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Multiobjective optimization of machining center process route: Tradeoffs between energy and cost

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Process route planning is vital for implementing energy saving and low-cost production in mechanical processing as it can directly affect the energy consumption and the cost of mechanical product processing. Therefore, a multiobjective optimization approach of machining center process routes to realize energy saving and low-cost mechanical processing is proposed in this paper. To provide theoretical support for this study, process route optimization problems of a machining center are analyzed, the concept of workstep element is introduced to represent the features of machined parts, and a multiobjective optimization model is established. The optimization model is solved based on the combination of a workstep chain intelligent generation algorithm and a non-dominated sorting genetic algorithm II. Finally, the emulsion pump case process route is used as a case study to verify the feasibility and practicability of the proposed method. Comparison with actual data shows that with the single objective of energy consumption and processing cost, based on the multiobjectives of energy saving and low cost as the optimization goal, the energy consumption was 1.018×10^7 J, and the processing cost was CNY32.65. Compared with the other two experimental results, the energy consumption and the processing cost demonstrated the best comprehensive performances, consistent with energy saving, low cost and sustainable production, thereby validating the established model. Furthermore, the optimization analysis shows that the combinatorial optimization algorithm has a better solution speed and optimization precision than the general genetic algorithm.

1. Introduction

With the severity of resource consumption and environmental pollution problems increasing in recent years, the green manufacturing mode characterized by “high energy efficiency, low pollution, and low emission” has become the focus of the manufacturing industry (Zhai and An, 2020). According to statistics, in 2018, industrial energy consumption constituted approximately 70% of China’s original energy consumption, whereas manufacturing constituted approximately 85% of China’s industrial energy consumption (Wang et al., 2019). Serious environmental pollution accompanies the energy consumption of the manufacturing industry (Cai et al., 2019). The traditional manufacturing process consumes a significant amount of energy and results in serious environment pollution. For instance, the energy consumption of a steel blank constitutes approximately 16.1%, whereas waste water, sulfur dioxide, and solid waste constitute approximately 8%, 8% and 16% of the industry, respectively (Lu et al., 2015). Evidently, traditional machining methods do not satisfy the demand of sustainable development (Ai et al., 2019). Over the lifetime of a product, six stages are involved: product planning, product design, product production, product transportation, product use, and product recycling (Du et al., 2015). Environmental pollution and resource consumption accompany each stage. However, in product processing, resource consumption and environmental pollution are the most serious issues; in addition, product recycling is in fact product reprocessing. Hence, in the last few decades, studies

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Nomenclature

a_e	the processing width (mm)
a_p	the processing depth (mm)
α	the labor cost per unit time (RMB)
β	the tool cost (RMB)
η	the efficiency of the machine tool
α	the feed speed of the tool $(mm/\min)$
f_z	the feed per tooth (mm)
λ_1	energy consumption weighting coefficient
λ_2	cost weighting coefficient
v_c	the processing speed (mm/s)
$v_{f\min}$	the minimum feed speed $(mm/\min)$
n	the spindle speed $(r/\min)$
AHP	Analytic Hierarchy Process
ANFIS	adaptive network-based fuzzy inference system
C_p	the average cost of processing (RMB)
$\overline{C_p}$	the normalized of cost objective function (RMB)
E_a	additional load energy consumption (KJ)
EA	the total energy absorption rate
E_c	cutting energy consumption (KJ)
E_d	tool change system energy consumption (KJ)
E_e	the total energy consumption (KJ)
$\overline{E_e}$	the normalized of energy consumption
E_o	auxiliary energy consumption (KJ)
E_s	machine tool generalized energy storage (KJ)
E_t	worktable rotation energy consumption (KJ)
E_u	no-load energy consumption (KJ)
F_i	the processing feature corresponding to the workstep
FLB	front longitudinal structural internals blank
ICA	imperialist competition algorithm
L	the part processing length (mm)
L_i	the path length of the tool (mm)
N_i	the workstep number
$N_{\min}$	the minimum speed allowed $(r/\min)$
NC	numerical control
NSGA-II	non-dominated sorting genetic algorithm II
P_{ui}	the no-load power of workstep (kW)
P_i	the processing method corresponding to the workstep
PRO	process route optimization
R(i)	the constraint vector
St_i	the workstep of the workpiece
T_i	the tool used in the i-th workstep
T_{ci}	the effective cutting time of workstep (s)
T_m	the processing time (s)
T_c	the effective processing time (s)
T_d	the tool change time (s)
T_o	the auxiliary processing time (s)

targeting green environmental protection and energy saving in product processing have gradually increased(B. H. Peng et al., 2019).

The process route governs the entire machining process from blanks to parts, thereby significantly affecting the energy consumption, processing efficiency, processing cost, processing quality, and other business objectives. Process route optimization is vital for improving production efficiency, reducing production cost, minimizing energy consumption, and increasing system flexibility (Chirag et al., 2019). In the past few decades, the multi-objective optimization of process routes has always been a hot issue for enterprise process designers and university researchers. A series of advanced multi-objective optimization algorithms have been developed for multi-objective optimization problems. Artificial neural network optimization, multi-objective particle swarm algorithm, ant colony algorithm, imperialist competition algorithm, NSGA-II, etc. Among these multi-objective optimization algorithms, NSGA-II is currently one of the most popular multi-objective genetic algorithms. It reduces the bad sort genetic algorithm complexity, with running speed, the convergence of solution set good advantage, becomes the benchmark of performance of other multi-objective optimization algorithms.The machining center is the main body of the flexible manufacturing system, and its energy consumption is a complex multidimensional problem. In the actual machining process of parts, energy consumption is related to many factors, including the characteristics of machine tools, process parameters, tool path, tools, processing environment, and other factors. However, in the process decision making stage of an actual production, it is not realistic to achieve energy saving production by changing the structure of the machine tool. Furthermore, the selection of reasonable processing methods is restricted by the conditions of the machine, whereas optimization is not significant (Yan et al., 2017). As an essential decision object in parts processing, the process route has strong operability and determines the production efficiency significantly; furthermore, the processing cost and workpiece quality are main influencing factors of electric energy consumption in the cutting process. Therefore, processing energy consumption and processing cost were used as optimization objectives in this study. Furthermore, a multiobjective optimization model was established to select the optimal process route such that manufacturing enterprise operators can make more informed process route decisions.

2. Literature review

This section comprises three parts. The first two parts introduce the two most typically used methods in energy saving optimization research and provide an evaluation analysis. The third part combines the research status and research gaps of the first two parts, introduces the research methods of process route optimization, evaluates the latest research results and existing problems of process route, and describes the research framework proposed herein.

2.1. Structure optimization design

The structure design of the product significantly affects the energy consumption, which can directly affect the selection of process route for operators. Dimension is the geometric representation of a product structure. Therefore, the shape of products must be optimized to achieve energy saving optimization. Feng et al. (2018) proposed a synthetical approach for the lightweight design of rough automotive structures, with total energy absorption rate and total weight as optimization indicators to improve the economic benefits of a product. Kitayama et al. (2016) proposed a response surface method to obtain the optimal product shape using a simplified process route. Li et al. (2020) studied the complex automobile shell structure, where the ant colony algorithm was applied to design the desired surface structure and more selections were available for the optimized process route. Yang et al. (2020) developed the structural optimization of the PCHE model and performed a comparative analysis regarding the relationship between design variables and target parameters. They discovered that the optimized structure had better processing parameters and required less processing energy. Based on the analysis above, studies regarding product structure optimization design oriented toward energy consumption optimization have garnered significant attention. However, the current product structure optimization design focuses on model simulation and theoretical modeling, where the constraints of processing equipment, processing auxiliary tools, etc. in the specific production process of products cannot be fully considered. Additionally, the specific energy consumption optimization value in the processing process cannot be effectively quantified, thereby increasing the computational complexity. Hence, the processing energy consumption in specific processing processes must be further optimized.

2.2. Process parameters optimization

The energy consumption in the actual processing of parts is related to many factors, including the characteristics of the machine tool, process parameters, tool path, tools, processing environment, and other factors. Therefore, the energy consumption changes dynamically with the processing process. Tian et al. (2019) proposed a cutting parameter optimization method considering the wear condition of the tool. They established a multiobjective optimization model of cutting parameters to determine the best cutting parameters and tools as well as adopted the modified NSGA-II algorithm to solve the optimization model. Li et al. (2019) developed a multiobjective NC milling parameter optimization method for NC machining, in which the low energy consumption and high processing efficiency are regarded the optimization objectives; subsequently, they performed a comparative analysis regarding the effects of parameters on energy consumption and efficiency. According to Ma et al. (2020), the current milling process optimization method is generally not applicable to the complex cutting parameter time-varying dynamic process; therefore, they introduced an instantaneous cutting condition and proposed a parameter optimization method for complex end milling, where the processing time and output were reduced. According to time and energy consumption problems in industrial process planning, Tian et al. (2011) proposed a new energy analysis method. They created a multiobjective optimization model and used a hybrid intelligent optimization algorithm combining fuzzy simulation, neural network, and genetic algorithm to solve the expected value model. Experiments show that the hybrid optimization algorithm is superior to the single algorithm in terms of precision and efficiency. Xu et al. (2020) constructed an adaptive intelligent model to estimate tool wear using a neurofuzzy reasoning system using improved particle swarm optimization. The method was proven to be a new intelligent model that can monitor tool wear in real time. However, from the literature review above, most of the specific energy consumption and process parameter quantitative models adopted data statistics, which cannot objectively reflect the effect of the actual operation. Hence, accuracy may not be guaranteed.

