIMIZATION OF MECHANICAL NUMERICAL CONTROL MACHINING PARAMETERS

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ABSTRACT: *In order to improve the energy efficiency of mechanical numerical control (NC) maching parameters, the main factors that affect the selection of process parameters are put forward first. Then, the energy efficiency optimization method of NC machining parameters is analyzed in detail. In addition,* ***optimization*** *test conditions of numerical control machining based on Taguchi method and multi-objective optimization model of NC machining parameters based on energy efficiency and time are discussed in detail. Moreover, the model is solved on the basis of particle swarm optimization. Finally, the energy efficiency optimization results of NC parameters are analyzed from three aspects. The results show that the proposed optimization method has a certain validity and feasibility and can provide a certain theoretical support for improving the energy efficiency of computer numerical control (CNC) machine tools.*

KEYWORDS: *Mechanical numerical control machining; process parameters; energy efficiency; optimization*

1 INTRODUCTION

The optimization of traditional process parameters is mainly based on the maximum profit, the highest production efficiency, the roughness and cutting force, and a large number of process parameter optimization methods have been accumulated(Li et al., 2015; Pare et al., 2015). With the improvement of energy saving awareness, some research on process parameter of CNC machining systems which consider energy consumption has been gradually appeared, and some progress has been made. At present, there are three kinds of research on energy saving optimization of CNC machining process: the first is to analyse the relationship between energy efficiency and process parameters (Sahoo et al., 2017). The second is that some scholars carry out the research on the energy efficiency optimization of the process parameters by building optimization model (Yıldız et al., 2017). The third method considers the difficulty of establishing the mathematical model of energy consumption. In order to simplify the cumbersome calculation process of formula, some scholars analyse process parameters and energy efficiency by design optimization experiment. The optimal combination of parameters is chosen or the optimization algorithm is used to further optimize the solution (Gulati et al., 2016).

To sum up, the research on the energy saving optimization of the process parameters in the process of NC machining is developing rapidly. Moreover, the third method with more literatures are selected from the experimental data to select the optimal combination (Goswami et al., 2017). However, the optimal solution may not be within the experimental combination. Moreover, the multiple targets are associated as an equation, and the interaction between the energy efficiency targets and the other targets and the process parameters is not very clear. The technology of energy efficiency optimization of NC machining system needs to be further deepened. The optimization rules need to be further explored and summarized.

2 METHODOLOGY

2.1 Analysis of the main factors affecting the selection of process parameters

The relationship between the process parameters and the independent variables and the non-independent variables is shown in figure 1.

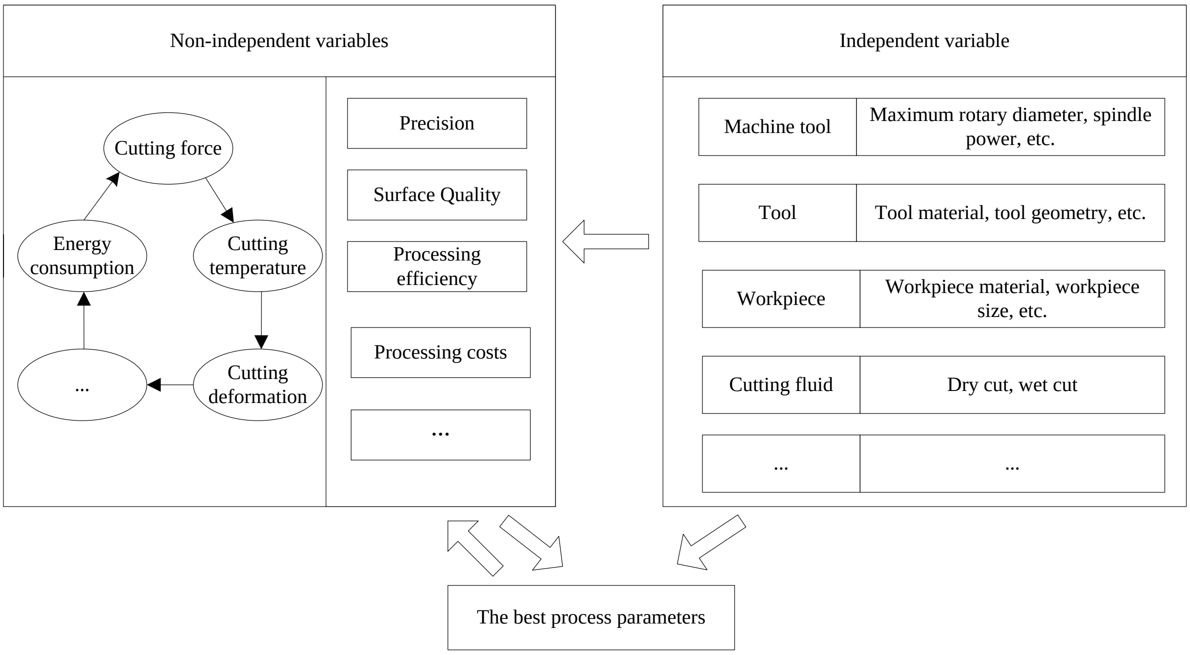

Figure 1. Analysis of CNC machining variables

The selection of process parameters is the most dynamic task in the actual processing, and it is not an independent decision making process. In general, the selection of process parameters is restricted by independent variables and non-independent variables. Independent variables are factors that can be controlled independently in the NC process without causing changes in other variables except themselves. In the NC machining process, it mainly refers to the machine tool, work-piece and cutting tool (Tiryaki et al., 2015). A non-independent variable is a factor that changes in response as independent variables change. The processing precision, the processing cost and the energy dissipation are the main processes (Krishna et al., 2015).

