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ORIGINAL ARTICLE

An optimization model of machining process route for low carbon manufacturing

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Abstract Process route planning selects and defines the whole machining process involved in transforming workblanks into end products. Our research finds that the decisions of processing methods, machines, cutting tools, and sequence of process stages during process route planning have significant impact on carbon emissions of the following manufacture processes. Firstly, a carbon emission and efficiency estimation model of process route is established to achieve the goal of reducing carbon emissions as well as increasing efficiency based on the machining features analyzing. Then, the mathematical model to express process route optimization problem is developed with objectives on minimizing the total carbon emission and total process time. A non-dominated sorting genetic algorithm is introduced to solve this problem, and a simulation study on a machine motor seat is conducted in order to verify the feasibility and practicability of the proposed model. The result of the experiment shows that our model can achieve the goal of reducing emission as well as maintaining system efficiency.

Keywords Process route planning · High efficiency and low carbon · Multi-objective optimization · Genetic algorithm

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1 Introduction

In the twenty-first century, resources and environment problems, with an increasingly worsening degree, become a serious threaten to the survival and development of society. During this critical time, an advanced manufacturing mode—green manufacturing (GM)—which is suitable for a sustainable development strategic is presented. With GM thought, the ultimate goal in manufacturing is reducing and minimizing environmental impact and resource consumption during a product life cycle, which includes design, synthesis, processing, packaging, transportation, and the use of products in continuous or discrete manufacturing industries [1, 2].

In our research, the goal of process route planning is to determine the detailed manufacturing requirements for transforming workblanks into specific end products with less carbon emission during the whole machining process. During process route planning, the processes and operations, together with the necessary machining resources and parameters, are determined with a major attention on carbon emission, as well as efficiency, quality, and cost.

Process route planning has been extensively studied and integrated with typical production environment, for example, in the distributed manufacture [3] and shop manufacture systems [4, 5]. However, most of the existing research in this area evaluates the process route based on one or more of the conventional management goals, such as minimum number of setups, shortest processing time, and minimum machining cost. With the development of low-carbon manufacturing, our research finds that the decisions of processing methods, machines, cutting tools, and sequence of process stages during process route planning have significant impact on carbon emission of the whole machining process. Process route planning with low carbon emission objective is worth studying while no research has begun on it yet.

In general, the planning problem mainly includes two parts: the processing method selection and process stage sequencing. In the selection stage, each machine features should be considered, so that one or several processing methods, involving the selection of machines, cutting tools, and tool approach directions based on the feature geometry and available resources can be determined [6]. In the view of low-carbon manufacturing, during the selection, more factors related to carbon emission should also be taken into account, for example, the energy consumption of machines, the usage of cutting fluids, and the usage and wear pattern of cutting tools. In the sequencing stage, the sequence all process stages require for the component is determined. The optimization decision must complete the two parts simultaneously to achieve an optimal or near-optimal process route against certain criteria. However, with low carbon concept, our research present a low carbon and high efficiency model, which aims to minimizing carbon emission and maximizing efficiency of the whole machining process.

This paper reports our research on optimizing process route planning by considering carbon emission as well as efficiency. Based on analyzing the machining features of the component, we first establish a carbon emission and efficiency estimation model of process route, through which the carbon emission of typical processing method can be estimated in general. Then, a mathematical model to express process route optimization problem is developed with objectives to minimize the total carbon emission and total process time. To solve this problem, a non-dominated sorting genetic algorithm (NSGA-II) is introduced. Furthermore, we conduct a simulation study on making a machine motor seat to verify the feasibility and practicability of the proposed model. The result of the experiment shows that our model can achieve the goal of reducing emission as well as maintaining system efficiency.

The paper is structured as follows. Section 2 reviews related research. We present our model in Section 3. After the introduction of our optimization algorithm in Section 4, we describe the simulation case study in Section 5. The paper is concluded with the discussion of our contribution and the future research direction.

2 Literature reviews

Process route planning has been well studied in traditional manufacture systems, and numerous approaches have been proposed to obtain optimal or near-optimal solutions. With respect to different evaluation criteria of process route planning problem, the existing research can be classified into the following directions: research on cost factors, research on time optimization, and research on other practical criteria.