2.3. Process route optimization

Process route planning directly affects the energy consumption, processing efficiency, and cost of a workpiece. An unreasonable process route design will significantly increase the manufacturing cost and reduce the economic benefits of processing equipment. In recent decades, the planning and decision making of process routes have become a popular topic amongst process designers. Reasonable process planning is the main approach for ensuring the smooth processing of products (Jiang et al., 2016).H. Peng et al. (2019) used the fault tree analysis method to extract the feature factors of gear blanks and applied a relevant algorithm to optimize the gear blank processing process route. Furthermore, an ecological benefit-oriented process route was proposed, which improved the speed and efficiency compared with the traditional process route. Deng et al. (2019) studied process route optimization, regarded the shortest processing time (high efficiency) as the optimization goal, and conducted case verification on a refining car box. Compared with the traditional process route, this method requires a shorter processing time. Krishna et al. (2006) proposed a new heuristic ant colony algorithm to search for the global optimal process route and then constructed the optimal objective function model and verified it. The model proved to be more efficient and faster. Salehi et al. (2009) proposed a two-level planning approach for process route planning. The initial stage is to establish an optimized operation sequence and then match feasible operation resources (including tools and machine tools) for each operation sequence. Finally, the optimization iteration of the genetic algorithm is used to generate the optimal process plan. Lian et al. (2012) developed an imperialist competition algorithm to solve the process planning problem, in which a low processing cost was regarded as the goal. He et al. (2015) regarded a production workshop as the object, proposed an energy saving method for a mechanical system by selecting the appropriate processing machine tool and reducing its idle time, all of which facilitated the investigation into the energy saving and optimal operation method. Zhou et al. (2018) constructed a multiobjective model to optimize a low-carbon-based process route optimization method, which quantifies the carbon emissions of each processing workstep and determines the minimum carbon emissions and processing time as the objective to optimize the process route through process bill of material(PBOM).

Based on the review above, two research gaps can be identified. First, most of the studies above used the traditional single objective model, such as energy consumption or processing time, to optimize the process route, whereas the multiobjective tradeoff between energy consumption and cost was not emphasized. Second, studies regarding energy reduction for machining centers are rare. Hence, this study attempts to fill these gaps. Fig. 1 shows the framework of this study.

First, the current research methods and deficiencies pertaining to energy saving optimization are reviewed critically, and the current research gaps are discussed. Based on literature review, a multiobjective optimization approach to achieve energy saving and low cost for machining center process routes is proposed.

Second, to realize the energy saving optimization of the process route of the machining center, a multiobjective optimization model was constructed. By analyzing factors that affect the process route, the concept of workstep element was introduced to construct the energy consumption object function and the cost function. The constraints in the actual machining process were analyzed, and a linear weighting method was introduced to develop a multiobjective linear optimization model.

Third, a combinatorial optimization algorithm based on the combination of the workstep chain intelligent generation algorithm and NSGA-II was applied to optimize the model; all feasible workstep chains were initially selected by creating priority constraints, and then NSGA-II was adopted to search and optimize feasible workstep chains.

Fourth, an emulsion pump case is presented to verify the feasibility of the proposed approach. The combinatorial optimization algorithm was used to obtain the optimal solution of the constructed multiobjective optimization model. To verify the practicability of the model, it was compared with the single objective optimization model. Moreover, to verify the superiority of the combinatorial optimization algorithm, it was compared with

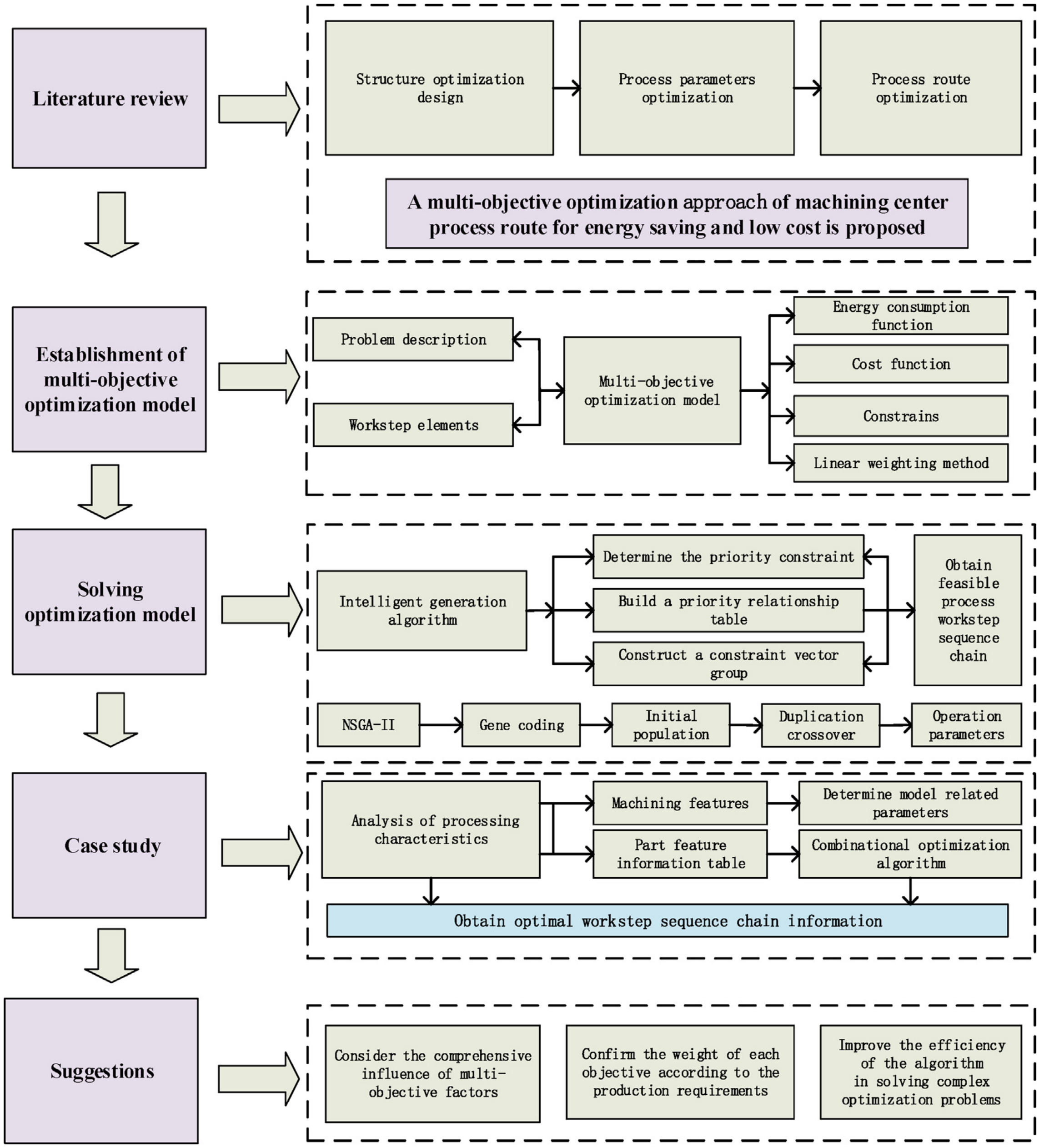

Fig. 1. Overall research framework.

the traditional genetic algorithm.

Fifth, a retrospective summary of this study is presented to comprehensively discuss the existing problems and limitations of this study, and future studies are proposed.

3. Establishment of multi-objective optimization model of process route

This section focuses on energy saving and low cost in the manufacturing process of the machining center, the two objectives the minimum energy consumption and minimum machining cost are considered as the optimization objects, and establishes a multiobjective optimization model. The detailed process is shown in Fig. 2. In general, the establishment of multiobjective optimization model process can be categorized into five steps.

Step 1: Determine the optimization goal of the model.
Step 2: Analyze the constraints of the machining center equipment performance, tool life, and other factors.
Steps 3 and Step 4: Construct the energy consumption objective function and cost objective function.
Step 5: To facilitate the optimization solution, the constructed multiobjective function is transformed into a single objective using the linear weighting method, and the final multiobjective optimization mathematical model is generated.