2.2 Energy efficiency optimization method for NC machining process parameters based on experimental data

According to the power curve, the composition characteristics of the energy consumption in each period of the NC machining are different. In order to establish the energy consumption model, the different kinds of power in each period need to be subdivided (Suresh et al., 2017). But in fact, if the NC machining system is regarded as black box problem, we only need to measure the total power of each period under different combinations of process parameters, so that we can avoid complicated power decomposition and get a more accurate relationship model between energy consumption and process parameters. The energy efficiency optimization method of process parameters based on experimental design takes the NC machining system as the core idea. This method has the characteristics of easy realization and high reliability. The optimal parameters can be obtained by selecting only small parts of the same batch as samples. It is especially suitable for mass production of parts.

In view of the Taguchi method, the test can be systematically planned and the optimal trend is pointed out by a few experiments. The response surface method can be used to associate the variables with the response equation in the case of the unknown two variables. The Taguchi method is used for the test, and the relationship between the energy efficiency of NC turning and NC milling process, as well as the processing time and the process parameters are analyzed respectively (Mandal et al., 2016). The multi objective optimization model, which takes the cutting parameters as the optimization variable and the energy efficiency and the regression equation of the processing time as the objective function, is established. The improved multi-objective particle swarm optimization algorithm is used to find the optimal solution. The specific method is shown in figure 2.

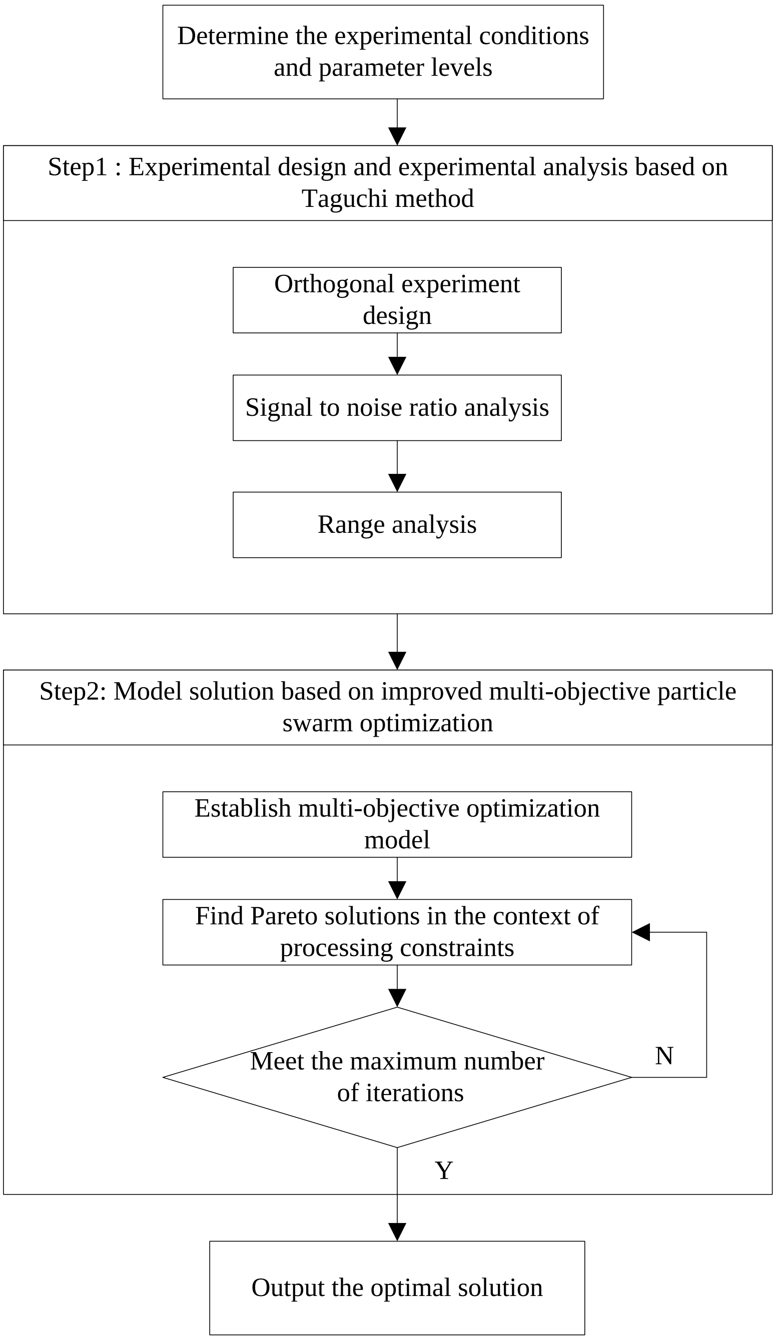

Figure 2. Flow chart of optimization method based on experimental data

2.3 Optimization test conditions of NC machining based on Taguchi method

The experimental research on the energy saving optimization of NC milling process parameters takes the milling plane of a part as an example. In the experiment, the numerical control milling machine of the Precise PL700 vertical machining center is used. The power of the main motor is 5.5/7.5Kw, and the spindle speed range is 40-6000r/min. The feed speed range is 2-15000mm/min, and the maximum tool diameter is 75mm. The work-pieces and processing methods are shown in table 1. The specific parameters of the integral milling cutter are shown in table 2.