3.1. Problem description

The process route sequencing problem of the machining center is affected by many factors, including the workpiece characteristics, machining methods, tool selection, and machining process

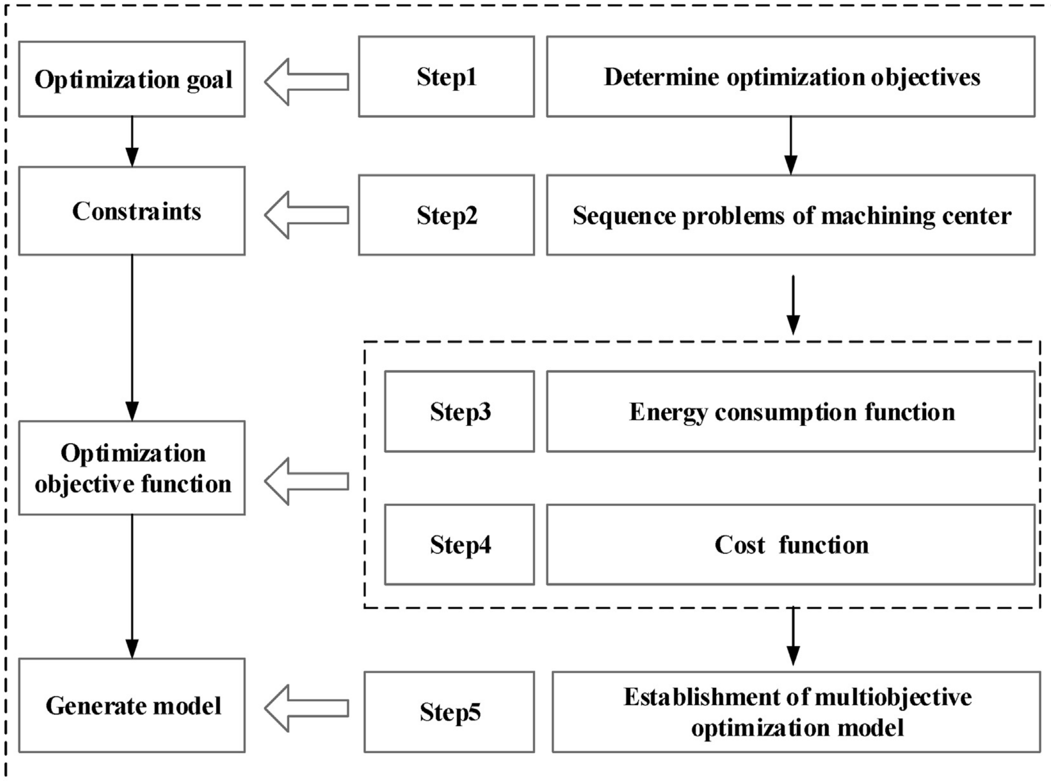

Fig. 2. Multiobjective optimization modeling flow chart of process route.

constraints; therefore, the problem is complicated (Ouchida et al., 2016). The basic idea of machining center process route sequencing is to reasonably arrange the processing worksteps of the workpiece. To facilitate the description of the optimization and decision-making problem of machining worksteps, the concept of machining workstep element is proposed to describe the features of the processed parts. The processing information contained in each workstep is defined as the workstep element, which is composed of the workstep number, processing characteristics, processing method, tool orientation, and machining plane. The introduction of the workstep element can effectively regard the processing route as a set of workstep elements, and each workstep element in the set contains detailed feature information. Through the analysis of each workstep element, researchers can perform a better in-depth analysis of the processing route optimization. Therefore, the workstep element can be expressed as Eq (1):

$$St_i = (N_i, F_i, P_i, T_i, D_i) \tag{1}$$

Where, St_i is the i workstep of the workpiece, N_i is the workstep number, F_i is the processing feature corresponding to the i-th workstep, P_i is the processing method corresponding to the i-th workstep, T_i is the tool used in the i-th workstep, $D_i$is the azimuth plane where the i-th workstep is located. Subsequently, $G = \{St_1, St_2, ..., St_n\}$ is defined as the set of worksteps of a workpiece. Therefore, the process route of the workpiece can be represented by Eq (2):

$$X = \left\{St_i, St_j, ..., St_k\right\} \tag{2}$$

Where, X is the sequence of worksteps from St_i to St_k, i.e., $\{St_i, St_j, ..., St_k\} = \{St_1, St_2, ..., St_n\}$. When all the worksteps are arranged according to certain constraints, the decision-making model of the workstep sequencing is completed.

Additionally, the machining center sequencing planning decision must adhere to the related sequencing constraint principles. For the different constraints, the constraint set can be categorized into mandatory and priority constraints. In the planning decision-making of an actual production process, the constraints between the processing surfaces of the workpieces and the various processing methods are analyzed. The abovementioned constraint principles must be considered in the process workstep optimization of machining centers based on the constraint principles, and the related machining operations should be performed systematically. The mandatory constraints are constraints that must be satisfied in the sorting process, which include the following: rough-then-refine, face-first-hole, and benchmark first. The priority constraints are constraints that should be satisfied as much as possible in the sorting process, including minimizing the number of workbench indexing and minimizing the number of machine tool changes. Therefore, the optimization of machining center sequencing can be regarded as the optimization of applying the priority constraint relationship between machining processes to the machining process set sequentially, which yields the optimal value of the workstep function under the order of certain constraints.

3.2. *Energy consumption function*

The total energy consumption of machine tool in machining center mainly consists of cutting energy consumption E_c, no-load energy consumption E_u, additional load energy consumption E_a, tool change system energy consumption E_d, worktable rotation energy consumption E_t, machine tool generalized energy storage E_s and auxiliary energy consumption E_o (Altıntaş et al., 2016). As the generalized energy storage and other auxiliary energy consumption of machine tools are very little affected by process sequencing, this paper takes it as a fixed value Q, $Q = E_s + E_o$. Therefore, the total energy consumption E_e can be expressed as Eq (3):

$$E_e = E_c + E_u + E_a + E_d + E_t + E_s + E_o \tag{3}$$

The cutting energy consumption E_c is the useful work produced in the process of part processing, which can be represented by Eq (4).

$$E_c = \sum_{i=1}^{n} P_{ci} \times T_{ci} \tag{4}$$

Where, n is the number of worksteps required to complete the part processing, P_{ci} is the cutting power of workstep i. T_{ci} is the effective cutting time of workstep i.

The total energy of machine tool transmission system E_L is composed of no-load energy consumption E_u and additional load energy consumption E_a. The expression can be express as Eq (5):

$$E_L = E_u + E_a = \sum_{i=1}^{n} P_{ui} T_{ui} + b \sum_{i=1}^{n} P_{ci} T_{ci} \tag{5}$$

Where, P_{ui} is the no-load power of workstep i, T_{ui} is the time consumed from the end of workstep $i-1$ to the completion of workstep i. The expressions of energy consumption E_d and E_t in this stage are as Eq (6) and Eq (7):

$$E_d = \sum_{i=1}^{n-1} P_d \times T_d \times \sigma(T_i, T_{i+1}) \tag{6}$$

$$E_t = \sum_{i=1}^{n-1} P_t \times T_t \times \sigma(D_i, D_{i+1}) \tag{7}$$

Where, T_d and T_t are respectively the waiting time of the machine tool under the condition of tool change and rotation; P_d and P_t are respectively the power of the motor for tool change and the motor for table rotation. T、D is tool code and orientation code.

$$\sigma(X_i, X_{i+1}) = \begin{cases} 1, X_i \neq X_{i+1} \\ 0, X_i = X_{i+1} \end{cases} \tag{8}$$

In Eq (8), when the tool number or the azimuth of the table changes, $\sigma(X_i, X_{i+1})$ is taken as 1, while when the tool number or the azimuth of the table does not change, $\sigma(X_i, X_{i+1})$ is taken as 0.

Generalized energy storage of machine tools E_s, the expression can be represented by Eq (9).

$$E_s = P_{st} \times T_{st} + P_{end} \times T_{end} \tag{9}$$

Where, T_{st} and T_{end} are the start-up time and shutdown time of the machine.

Auxiliary energy consumption E_o, which is described as Eq (10):

$$E_o = P_{o1} \times T_{o1} + P_{o2} \times T_{o2} \times P_{o3} \times T_{o3} \tag{10}$$

Where, T_{o1}, T_{o2} and T_{o3} are working hours of electrical control system, lighting system and cooling system.

From the above analysis, the energy consumption function of the machining process of the machining center can be expressed as Eq (11):

$$E_e = (1+b)\sum_{i=1}^{n} P_{ci} \times T_{ci} + \sum_{i=1}^{n} P_{ui} T_{ui} + \sum_{i=1}^{n-1} P_d \times T_d \times \sigma(T_i, T_{i+1}) + \sum_{i=1}^{n-1} P_t \times T_t \times \sigma(D_i, D_{i+1}) + Q \tag{11}$$

3.3. Cost function

The process cost of machining center mainly includes machining cost, tool changing cost and other auxiliary costs(Mcbrien et al., 2016). Therefore, the cost function of machining process of machining center can be expressed as Eq (12):

$$C_p = \alpha\left(T_o + T_m + T_r \frac{T_c}{T}\right) \tag{12}$$

Where, in Eq (12), T_r, T_c, n, T can be express as follows

$$T_r = T_d + \frac{\beta}{\alpha} \tag{13}$$

$$T_c = \frac{L}{n f_z z} \tag{14}$$

$$n = \frac{1000 v_c}{\pi D} \tag{15}$$

$$T = \left(\frac{C_v D^o}{v_c f_z^k (a_e/D)^q a_p^u HB^g}\right)^{1/m} \tag{16}$$

In Eq (12)-Eq (16), C_p is the average cost of processing a single workpiece; T_o is the auxiliary processing time; T_m is the processing time; $\beta$is the tool cost; α is the labor cost per unit time; T_c is the effective processing time; T_d is the tool change time; L is the part processing length; v_c is the processing speed; f_z is the feed per tooth; n is the spindle speed; a_e is the processing width; a_p is the processing depth; Z is the number of tool teeth; D is the tool diameter; T is the tool life; C_v, o, k, q, u, g, HB is the tool life correlation coefficient.

In the machining center machining process, due to the down and retract times of tool are quite short, the effective machining time T_c can be approximately considered to be equal to the machining time $T_m$of this procedure (Kitayama et al., 2016). The cost objective function of the processing process can be expressed as Eq (17).

$$C_p = \alpha\left(T_o + \frac{\pi D L}{1000 v_c f_z z}\left(1 + \left(T_d + \frac{\beta}{\alpha}\right)\left(\frac{C_v D^o}{v_c f_z^k (a_e/D)^q a_p^u HB^g}\right)^{-1/m}\right)\right) \tag{17}$$

3.4. Constrains

As mentioned in section 3.2 and 3.3, the energy consumption function and cost function have been established, the optimization objectives are the minimum energy consumption and the minimum processing cost respectively. However, the two objective functions are usually constrained by the performance of machine tools, tool life and other factors(Wang et al., 2013). In the milling process of CNC machining center, milling parameters mainly include cutting speed v_c, milling depth a_p, milling width a_e and feed per tooth f_z. As the milling depth and width are known, the multi variables are cutting speed$v_c$and feed per toothf_z.Therefore, it is essential to make a reasonable choice under the relevant constraints (Albertelli et al., 2016).

Spindle speed constraint, as shown in Eq (18).

$$g_1(v_c,f_z)=\frac{N_{\min}\pi D}{1000}-v_c\le 0 \tag{18}$$

Where, $N_{\min}$ is the minimum speed allowed for the machine spindle.

Feed restriction, as shown in Eq (19).

$$g_2(v_c,f_z)=\frac{v_{f\min}\pi D}{1000zv_c}-f_z\le 0 \tag{19}$$

Where, $v_{f\min}$ is the minimum feed speed.

Power constraint, as shown in Eq (20).

$$g_3(v_c,f_z)=\frac{F_c v_c}{60\times 1000}-\eta P_{\max}\le 0 \tag{20}$$

Where,η is the efficiency of the machine tool, $P_{\max}$ is the rated power.

Torque constraint, as shown in Eq (21).

$$g_4(v_c,f_z)=\frac{F_c D}{2\times 10^3}-M_{\max}\le 0 \tag{21}$$

Where, $M_{\max}$ is the maximum torque that the main shaft can bear.

Tool life constraint, as shown in Eq (22).

$$g_5(v_c,f_z)=T_{\min}-T\le 0 \tag{22}$$

Where, $T_{\max}$, $T_{\min}$ are the upper and lower limits of tool life respectively.

3.5. Multiobjective optimization model

Since the energy consumption function and cost function of the machining center are obtained, the corresponding parameter constraints have also been confirmed. Therefore, the process route optimization is a typical constrained optimization problem(Junior et al., 2016), and its mathematical model can be expressed as Eq (23).

$$\begin{cases}\min\ F(v_c,f_z)=\left[f_{Ee}(v_c,f_z),f_{C_p}(v_c,f_z)\right]\\ s.t.\ \ g_i\ (v_c,f_z)\le 0; i=1,2,3\ldots,9\end{cases} \tag{23}$$

It is difficult to get the optimal solution of multiple objective functions simultaneously, in order to facilitate the solution, a weighted summation method is introduced to convert the multi-objective function into a single objective(Tian et al., 2013), as shown in Eq (24):

$$\min\ \left[f_{E_e}(v_c,f_z),f_{C_p}(v_c,f_z)\right]=\min\ \left[\lambda_1 f_{Ee}(v_c,f_z)+\lambda_2 f_{C_p}(v_c,f_z)\right] \tag{24}$$

Where, $\lambda_1+\lambda_2=1$, λ_1 and λ_2 are energy consumption weighting coefficient and cost weighting coefficient, which can be determined by analytic hierarchy process (AHP), (Li et al., 2015) λ_1=0.5, λ_2=0.5.Since the dimensions of cost function and energy consumption function are different, it needs to be normalized. The specific operations are as Eq (25).

$$\overline{E_e}=\frac{E_e-E_{\min}}{E_{\max}-E_{\min}} \tag{25}$$

Where, $E_{\max}$ and $E_{\min}$ are the maximum and minimum energy consumption when the single objective energy consumption function is the optimization objective, and $C_{\max}$ and $C_{\min}$ are the maximum and minimum when the single objective cost function is the optimization objective. Therefore, the optimized function after normalization can be represented as Eq (26).

$$\min F(v_c,f_z)=\min\ \left(\lambda_1\overline{E_e}+\lambda_2\overline{C_p}\right)\ =\min\left(\lambda_1\frac{E_e-E_{\min}}{E_{\max}-E_{\min}}+\lambda_2\frac{C_p-C_{\min}}{C_{\max}-C_{\min}}\right) \tag{26}$$

4. Solving model based on combinatorial optimization algorithm

To solve the multiobjective combination optimization problem (Liu et al., 2013), the combination of an intelligent workstep generation algorithm and the NSGA-II is proposed. Under the principle of processing constraints, all the feasible workstep sequencing chains that satisfy the constraints were first obtained using the intelligent generation algorithm of the workstep chain; subsequently, the NSGA-II was combined to set the relevant parameters for a multiobjective optimization(Wang et al., 2020).

4.1. Intelligent generation algorithm of workstep chain

The intelligent workstep chain generation algorithm is based on constraint analysis(Wand et al., 2006). First, the priority constraint relationship between worksteps must be determined; subsequently, a priority relationship table between workpiece processing worksteps is constructed. Based on the table, a constraint vector group R that must be satisfied by the sequence of the worksteps is constructed. Finally, by constructing the constraint vector and using the intelligent generation algorithm of the worksteps chain, a sequence workstep chain that satisfies the constraint conditions is obtained.

To briefly explain the operation process of the algorithm, a feasible workstep sequence chain of a workpiece is used as an example herein. The priority relation table of worksteps

Table 1
Priority relationships between worksteps.

S.No.	Previous workstep	Post workstep
1	2	1、3、4、5、6、7、8
2	4	5
3	7	6
4	8	1

constructed by constraint analysis (the total number of worksteps is 8) is summarized in Table 1. The number in column one of the table represents the number of constraint vectors, which must be satisfied in the workstep sorting chain. Column two is the preceding workstep relative to column three, indicating the workstep must be processed before that in column three. Column three is the posterior workstep of column two, indicating the workstep that must be processed after that in column two is completed.

The constraint vectors obtained by constructing the priority relation table of the workstep are as follows:

$$R_1 = [2,\ 1,\ 3,\ 4,\ 5,\ 6,\ 7,\ 8] \quad R_2 = [4,\ 5]$$
$$R_3 = [7,\ 6] \quad R_4 = [8,\ 1]$$

Where the first column of the constraint vector is the number of the previous workstep, and the remaining columns are the numbers of the next worksteps. When constructing the constraint vectors, operators can add additional constraint vectors to satisfy the processing requirements according to the characteristics of the workpiece. By constructing the constraint vectors and then using the intelligent generation algorithm of the workstep chain, we can obtain the feasible sequence chain of the process workstep. The operation flow of the intelligent generation algorithm of the workstep chain is shown in Fig. 3. The operation process of the intelligent generation algorithm of the working step chain is as follows:

First, randomly generate N free combinations of process workstep sequence chains, which are defined as vectors $S_1, S_2, \ldots, S_n$.

2) Extract the sequence chain of N free combinations individually, assuming that the extracted vector is S_k.
3) Compare each element in S_k with each element in constraint vector group R and obtain the corresponding subscript of each constraint vector in random vector S_k (subscript represents the position of each element in the vector). If A = [A,b,c], then subscripts a, b, and c are 1, 2, and 3, respectively), and the subscripts in vector group $X_1, X_2, \ldots, X_m$ (m is the number of constraint vectors) are assessed.
4) If the first column element of each vector in the subscript vector group is the minimum value of the subscript vector, then the workstep sequence vector S_k is a feasible workstep sequence chain that satisfies the constraints. If some vector X_i in the subscript vector group does not satisfy the condition that the first column element should be the minimum value of the subscript vector, it must be varied by exchanging the value of S_k corresponding to the minimum value element of the subscript vector X_i with the value of X_i corresponding to the first column element of S_k, such that the workstep sequencing vector S_k satisfies the constraint of X_i.
5) According to this, adjust S_k until it satisfies all constraints expressed by the constraint vectors, and then output S_k.

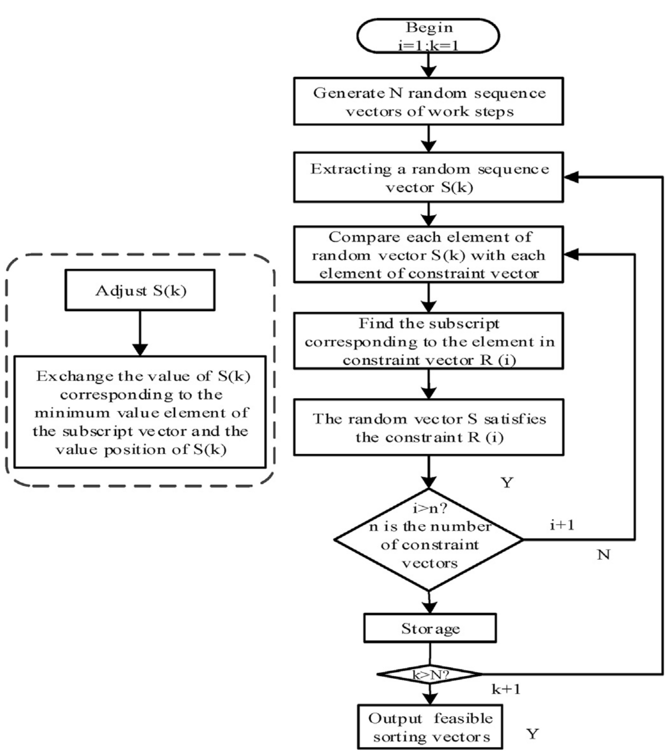

Fig. 3. Flow chart of intelligent generation algorithm of workstep chain.