Table 1. Workpiece and processing methods

Workpiece material	Workpiece length	Workpiece width	Milling method	Processing path
45# steel	70mm	12mm	Milling	“S”type

Table 2. Type of milling tool and its parameters

Tool material	Number of cutting edges	Cutting edge length	Tool diameter	Front corner	Clearance angle	Helix angle
High-speed steel	4	20mm	4mm	10°	15°	35°

The energy saving optimization of NC turning process parameters takes the outer circle of batch turning as an example. In the experiment, a CNC turning machine with a model of C2-360HK is used. The power of the main motor is 5.5Kw, and the spindle speed range is 180-1600r/min. The feed speed range is 1-6000mm/min. The maximum allowable diameter of rotation is 360mm. The information of the work-pieces and processing methods is shown in table 3. The specific parameters of the external circle tool are shown in table 4.

Table 3. Workpieces and processing methods

Workpiece material	Workpiece length	Workpiece diameter	Turning method
40Cr	64mm	30mm	Cylindrical processing

Table 4. Type of turning tool and its parameters

Tool material	Tool type	Tool rake angle	Cutter angle	Tool main declination	Arc radius of the tool
Carbide	Cylindrical turning	15°	10°	95°	0.4mm

2.4 Multi objective optimization model for NC machining process parameters

Variable optimization: In NC milling, specific energy and time objectives are mainly affected by the spindle speed n, feed per tooth *fz*, cutting depth and a_p and working engagement a_e. However, in NC machining, specific energy and time objectives are mainly affected by the cutting speed v_c, feed rate f and cutting depth a_p. Therefore, the four elements of milling and the three factors of turning are used as the optimization decision variables respectively.

Objective optimization: The specific energy regression model is used as the objective function of the milling process. The processing time regression model is used as the time objective function of the milling process. The specific energy regression model is used as the objective function of the turning process. The processing time regression model is used as the time objective function of the turning process.

Constraint condition: In the process of NC machining, the decision variables should meet the constraints of various processing conditions. According to the actual cutting process, the machine tools constraints, tool constraints and machining quality constraints are selected.

Machine tool constraint: Any cutting process needs to be carried out within the allowable range of the machine's rigidity, which is the main constraint to limit the processing.

$$\begin{cases} x_{min} < x_i < x_{max} (i = 1, \Lambda\ , n) \\ F_C < F_{max} \\ P_C = 60 F_c v_c < \eta P_{max} \end{cases} \quad (1)$$

In the formula, x_i is an optimized variable. F_{max} is a cutting force that is allowed by a machine tool. P_{max} is the rated power of the machine tool. η is the efficiency of the machine tool.

Tool constraints: The frequent knife change will affect the processing continuity and precision. Its constraints should meet the following expression:

$$T_{min} < T \quad (2)$$

In the formula, T_{min} is the lower limit of tool life.

Constraints of processing quality: Processing quality can also be used as an optimization goal. However, in the optimization of other functions, the quality of processing is the precondition of optimization. Formula (3) is used for plane milling, and formula (4) is used for turning.

$$R_a = 318 \frac{fZ}{tg(L_a) + ctg(C_a)} < [R_a] \quad (3)$$

$$R_a = \frac{31.25 f^2}{r} < [R_a] \quad (4)$$

In the formula, L_a is the front angle of the tool. C_a is the rear angle of the tool. [R_a] is the maximum surface roughness allowed by the work-piece. r is the radius of the cutter's arc.

To sum up, the mathematical model of the multi-objective optimization model of the process parameters in the NC machining process is as follows:

$$\min F = (\min T_P, \min SEC)$$

$$\begin{cases} x_{\min} < x_i < x_{\max} \\ F_C \leq FC_{\max} \\ P_C < \eta P_{\max} \\ T_{\min} < T \\ R_a < [R_a] \end{cases} \quad (5)$$

2.5 Multi objective particle swarm optimization algorithm based on cross method

The multi-objective particle swarm optimization (MOPSO) algorithm with high quality and good robustness is used to solve the multi-objective optimization model of NC milling process parameters. In the optimization solution process, all possible solutions within the feasible domain are considered as a position in the search space, that is, "particle". Each particle is characterized by three indicators: position, speed and fitness. In this case, each individual in the particle population represents a processing scheme for the optimization of NC milling process parameters. The fitness value is the target value of the specific energy and the target value of the processing time. Because the decision variables are the cutting elements, the decision variables for each processing scheme are stored in multidimensional space according to the different kinds of process. The best position it experiences is P_i. The best particle position in the group is recorded as P_{gb}. During the evolutionary process of particle, its speed and position are updated as follows:

$$\begin{cases} V_i^{k+1} = \omega \times V_i^k + c_1 r_1 (P_i^k - X_i^k) + c_2 r_2 (P_{gb}^k - X_i^k) \\ X_i^{k+1} = X_i^k + V_i^{k+1} \end{cases}$$