4.2. Improved genetic algorithm

The NSGA-II adopts the fast non-dominated sorting algorithm and the elite strategy, which can result in excellent individuals and the original population can be preserved well. In addition, the computational complexity of the algorithm can be reduced significantly (Liao et al., 2020).

4.2.1. Gene coding

The machining process of the workpiece comprises a sequence of multiple worksteps; each workstep in the sequence workstep chain is attached with the goal of optimizing energy consumption and achieving low cost. The position of the tool and the processing feature correspond to each workstep face information. Therefore, to fully express the relevant information of a sequence workstep chain, the gene of a chromosome should contain three parts when coding genes. The first part is the workstep number, and the second part is the tool number corresponding to the workstep. The third part is the number of the azimuth plane where the processing feature corresponding to this workstep is located. The gene coding procedure is shown in Fig. 4.

4.2.2. Initial population

To obtain the initial population with complete information, it is critical to determine the number of feasible sequence of worksteps (the number of initial population), and then establish the corresponding tool and azimuth information of all worksteps in each sequence individually; subsequently, the population can be initialized. The specific process is as follows: first, according to the intelligent generation algorithm of the workstep chain, obtain the initial population number N that conforms to the priority constraint relationship; next, select a sequence from it, access the first machining workstep of the sequence, match the corresponding tool number and the number of the azimuth plane of the corresponding machining feature for the workstep, and traverse all the worksteps sequentially until the tool of all the worksteps in the sequence corresponds to the corresponding tool. The information matching of the machining features is then completed. Repeat the steps above until all the sequences complete the matching of the workstep information; subsequently, the initialization of the population is completed.

4.2.3. Duplication, crossover and mutation

During gene replication, to prevent the destruction of optimal individuals in the subsequent crossover and mutation operations, which prevents the algorithm from searching for the global optimal solution, the elitist retention strategy was adopted as the

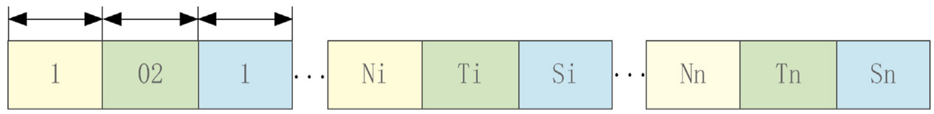

Fig. 4. Gene coding.

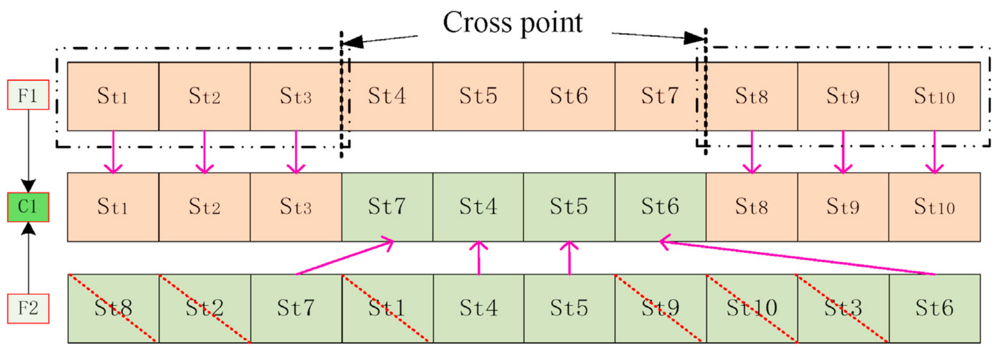

Fig. 5. Two-point crossover process.

replication mode of the population. To ensure the efficiency of the algorithm and the effectiveness of the offspring chromosomes after crossing, two crossing points were adopted in this study, and the specific process is shown in Fig. 5.

First, two chromosomes F1 and F2 were randomly selected from the population after replication as the parent chromosomes; subsequently, two points were randomly generated in the parent chromosome F1 as the intersections such that F1 was separated into three parts. Next, the left and right parts of F1 were copied to the left and right parts of the same position of the child chromosomal C1. Finally, the remaining parts of F1 were removed from F2. The subgenes were copied to the middle part of C1 in the original order to complete the creation of the offspring chromosome C1. Using the same method, we can obtain another offspring chromosome C2. This two-point crossing method can ensure that the progeny chromosomes satisfy the priority constraint relationship between the workstep elements, without having to adjust the position between the workstep elements.

Through the intersecting daughter chromosomes, the internal genes will be randomly exchanged for two or more gene positions under the constraint of a certain mutation rate to generate new offspring. In this study, a random exchange of any two gene positions in the progeny chromosomes was applied to perform the mutation operation. The mutation process is shown in Fig. 6.

$$E = \int_0^{T_z} P dt$$

As shown in Fig. 6, the internal genes of the new subchromosomes were exchanged, which may result in chromosomes that violate the priority constraint relationship vector. Because the elements outside the intersection satisfy the constraint conditions, only the genes between the intersections require verification.

4.2.4. Operation parameters and termination

When the genetic algorithm is adopted to solve optimization problems, two types of termination conditions are involved, i.e., those pertaining to fixed genetic iteration and constant fitness methods. The first termination condition is to set the number of genetic iterations at the beginning of the algorithm. Instead of setting the number of search iterations, the second termination condition is to terminate the calculation and output the result when the fitness of individuals in the population does not change or changes slightly. The first method was selected as the termination condition in this study.

5. Case study

In this section, an emulsion pump case is presented to verify the feasibility of the proposed approach. Three views of the emulsion pump casing are shown in Fig. 7.

5.1. Analysis of processing characteristics of emulsion pump case

The emulsion pump considered comprises 12 typical machining features, including end face, hole, thread, and other machining features, which were completed in 28 machining worksteps. The

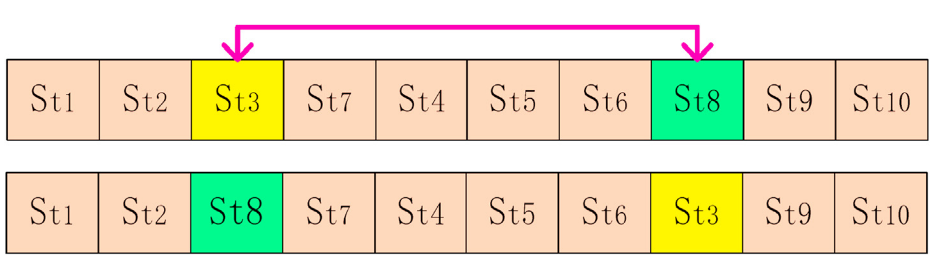

Fig. 6. Gene mutation process.

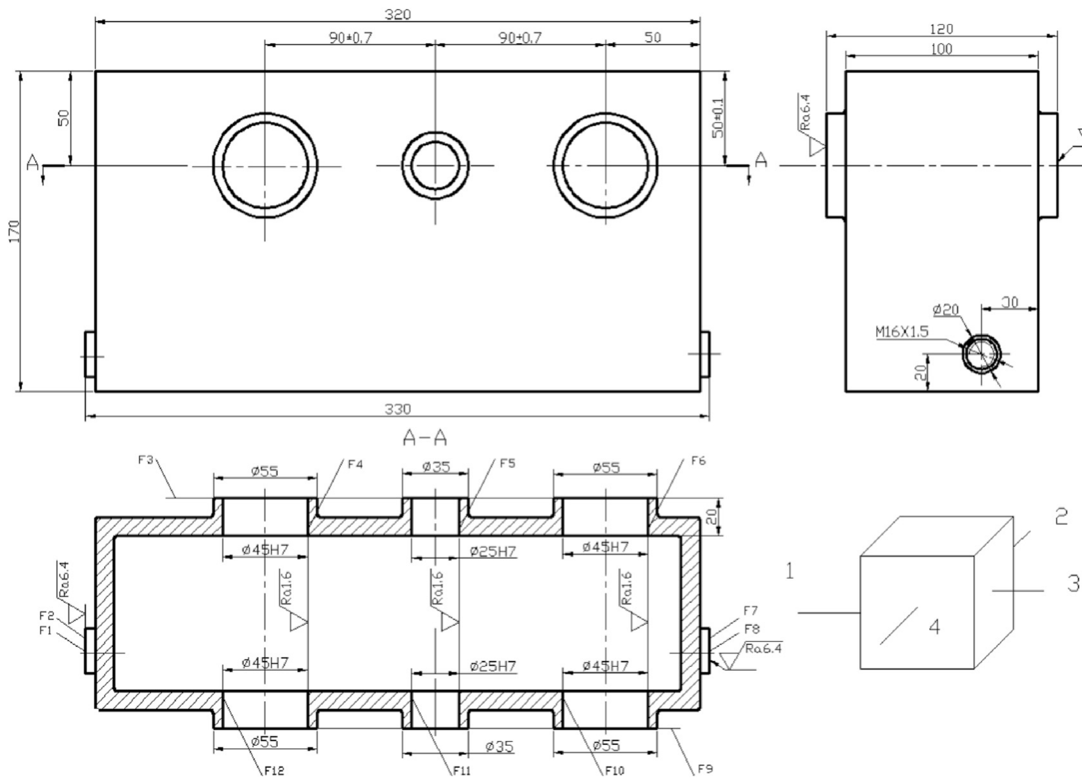

Fig. 7. Characteristic analysis of emulsion pump case.

Table 2
Part feature information table.

Feature No.	Feature description	Azimuth plane	Feature No.	Feature description	Azimuth plane
F1	End face	1	F7	End face	3
F2	M16 × 1.5 Threaded hole	1	F8	M16 × 1.5 Threaded hole	3
F3	End face	2	F9	End face	4
F4	Φ45Through hole	2	F10	Φ45Through hole	4
F5	Φ35Through hole	2	F11	Φ35Through hole	4
F6	Φ45Through hole	2	F12	Φ45Through hole	4

feature information of each azimuth plane corresponds to the corresponding position in the three views shown in Fig. 7. The orientation information of the 12 features of the emulsion pump is summarized in Table 2.

5.2. Determine model related parameters

(1) Machine tool information required by the model

The relevant machine tool parameters required for the energy consumption calculation model are shown in Table 3.

(2) Acquisition of effective cutting time $n = \frac{1000 v_c}{\pi D}$

The effective cutting time of the workstep ($n = \frac{1000 v_c}{\pi D}$) is the contact processing time of the tool and the workpiece under the processing condition of the workstep. $n = \frac{1000 v_c}{\pi D}$can be calculated by Eq (27):

$$T = \left(\frac{C_v D^o}{v_c f_z^k (a_e/D)^q a_p^u HB^g} \right)^{1/m} \tag{27}$$

where L_i is the path length of the tool in the workstep; f_i is the feed speed of the tool in the workstep. Therefore, the effective cutting time information corresponding to each processing workstep of the processed pump case is summarized in Table 4. Using the feature number F2 as an example, the position is required to process an M16 thread, which is composed of three machining worksteps: workstep No. 02, where the center hole is drilled; workstep No. 03,

Table 3
Machine tool information required for energy consumption model.

Machine type	Tool changing motor power	One tool change time	Power of table transposing motor	Transpose 90° time
Horizontal machining center (model no.: TH6350)	0.75 KW	6S	2 KW	2.5S

Table 4
List of workstep element information.

Feature No.	Feature info.	Workstep No.	Workstep info.	Tool No.	Work azimuth plane	Effective cutting times
F1	End face	01	Milling	T01	1	145
F2	M16 Thread	02	Drill the center hole	T02		11
		03	Drilling	T03		15
		04	Tapping	T04		6
F3	End face	05	Milling	T01	2	55
F4	Φ45 Through hole	06	Rough boring	T05		20
		07	Semi-fine boring	T06		30
		08	Fine boring	T07		30
F5	Φ35Through hole	09	Rough boring	T08		20
		10	Semi-fine boring	T09		30
		11	Fine boring	T10		30
F6	Φ45Through hole	12	Rough boring	T05		20
		13	Semi-fine boring	T06		30
		14	Fine boring	T07		30
F7	End face	15	Milling	T01	3	20
F8	M16 Thread	16	Drill the center hole	T02		11
		17	Drilling	T03		15
		18	Tapping	T04		6
F9	End face	19	Milling	T01	4	145
F10	Φ45 Through hole	20	Rough boring	T05		20
		21	Semi-fine boring	T06		30
		22	Fine boring	T07		30
F11	Φ35 Through hole	23	Rough boring	T08		20
		24	Semi-fine boring	T09		30
		25	Fine boring	T10		30
F12	Φ45 Through hole	26	Rough boring	T05		20
		27	Semi-fine boring	T06		30
		28	Fine boring	T07		30

where drilling is performed; and workstep No. 04, where tapping is performed. The corresponding tools used were T02, T03, and T04, the workstep orientation was 1, and the effective cutting times were 11, 15, and 6 s, respectively.

5.3. Process route optimization

To obtain the sequencing chain of machining worksteps that satisfy the constraints (Carvalho et al., 2017), it is critical to first determine the priority constraint table that the emulsion pump case must satisfy during the machining process in the machining center. The corresponding detailed information is listed in Table 5, which shows the actual constraint information that must be satisfied in every working step of the emulsion pump case, and optimization must be performed under this constraint.

To determine the start machining workstep of machining, a constraint vector R(21) = [5,1,15,19] was added manually, i.e., workstep 5 was set as the start machining workstep of machining. Based on the constraint vectors above, the intelligent generation algorithm of the workstep chain was adopted, and some feasible worksteps sequence were generated; the detailed workstep sequence list is summarized in Table 6.

The NSGA-II was selected to make a multiobjective process route optimization decision for the feasible process sequencing chain generated by the intelligent generation algorithm. The emulsion pump case involved 12 process characteristics, and 28 process worksteps were required to complete the processing. The process route was an ordered set of 28 process worksteps. The coding scheme of the worksteps is summarized in Table 4. The number of feasible worksteps that satisfy the constraints determines the number of iterations that the population requires in the genetic operation. Because many feasible worksteps satisfy the constraints in this example, to obtain values of the iterative worksteps that render the chain optimal or near optimal, in the parameter decision-making of the algorithm, the range of the initial population should be expanded to the maximum possible extent, and the probability of crossover and mutation should be made larger.

Table 5
Constraints of priority relationships between worksteps of the emulsion pump case.

No.	Preceding workstep	Post workstep	Constraint vector	No.	Preceding workstep	Post workstep	Constraint vector
1	1	2,3,4	R(1) = [1,2,3,4]	11	15	16,17,18	R(11) = [15,16,17,18]
2	2	3,4	R(2) = [2,3,4]	12	16	17,18	R(12) = [16,17,18]
3	3	4	R(3) = [3,4]	13	17	18	R(13) = [17,18]
4	5	6,7,8,9,10,11,12,13,14	R(4) = [5,6,7,8,9,10,11,12,13,14]	14	19	20,21,22,23,24,25,26,27,28	R(14) = [19,20,21,22,23,24,25,26,27,28]
5	6	7,8	R(5) = [6,7,8]	15	20	21,22	R(15) = [20,21,22]
6	7	8	R(6) = [7,8]	16	21	22	R(16) = [21,22]
7	9	10,11	R(7) = [9,10,11]	17	23	24,25	R(17) = [23,24,25]
8	10	11	R(8) = [10,11]	18	24	25	R(18) = [24,25]
9	12	13,14	R(9) = [12,13,14]	19	26	27,28	R(19) = [26,27,28]
10	13	14	R(10) = [13,14]	20	27	28	R(20) = [27,28]

Table 6
Feasible worksteps sequencing chain.

Serial No.	Generated feasible worksteps sequencing chain
1	5 → 1→19 → 26→9 → 20→2 → 15→12 → 10→16 → 21→23 → 17→18 → 13→3 → 27→28 → 24→6 → 4→25 → 14→11 → 7→8 → 2
2	5 → 15→1 → 19→12 → 13→6 → 20→9 → 21→22 → 16→7 → 10→26 → 23→8 → 24→25 → 2→28 → 11→27 → 3→14 → 17→18 → 4
3	5 → 9→6 → 15→19 → 20→21 → 10→1 → 26→27 → 22→16 → 12→2 → 13→28 → 7→17 → 23→24 → 3→18 → 14→4 → 8→11 → 25
4	5 → 19→20 → 26→1 → 6→12 → 13→15 → 7→23 → 2→9 → 21→22 → 3→16 → 24→17 → 8→10 → 4→18 → 25→28 → 14→11 → 27

According to the analysis above, the algorithm parameters were set as follows:

a) The number of iterations was 500.
b) The initial population was set as M = 400 (obtained by matching the corresponding tool and azimuth information with the feasible workstep chain).
c) The cross probability was 0.8; the variation rate was 0.6.
d) The selected machining center was calculated at RMB 80/h.
e) The tool change time was 6 s, and the transposition time was 2.5 s.
f) Additionally, the multiobjective optimization result was compared with the single objectives of energy saving and low cost processing, separately. The comparison data are shown in Table 7.

The algorithm convergence diagram of the energy saving and low-cost process is shown in Fig. 8.

Fig. 8 (a) shows the average energy consumption of each generation, whereas Fig. 8. (b) shows the average processing cost of each generation. When optimizing with the goal of energy saving and low cost, the optimal chromosome gene expression form of the processing sequence is shown in Fig. 9. As shown, during the entire processing, the worktable was transposed seven times, the machine tool was changed 19 times, the energy consumption was 10184550j, the processing cost was CNY32.65, and the processing time was 18 min and 30 s.

To verify the superiority and practicability of the combinatorial optimization algorithm used in this study, the related programs of the genetic algorithm and the combinatorial optimization algorithm were written separately. The iterative convergence graph obtained is shown in Fig. 10. Curve 1 is the optimization result obtained by the typically used genetic algorithm, and curve 2 is the optimization result obtained using the combinatorial optimization algorithm.

As shown in Fig. 10, the convergence speed of the combinatorial optimization algorithm is higher than that of the typical genetic algorithm; further, the value of the objective function is smaller, which indicates both improved problem solving speed and optimization result accuracy. In addition, the optimal solution yielded by the multiobjective optimization model can prove the effectiveness of the optimization model, and the optimal process route can directly guide the operator to perform adjustments according to the optimized processing route without any additional equipment.

5.4. Results and discussions

Comparing the multiobjective optimization model proposed herein and the single objective optimization model, relevant conclusions can be drawn from Table 7, as follows:

Based on the single objective energy saving as the optimization goal, the energy consumption was 0.936×10^7 J and the processing cost was CNY33.78. Compared with the other two groups of experimental results, the energy consumption value was the smallest, which significantly improved the energy consumption optimization of processing. However, the processing cost increased; therefore, the economic benefits were not ideal.

Based on the single objective low cost as the optimization goal, the energy consumption was 1.154×10^7 J, and the processing cost was CNY31.59. Compared with the experimental results of the other two groups, the processing cost value was the lowest, indicating that the processing cost for the processing process reduced significantly reduced. However, the energy consumption for processing was the highest, which is inconsistent with energy saving production.