(6)

In the formula, ω is an inertia weight. r_1 and r_2 are the random numbers between [0,1]. c_1 and c_2 are learning factors. Although the particle swarm optimization algorithm has strong generality, it also has the disadvantages such as precocious convergence and low efficiency in later iteration. Based on this, the following two improved particle learning strategies are used in this paper.

The first is the adaptive inertia weight. The inertia weight adjustment strategy can better balance the global search and local search capability of the algorithm. When ω takes a larger value, the global search capability is improved. When ω takes smaller value, the local search capability is enhanced. In the current research, the inertial adjustment strategy is mainly divided into three kinds: linear decreasing strategy, nonlinear decreasing strategy and adaptive adjustment strategy.

The second is the cross method. After introducing the selective cross operation in the genetic algorithm, the algorithm jumps out the local optimal and speeds up the convergence speed. After improving the cross mechanism proposed by Lovbjerg and others, it is used in the solution of MOPSO. By using the optimal preservation strategy, the individuals with better fitness are retained in the next generation population at each operation. The key step of particle swarm optimization based on crossover is to classify all the particles in the population and calculate the crowding distance of each particle. The population is divided into two subgroups. Particles closer to the Pareto front and with a greater crowded distance are called particles with better fitness values. The next half particles are selected directly to the next generation, and the latter half of the particles are selected as the position of the random cross particles. In other words, the corresponding process parameters in the process parameter scheme represented by two particles are interchanged to execute the cross particle generation. The cross between the parent particles and the progeny particles is compared. Half of the particles with high fitness value enter the next generation. The overall algorithm flowchart is shown in figure 3.