Based on the multiobjectives of energy saving and low cost as the optimization goal, the energy consumption was 1.018×10^7 J, and the processing cost was CNY32.65. Compared with the other two experimental results, the energy consumption and the processing cost demonstrated the best comprehensive performances, consistent with energy saving and low-cost production.

By comparing the combinatorial optimization algorithm adopted in this study with the general genetic algorithm, it can be conducted that the convergence speed of the combinatorial optimization algorithm was higher than that of the typical genetic algorithm (see Fig. 10), and the value of the objective function was smaller, which improved the problem solving speed and the accuracy of the optimization result.

The optimal sequencing gene encoding as shown in Fig. 9 was compiled, and the optimal process route was obtained, as summarized in Table 8. The workstep sequencing chain of the optimized process route, the processing information of each workstep, the processing characteristics of the parts to be processed, the processing tools used, and the workstep orientation are summarized in the table.

As summarized in Table 8, the optimal process route was obtained, the worktable was rotated seven times, the cutter was changed 19 times, and the processing surface was relatively concentrated, which reduced the required energy and processing cost for processing; therefore, the effectiveness of the optimization model proposed herein was validated.

6. Conclusions and limitations

Optimizing energy reduction in mechanical processing and reducing processing cost are important approaches for realizing a green and sustainable manufacturing industry. Hence, this study

Table 7
The comparison optimization results.

Optimization results	Energy saving as the goal	Low cost as the goal	Energy saving and low cost as the goal
Energy consumption/J	0.936×10^7	1.154×10^7	1.018×10^7
Cost/CNY	33.78	31.59	32.65

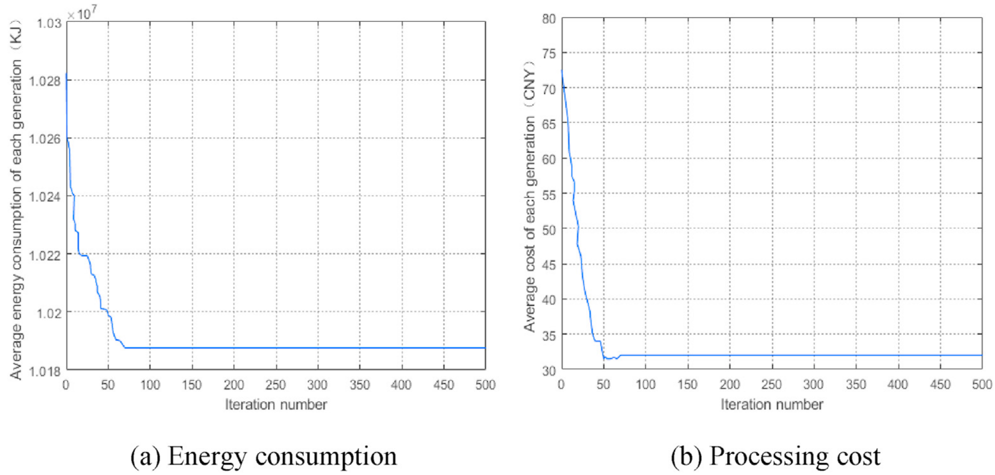

Fig. 8. Iterative convergence graph of algorithm.

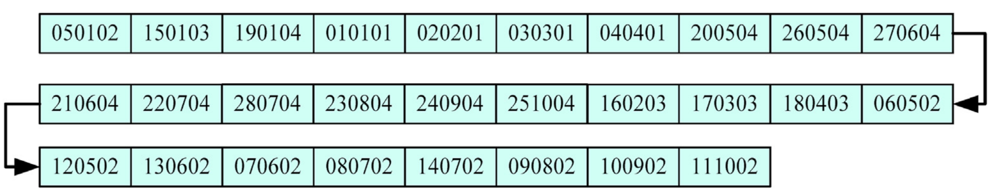

Fig. 9. Optimized gene coding of workstep chain sequencing.

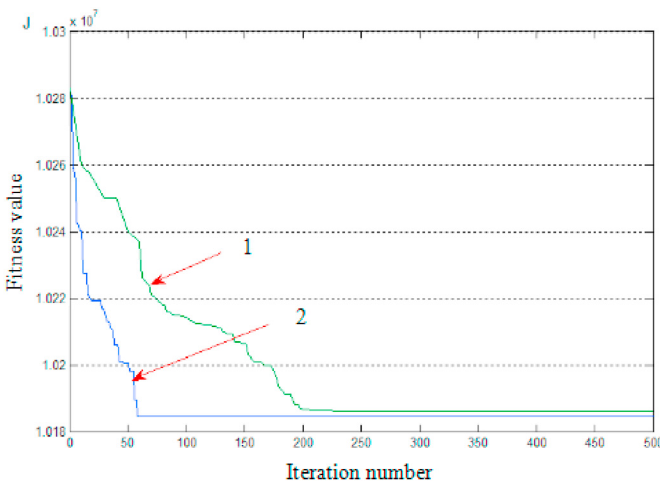

Fig. 10. Comparison of iterative convergence of two algorithms.

investigated the energy saving and low cost processing of a machining center, analyzed the underlying effects of the mechanism of process route optimization on machining energy consumption and processing cost, and discussed the effect of using different algorithms on the optimization results. The conclusions obtained were as follows:

First, based on the analyses of the operation and energy flow characteristics of the machining system in the machining center, the cost objective function and energy consumption objective function of the machining center were established, and the weighted sum method was introduced, by which a multiobjective optimization model of the machining center process route for energy saving and low cost was built.

Second, the concept of workstep element was proposed, and the characteristics of the parts to be processed were described using this concept. With full consideration of the priority constraints between the workstep elements, an intelligent generation algorithm for the workstep chain was proposed. A combinatorial optimization algorithm based on the combination of the intelligent generation algorithm of the workstep chain and the NSGA-II yielded the optimal decision of the multiobjective optimization model.

Third, comparing the combinatorial optimization algorithm with the general genetic algorithm, the iteration number of the typical genetic algorithm is 231, the iteration number of the combinatorial optimization algorithm is 57, which indicates the convergence speed of combinatorial optimization algorithm was higher. In addition, the optimal solution provided by the multiobjective optimization model can directly guide an operator to perform adjustments according to the optimized processing route, without any additional equipment, which is economical and practical.

Fourth, based on the multiobjectives of energy saving and low cost as the optimization goal, the energy consumption was 1.018×10^7 J, and the processing cost was CNY32.65. Compared with the other two experimental results, based on the single objective energy saving as the optimization goal, the energy consumption was 0.936×10^7 J and the processing cost was CNY33.78, based on the single objective low cost as the optimization goal, the energy consumption was 1.154×10^7 J, and the processing cost was CNY31.59. Comparison the data shows that based on the multiobjectives of energy saving and low cost as the optimization goal, the energy consumption and the processing cost demonstrated the best comprehensive performances, consistent with energy saving and low-cost production. However, several limitations of this study should be considered.

First, owing to the complexity of the machining center system, the aim of this study was to realize an energy saving and low cost

Table 8
Optimal workstep sequence chain information.

Processing sequence	Workstep No.	Processing info.	Processing features	Machine tool	Workstep azimuth surface
1	5	Milling	F3 End face	T01	2
2	15	Milling	F7 End face	T01	3
3	19	Milling	F9 End face	T01	4
4	1	Milling	F1 End face	T01	1
5	2	Drilling center hole	F2M16 Thread	T02	1
6	3	Drilling	F2M16 Thread	T03	1
7	4	Tapping	F2M16 Thread	T04	1
8	20	Rough boring	F10Φ45 Through hole	T05	4
9	26	Rough boring	F12Φ45 Through hole	T05	4
10	27	Semi-fine boring	F12Φ45 Through hole	T06	4
11	21	Semi-fine boring	F10Φ45 Through hole	T06	4
12	22	Fine boring	F10Φ45 Through hole	T07	4
13	28	Fine boring	F12Φ45 Through hole	T07	4
14	23	Rough boring	F11Φ35 Through hole	T08	4
15	24	Semi-fine boring	F11Φ35 Through hole	T09	4
16	25	Fine boring	F11Φ35 Through hole	T19	4
17	16	Drilling center hole	F8M16 Thread	T02	3
18	17	Drilling	F8M16 Thread	T03	3
19	18	Tapping	F8M16Thread	T04	3
20	6	Rough boring	F4Φ45 Through hole	T05	2
21	12	Rough boring	F6Φ45 Through hole	T05	2
22	13	Semi-fine boring	F4Φ45 Through hole	T06	2
23	7	Semi-fine boring	F4Φ45 Through hole	T06	2
24	8	Fine boring	F6Φ45 Through hole	T07	2
25	14	Fine boring	F6Φ45 Through hole	T07	2
26	9	Rough boring	F5Φ35 Through hole	T08	2
27	10	Semi-fine boring	F5Φ35 Through hole	T09	2
28	11	Fine boring	F5Φ35 Through hole	T10	2

optimization of the manufacturing process through a reasonable process route, although the optimal solution solved by the model reflected the production cost and energy consumption efficiency to a certain extent. However, in the actual production process, it is often necessary to consider the comprehensive effect of multi-objective factors and decide the weight of each objective according to the production requirements. Therefore, the approach to comprehensively consider the effects of multiobjective factors and realize the unified coordination and optimization of energy consumption goals and other goals will be investigated in the future.