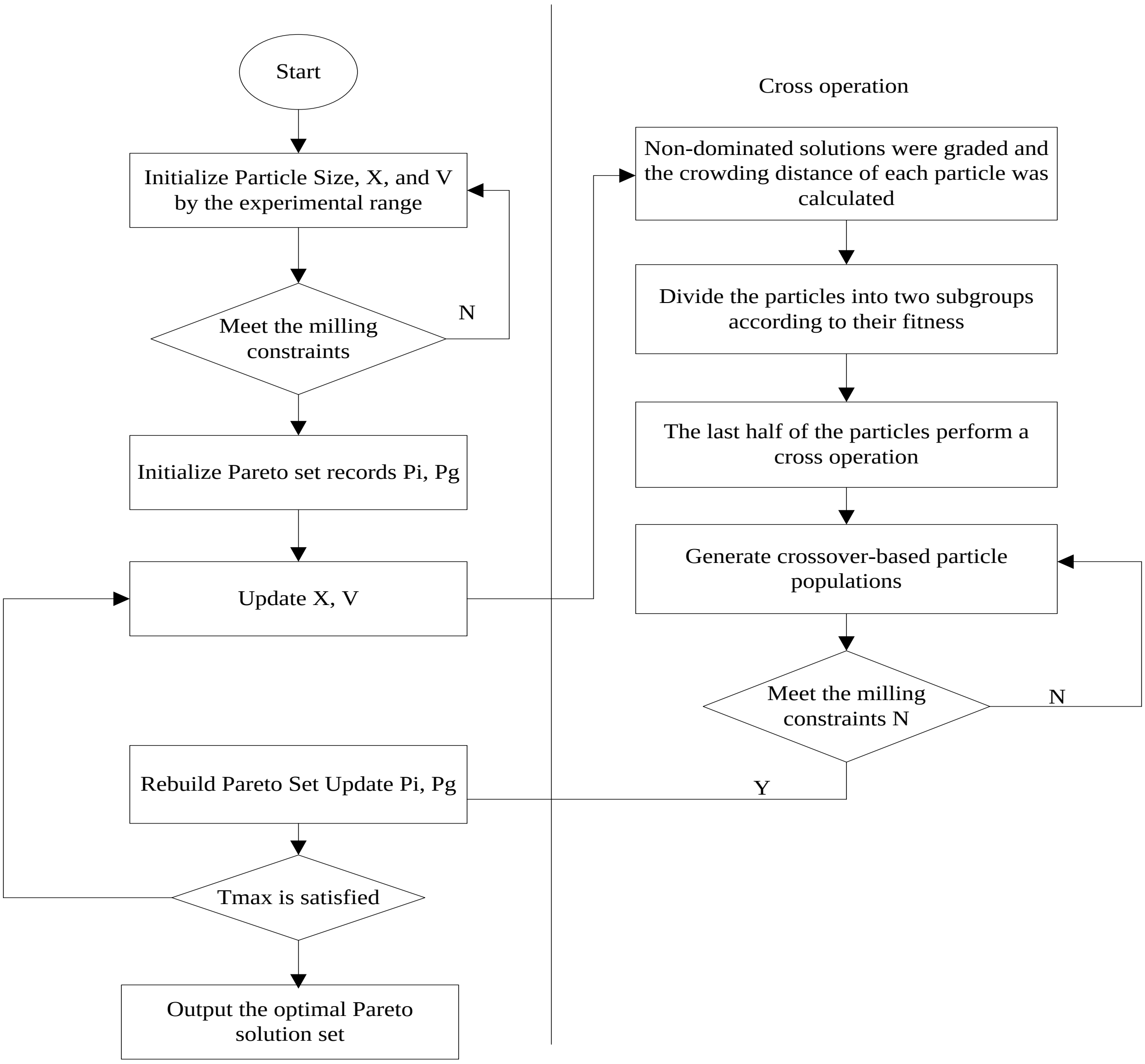

Figure 3. Flow chart of the MOPSO algorithm based on cross operation

3 RESULTS AND DISCUSSION

3.1 Results and analysis of energy efficiency optimization of NC processing parameters based on experimental data

The basic parameters are adjusted as follows: The value of learning factors c_1 and c_2 is 1. The values of the inertia weight ω_{max} and ω_{min} are 0.2 and 0.6. The number of population is 80. The number of iterations is 100. The speed Vmax and Vmin are 1.5 and -1.5, respectively. The Matlab programming is used to solve the model. Figure 4 shows the convergence of the algorithm when it reaches the 70th generation. The solid line part is the convergent frontier of the improved algorithm proposed in this paper. The dotted line is the convergent frontier of the standard particle swarm optimization algorithm. It can be seen from the graph that the convergence speed of the optimization algorithm is faster and the convergence edge is closer to the real Pareto frontier after the improved strategy.

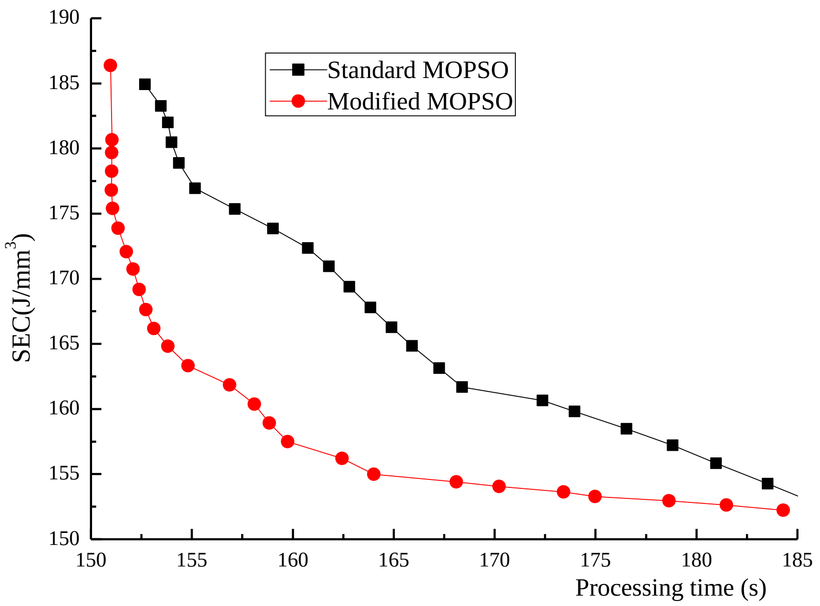

Figure 4. The convergence of algorithm

The multi-objective particle swarm optimization and the single target particle swarm optimization are used to solve the optimization model. There are 6 kinds of optimization schemes: SECdir+indir&Tp $SEC^{dir+indir}$&T_p.

Scheme 1: A multi-objective optimization scheme with SEC^{dir} and processing time as the optimization target;

Scheme 2: A multi-objective optimization scheme with $SEC^{dir+indir}$ and processing time as the optimization target;

Scheme 3: A single objective optimization scheme with SEC^{dir} as the optimization target;

Scheme 4: A single objective optimization scheme with $SEC^{dir+indir}$ as the optimization target;

Scheme 5: A single objective optimization scheme with the processing time as the optimization target;

Scheme 6: The skilled operator gives the experience process parameters on the spot.

3.2 Optimization results of milling process parameters

The results of the six process parameters are summarized in table 5.

Table 5. The optimization results for milling parameters

Types	N(r/min)	f_z(mm/t)	a_p(mm)	a_e(mm)	T_p(s)	SEC^{dir}	$SEC^{dir+indir}$
Scheme1	3486	0.0266	0.384	3.965	162.25	150.01	6220.15
Scheme2	2668	0.0260	0.375	3.965	154.49	160.02	5248.03
Scheme3	4190	0.0261	0.493	3.980	178.67	149.02	6734.16
Scheme4	2210	0.0254	0.493	3.980	171.65	168.08	4932.2
Scheme5	3156	0.0257	0.294	3.901	150.94	173.05	7020.2
Scheme6	2489	0.02	0.23	3	189.2	186.5	9684.6

Comparing milling optimization scheme one and scheme two, it shows that when SEC^{dir} and processing time are selected as optimization objectives, although the SEC^{dir} value is 0.7% higher than the SEC^{dir} that is optimized alone, the time value is reduced by 8.7%. Similarly, the first scheme is compared with the fifth scheme, though the time value of NC milling process parameter is 8.1% higher than single optimization processing time, the SEC^{dir} value is reduced by 14.1%.

The problems that the optimized technological parameters of the SECdir target are higher, the tool life is shorter and the tool shared in a certain process has more energy are considered. As a result, the third scheme is 8.2% higher than the $SEC^{dir+indir}$ in first scheme. The technical parameters formulated by the operator are more conservative. Because the value of the process parameters is small, the energy consumption of the machine tool is increased during the cutting period. Therefore, both time and specific energy are higher. Compared with the experience parameter scheme, the processing time value of the optimization scheme one is reduced by 13.9% and the SEC^{dir} value is reduced by 19.4%.

Compared with the scheme two and scheme four in milling optimization, it shows that when $SEC^{dir+indir}$ and processing time are selected as the optimization objectives, although the $SEC^{dir+indir}$ value is 6.4% higher than the $SEC^{dir+indir}$ that is optimized alone, the time value is reduced by 10.4%. The comparison between scheme two and scheme five shows that the time value is 2.4% higher than the NC milling process parameter optimized by single processing time, but the $SEC^{dir+indir}$ value is reduced by 25.2%. after comparing the scheme one and scheme two, it shows that the ratio of the indirect energy consumption can be influenced by the internal energy of the tool, and the process parameter is smaller than the optimization scheme one. However, compared to the values of the two specific energy, although the SEC^{dir} of the scheme two is 9.1% higher than the scheme one, the $SEC^{dir+indir}$ value is reduced by 15.7%. Therefore, the energy efficiency multi-objective optimization, considering the indirect energy consumption, can greatly reduce the generation of indirect energy consumption in the processing process. Therefore, the energy efficiency of the NC machining system has achieved the effect of energy saving and emission reduction.

3.3 Optimization results of processing parameters in turning

The results of the six process parameters are summarized in table 6.

Table 6. The optimization resultsfor turning process

Types	v_c(m/min)	f(mm/r)	a_p(mm)	T_p(s)	SEC^{dir}	$SEC^{dir+indir}$
Scheme1	70.53	0.196	1.161	94.30	10.65	25.10
Scheme2	46.56	0.184	1.142	90.75	11.42	19.64
Scheme3	78.52	0.197	1.244	109.74	9.40	28.44
Scheme4	41.14	0.186	1.254	104.82	12.56	17.75
Scheme5	68.40	0.195	0.751	87.30	14.30	29.03
Scheme6	36.86	0.148	0.6	116.85	17.30	34.62

The optimized combination result of turning and milling at each target shows that the results of turning and milling are basically the same. Compared with the scheme one and scheme three, when optimizing the processing parameters of SEC^{dir} and processing time, the SEC^{dir} value is 13.2% higher than SEC^{dir} that is optimized alone, but the time value is reduced by 14.1%. Similarly, compared scheme one with scheme five, the processing time value of the scheme one is 8% higher than the scheme five, but the SEC^{dir} value is reduced by 13.5%. Compared with turning scheme two and scheme four, when $SSEC^{dir+indir}$ and processing time are taken as optimization objectives, the $SEC^{dir+indir}$ value is 10.6% higher than $SEC^{dir+indir}$ that is optimized alone, but the time value is reduced by 13.4%. In scheme two, compared with the scheme five with the single processing time, although the time value is increased by 3.9%, the $SEC^{dir+indir}$ is reduced by 32.3%.

Because the target function of scheme two considers the internal energy consumption of the material, the selection of the process parameters is lower than the scheme one. At this time, MRR is located in the region two, and the processing time increases with the increase of MRR. Although the SEC^{dir} of scheme two is 7.1% higher than the scheme one, both time and $SEC^{dir+indir}$ have been reduced. The time is reduced by 3.8%, and $SEC^{dir+indir}$ is reduced by 21.8%. When the processing time requirement is not severe, the energy efficiency and multi-objective optimization plan considering indirect energy consumption is better than energy efficiency and multi-objective optimization without considering direct energy consumption. Compared with the experience parameter scheme, the processing time value of the optimization scheme is reduced by 22.3% and the $SEC^{dir+indir}$ value is reduced by 42.3%.

The optimized results of milling processing show that the proposed method can balance the two target. Thus, the optimization results are coordinated between time and energy efficiency targets. The choice of multi-objective energy efficiency optimization is superior to the single pursuit of the highest energy efficiency or the lowest time in the cutting process. In addition, from the energy loss of the NC system, the multi-objective optimization process of indirect energy efficiency is considered Because of the energy consumption in the process of direct and indirect energy consumption, the effect of energy efficiency and emission reduction is improved compared with the result of energy efficiency multi-objective optimization which considers the direct energy consumption.

In order to further explain the optimization results, the test data in the case are drawn and the trend lines are added. The time analysis of the NC machining process is shown in figures 5 and figure 6. The analysis of energy consumption is shown in figure 7.