Second, to obtain the optimal workstep chain and shorten the iteration time of the algorithm, a large number of experiments were performed in this study that pertained to the value of each parameter of the genetic algorithm. Although the optimization problem of the workstep chain was solved to some extent, because of the uncertainty and subjectivity of the parameter value during testing, the entire testing process required a significant amount of time, which included the time required for algorithm parameter testing and algorithm optimization iteration. This might not affect the optimization of simple problems, but the efficiency of this algorithm is particularly important when performing more complex operations. Therefore, the efficiency of the algorithm must be improved for solving complex optimization problems in the future.

Credit author contribution statement

Yongmao Xiao: Conceptualization, Methodology, Software, Data curation, Writing - original draft, preparation. Writing - original draft.Writing - Revised draft. **Hua Zhang:** Methodology, Resources, Visualization, Project administration, Funding acquisition. **Zhigang Jiang:** Methodology, Resources, Visualization, Validation. **Quan Gu:** Formal analysis, Validation. **Wei Yan:** Investigation, Data curation, Funding acquisition.

Declaration of competing interest

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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References

Ai, X.F., Jiang, Z.G., Zhang, H., Wang, Y., 2019. Low-carbon product conceptual design from the perspectives of technical system and human use. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2019.118819.
Albertelli, P., Keshari, A., Matta, A., 2016. Energy oriented multi cutting parameter optimization in face milling. J. Clean. Prod. 137, 1602–1618.
Altıntaş, R.S., Kahya, M., Unver, H.O., 2016. Modelling and optimization of energy consumption for feature based milling. Int. J. Adv. Manuf. Technol. 86 (9–12), 3345–3363.
Cai, W., Lai, K.H., Liu, C.H., Wei, F.F., Ma, M.D., Jia, S., Jiang, Z.G., Lv, L., 2019. Promoting sustainability of manufacturing industry through the lean energy-saving and emission-reduction strategy. Sci. Total Environ. 665, 23–32.
Carvalho, H., Govindan, K., Azevedo, S.G., Cruz-Machado, V., 2017. Modelling green and lean supply chains: an eco-efficiency perspective. Resour. Conserv. Recycl. 120, 75–87.
Chirag, M., Yuan, J., Debangsu, B., 2019. Techno-economic optimization of shale gas to dimethyl ether production processes via direct and indirect synthesis routes. Appl. Energy 238, 119–134.
Deng, Z.H., Lv, L.S., Huang, W.L., Shi, Y.D., 2019. A high efficiency and low carbon oriented machining process route optimization model and its application. International Journal of Precision Engineering and Manufacturing-Green Technology 6 (1), 23–41.
Du, Y.B., Yi, Q., Li, C.B., Liao, L., 2015. Life cycle oriented low-carbon operation models of machinery manufacturing industry. J. Clean. Prod. 91, 145–157.

Feng, X.X., Zhang, S., Wu, K.Y., Dong, Z.L., 2018. Multi-response optimization design of tailor-welded blank (TWB) thin-walled structures using Taguchi-based gray relational analysis. Thin-Walled Struct. 131, 286–296.
He, Y., Li, Y.F., Wu, T., et al., 2015. An energy-responsive optimization method for machine tool selection and operation sequence in flexible machining job shops. J. Clean. Prod. 87, 245–254.
Jiang, Z.G., Jiang, Y., Wang, Y., Zhang, H., Cao, H.J., Tian, G.D., 2016. A hybrid approach of rough set and case-based reasoning to remanufacturing process planning. J. Intell. Manuf. 30, 19–32.
Junior, V.B.D.O., Pena, J.G.C., Salles, J.L.F., 2016. An improved plant-wide multiperiod optimization model of a byproduct gas supply system in the iron and steel-making process. Appl. Energy 164, 462–474.
Kitayama, S., Natsume, S., Yamazaki, K., et al., 2016. Numerical optimization of blank shape considering flatness and variable blank holder force for cylindrical cup deep drawing. Int. J. Adv. Manuf. Technol. 85 (9–12), 1–12.
Krishna, A.G., Rao, K.M., 2006. Optimization of operations sequence in CAPP using an ant colony algorithm. Int. J. Adv. Manuf. Technol. 29 (1–2), 159–164.
Li, L., Wang, Y.C., Tang, Y., Liu, X.C., Ye, L., 2015. Mechanical material selection based on FAHP. Modular Machine Tool & Automatic Manufacturing Technique 11, 8–12.
Li, C.B., Li, L.L., Tang, Y., et al., 2019. A comprehensive approach to parameters optimization of energy-aware CNC millin. J. Intell. Manuf. 30 (1), 123–138.
Li, Y.P., Guo, Z.I., Liu, H., 2020. Structure optimization method based on automatic vectorization. Evolutionary Intelligence 13 (7), 51–58.
Lian, K.L., Zhang, C.Y., Shao, X.Y., et al., 2012. Optimization of process planning with various flexibilities using an imperialist competitive algorithm. Int. J. Adv. Manuf. Technol. 59 (2), 815–828.
Liao, W.Z., Zhang, L.Y., Wei, Z.Z., 2020. Multi-objective green meal delivery routing problem based on a two-stage solution strategy. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2020.120627.
Liu, X.J., Yi, H., Ni, Z.H., 2013. Application of ant colony optimization algorithm in process planning optimization. J. Intell. Manuf. 24 (1), 1–13.
Lu, F.C., He, W., Ning, L., Mei, X.A., Cheng, Y., Chen, S.H., 2015. Exploring the upgrading of Chinese automotive manufacturing industry in the global value chain: an empirical study based on panel data. Sustainability 7 (5), 6189–6211.
Ma, H.Y., Liu, W., Zhou, X.H., et al., 2020. An effective and automatic approach for parameters optimization of complex end milling process based on virtual machining. J. Intell. Manuf. 31, 967–984.
Mcbrien, M., Serrenho, A.C., Allwood, J.M., 2016. Potential for energy savings by heat recovery in an integrated steel supply chain. Appl. Therm. Eng. 103, 592–606.
Ouchida, K., Kikuchi, Y., Okubo, T., 2016. Integrated modeling of agricultural and industrial processes within life cycle design for environment. Computer Aided Chemical Engineering 38, 1947–1952.
Peng, B.H., Zheng, C.Y., Guo, W., Ehsan, Elahi, 2019. The cultivation mechanism of green Technology innovation in manufacturing industry: from the perspective of ecological niche. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2019.119711.
Peng, H., Wang, H., Chen, D.J., 2019. Optimization of remanufacturing process routes oriented toward eco-efficiency. Front. Mech. Eng. 14 (2), 422–433.
Salehi, M., Tavakkoli-Moghaddam, R., 2009. Application of genetic algorithm to computer-aided process planning in preliminary and detailed planning. Eng. Appl. Artif. Intell. 22 (8), 1179–1187.
Tian, G.D., Chu, J.W., Liu, Y.M., 2011. Expected energy analysis for industrial process planning problem with fuzzy time parameters. Comput. Chem. Eng. 35 (12), 2905–2912.
Tian, G.D., Chu, J.W., Qiang, T.G., 2013. Influence factor analysis and prediction models for component removal time in manufacturing. Proc. Inst. Mech. Eng. 227 (10), 1533–1540.
Tian, C.L., Zhou, G.H., Zhang, J.J., et al., 2019. Optimization of cutting parameters considering tool wear conditions in low-carbon manufacturing environment. J. Clean. Prod. 226, 706–719.
Wand, L., Cain, Feng, H.Y., Liu, Z., 2006. Enriched machining feature-based reasoning for generic machining process sequencing. Int. J. Prod. Res. 44 (8), 1479–1501.
Wang, Q., Liu, F., Wang, X., 2013. Multi-objective optimization of machining parameters considering energy consumption. Int. J. Adv. Manuf. Technol. 71 (5–8), 1133–1142.
Wang, Q., Hu, Y.J., Hao, J., Lv, N., Li, T.Y., Tang, B.J., 2019. Exploring the influences of green industrial building on the energy consumption of industrial enterprises: a case study of Chinese cigarette manufactures. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2019.05.136.
Wang, W.J., Tian, G.D., Chen, M.N., et al., 2020. Dual-objective program and improved artificial bee colony for the optimization of energy-conscious milling parameters subject to multiple constraints. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2019.118714.
Xu, L.X., Huang, C.Z., Li, C.W., et al., 2020. Estimation of tool wear and optimization of cutting parameters based on novel ANFIS-PSO method toward intelligent machining. J. Intell. Manuf. https://doi.org/10.1007/s10845-020-01559-0.
Yan, W., Zhang, H., Jiang, Z.G., Hon, K.K.B., 2017. Multi-objective optimization of arc welding parameters: the trade-offs between energy and thermal efficiency. J. Clean. Prod. 140, 1842–1849.
Yang, Y., Li, H.Z., Yao, M.Y., Zhang, Y.F., Zhang, C., Zhang, L., Wu, S.S., 2020. Optimizing the size of a printed circuit heat exchanger by multi-objective genetic algorithm. Appl. Therm. Eng. https://doi.org/10.1016/j.applthermaleng.2019.114811.
Zhai, X.Q., An, Y.F., 2020. Analyzing influencing factors of green transformation in China's manufacturing industry under environmental regulation: a structural equation model. J. Clean. Prod. https://doi.org/10.1016/j.jclepro.2019.119760.
Zhou, G.H., Tian, C.L., Zhang, J.J., Chang, F.T., Lu, Q., 2018. Multi-objective process route optimization considering carbon emissions. Int. J. Adv. Manuf. Technol. 96, 1195–1213.

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