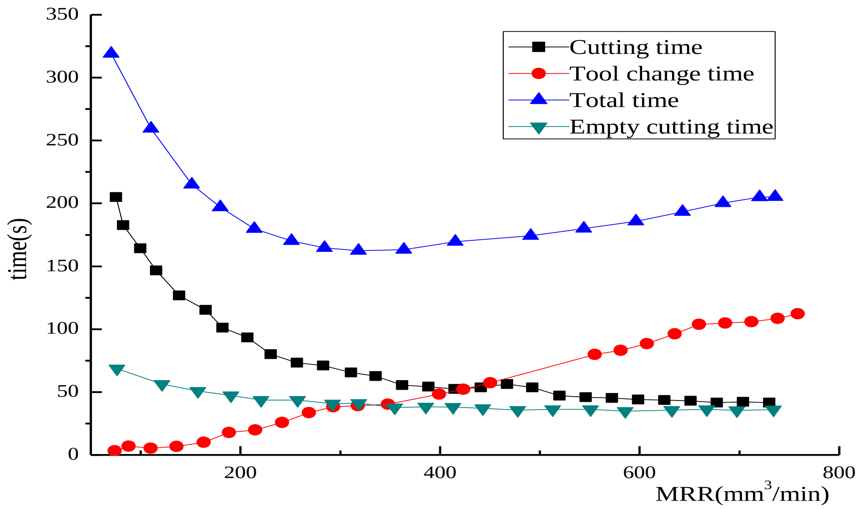

Figure 5. Time as a function of MRR for milling case

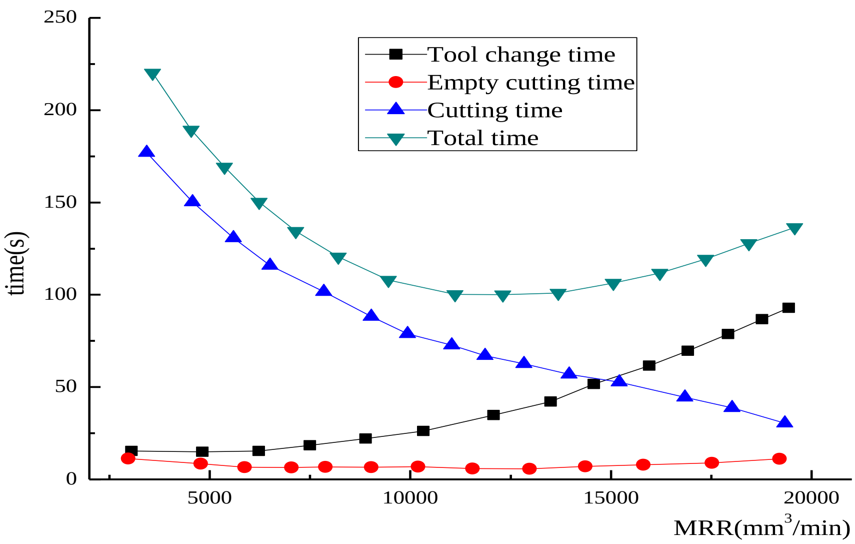

Figure 6. Time as a function of MRR for turning case

Figure 5 and figure 6 show the changing trend of the total time, cutting time, knife change time and space cutting time with MRR in NC milling and NC turning. The comparison trend line shows that the changing rule of time with MRR is more consistent whether it is NC milling or NC turning. The time of each part is analyzed one by one: According to the graph, the proportion of air cutting time to total time is the smallest, and the air cutting time of NC milling decreases with the increase of MRR. The air cutting process consists of two parts. One is the time from cutting point to the edge of the workpiece, and the other is the cutting time that the tool exceeds the workpiece contour during the cutting process. In order to improve the processing efficiency, the operator avoids the larger air cutting path as far as possible when designing the tool path. Therefore, the air cutting time is very short. The total processing time is mainly influenced by the cutting time and the changing time. It can be seen that when the tool path length is fixed, the cutting time decreases with the increase of MRR. However, the changing time is mainly controlled by the tool life. When the MRR is larger, the tool wear is aggravated and the tool life is shorter. At this time, the changing time is the main factor affecting the processing time. Therefore, the total time is gradually rising after the B point. Comparing with the above figure, it shows that NC cutting has larger cutting rate, higher tool wear and shorter tool life than NC milling, and the trend of total time is more obvious.

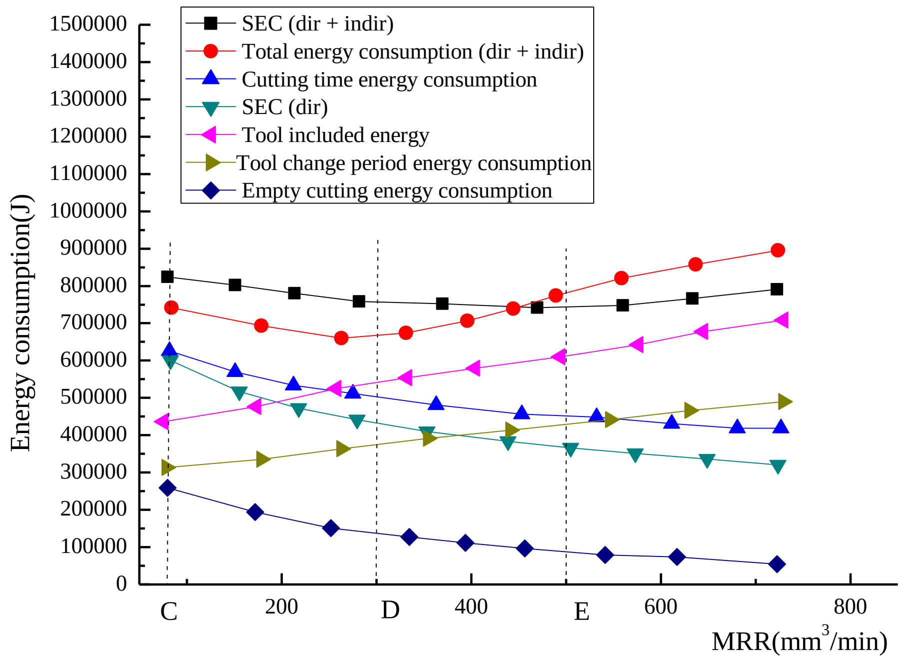

Figure 7. SEC as a function of MRR for milling case

Figure 7 shows the trend of total processing energy consumption, cutting energy consumption, knife exchange energy consumption and no-load energy consumption, and the increase of tool internal energy with the increase of material removal rate. When the material removal rate is small, the energy consumption decreases with the increase of the material removal rate. However, with the increase of MRR, the trend gradually weakens until it becomes constant. Therefore, the total processing energy consumption is mainly influenced by the cutting energy consumption, the energy consumption of the cutter and the internal energy of the tool.

From the point C to point D, the cutting energy consumption decreases significantly with the increase of the cutting time because of the sharp cutting time. Although the energy consumption of the cutter and the internal energy of the tool have a certain rising trend, the total energy consumption is mainly controlled by the cutting energy consumption. After it is over D point, as the MRR continues to rise, the decreasing trend of cutting energy consumption becomes slow. In this area, although the MRR increases, the cutting time decreases. The increase of the cutting area leads to the larger deformation force and friction force, and the cutting force increases. Therefore, the cutting energy consumption is not as severe as before.

From point D to point E, the tool wear and the tool changing time increase because of the higher MRR. Therefore, the energy consumption of the cutter increases exponentially. In addition, the sharp increase in the internal energy consumption of the tool makes the total energy consumption increase obviously. Although the total energy consumption increases with MRR during this period, SEC^{dir} and $SEC^{dir+indir}$ are still declining. When MRR increases to point E, $SEC^{dir+indir}$ is down to the lowest. Since then, the influence of the $SEC^{dir+indir}$ on the internal energy of the tool has an obvious upward trend.

3.4 Signal to noise ratio analysis and range analysis

The difference analysis in the specific energy of the NC turning is shown in table 7.

Table 7. Range analysis for SEC in CNC turning process

Level	v_c(r/min)		f(mm/r)		a_p(mm)	
	SEC^{dir}	$SEC^{dir+indir}$	SEC^{dir}	$SEC^{dir+indir}$	SEC^{dir}	$SEC^{dir+indir}$
1	-23.32	-23.68	-24.45	-28.39	-24.25	-29.23
2	-22.85	-26.18	-22.75	-27.65	-23.01	-27.81
3	-22.73	-33.58	-21.73	-27.38	-21.65	-26.40
Extremely poor	0.6	9.87	2.72	1.00	2.60	2.80
Ranking	3	1	1	3	2	2

As shown in the table, in the processing conditions, the parameter effect of SEC^{dir} CNC turning process is the cutting depth, feed rate and cutting speed according to the effect of the size of the order. The process parameters of $SEC^{dir+indir}$ NC turning process is cutting speed, cutting depth and feed rate according to the effect of the size of the order. Among them, the feed rate has the greatest effect on the time target in the process of CNC turning, followed by the cutting speed and cutting depth. Therefore, when the optimization target is SEC^{dir} and the processing time, the larger feed rate and medium cutting speed can be selected to control the cutting depth. When the optimization target is $SEC^{dir+indir}$ and the processing time, the larger feed rate and moderate-to-low cutting speed can be selected to control the cutting depth.

4 CONCLUSION

In the study, the main factors that affect the selection of process parameters are analyzed. Then, the energy efficiency optimization method of NC machining process parameters based on the experimental data, the experimental conditions of energy saving optimization based on Taguchi method, and the multi-objective optimization model of NC machining process parameters and the solution model of multi-objective particle swarm optimization algorithm based on crossover method are proposed. After introducing the related model method, the results of the energy efficiency optimization of the numerical control process parameters are analyzed. The optimization results of the milling process parameters, the optimization results of the turning process parameters and the SNR analysis and range analysis are discussed. The results show that the proposed optimization method has a certain validity and feasibility and can provide a certain theoretical method for improving the energy efficiency of CNC machine tools.

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