The cost factors are most commonly used as evaluation criteria in traditional process route planning optimization. The machine cost, tool cost, machine change cost, tool change cost, and setup change cost were proposed and used either individually or collectively to evaluate the process route of components and parts [7]. Ma et al. [8] described an approach to model the constraints of process planning problems in a concurrent manner. An algorithm based on simulated annealing was developed to search for the optimal solution, and the cost factors were used flexibly as an objective function. Hua et al. [9] presented a fuzzy logic neural network to determine the priorities of alternative machining operations for each feature and use a genetic algorithm (GA) as a global search technology to obtain the global optimal solution for operation sequencing optimization. Salehi et al. [10] divided a process planning problem into two stages. At the first stage, the feasible sequences of operations were generated based on the analysis of constraints and using a GA. Then, at the detailed planning stage, GA was used again to obtain the optimized operations sequence and the optimized selection of the machining resources for each operation. Lian et al. [11] took various flexibilities into consideration and employed an imperialist competitive algorithm to minimize total weighted sum of manufacturing costs in process planning optimization. Liu et al. [12] mapped a process planning to a constraint-based traveling salesman problem and implemented an ant colony optimization algorithm to solve this problem.

Research integrating process planning with scheduling evaluates the performance of process route optimization based on time. Kim et al. [4] investigated the integration problem in job shop manufacturing systems. The two functions of process planning and scheduling were interwoven target on minimize makespan and mean flow time. Symbiotic evolutionary algorithm (SEA) was presented to handle the combination optimization problem. Shao et al. [5] studied the same problem and developed a new integration model with a modified GA-based approach to facilitate the integration and optimization of the two functions. Li et al. [13] systematically defined a set of performance criteria based on time, including single or combination of makespan, the balanced level of machine utilization, job tardiness, and manufacturing cost. Based on these criteria, some research optimized the process planning problem by using particle swarm algorithm [14, 15], ant colony optimization algorithms [16], and evolutionary algorithm [17].

Other criteria have also been presented to meet various practical requirements. Li et al. [18] considered process route planning in a dynamic workshop environment aimed to achieve the global lowest machining cost. Li et al. [3] studied a process planning in distribute manufacture environment. To achieve the highest efficiency, processing time and cost were presented as optimization objectives, and GA was adapted to search the optimal or near-optimal process plan. Shin et al. [19] addressed the process planning problem in flexible manufacture system. Three objectives—balancing the machine workload, minimizing part movements, and minimizing tool changes—were taken into account, and a multi-objective SEA was presented to solve multi-objective process planning problem.

A review of the related work reveals that most of the existing research focuses on process route planning problem in conventional manufacture environment, with simple evaluation criteria like cost and time, endeavoring to improve production efficiency. Process route planning in low-carbon manufacture environment has not been fully investigated and is in urgent need of exploitation and research. As far as we know, our research is one of the early attempting to address the process route planning problem with low carbon emission concept. To evaluate the performances, we propose a new framework model of carbon emission and efficiency, through which the carbon emission and total processing time of the process route can be analyzed and calculated.

3 The optimization model of process route planning

In this section, feature and machining elements are first introduced to describe the process route planning problem. Then, the framework of carbon emission and efficiency estimation model is established in Section 3.2. In Section 3.3, the process route planning problem is expressed in detail as a constraint combinatorial optimization problem.

3.1 Feature element and machining element

Features are widely used to describe parts and components in process route planning and optimization decision making. In general, each component is composed of one or several basic machining features, such as holes, faces, steps, and chamfers. These features can be divided into two categories: the main and the auxiliary features. The main features are used to build the overall structure of the component that cannot be split again in geometric topology, such as faces, excircles, and holes. The auxiliary features are local geometric structure of the main feature that modifies it in some extent, such as chamfers, keyways, and threads.

Each machining feature, as a standard shape, has a uniform processing technique which contains a series of process stages. Generally, for one process stage, there is usually more than one processing method to choose. Process route planning for components not only devotes to deal with multiple features processing, but also faces the challenge of selecting the processing methods and related resources in multiple process stages, as shown in Fig. 1. A component contains a series of machining features, each of which has several process stages. In each process stage, alternative processing methods with choice of variety processing resources are provided, leading a high flexibility in process route planning and optimization decision-making.

For the convenience of describing the process route planning problem here, we introduce the definition of feature element and machining element first.

In a component, all the features constitute to a feature element set F, where each feature is known as a feature element. It can be written as:

$$F = \{F_1, F_2, \cdots F_i, \cdots, F_n\}$$

F_i is the i^{th} feature of the component, and the total number of feature elements is represented as n.

The core of a machining element is machining feature, with related information during processing. In this paper, a machining element includes machining feature, process stage, processing method, processing resource, and the clamping position. It can be written as:

$$me_{ij} = \left\{F_i, S_j, P_l, R_u, D\right\}$$

where, F_i is the i^{th} feature of the component; S_j is the j^{th} process stage of feature F_i; P_l is the l^{th} processing method of S_j; and R_u is the u^{th} processing resources of S_j and D is the clamping position of S_j.

Generally, during the component machining process, the same processing method can be achieved by using different combinations of processing resources, such as machines, cutting tools, fixtures, etc. Hence, R_u can also be perceived as a set of processing resources. Let $m=\{m_1,m_2,\cdots,m_o\}$ represent the set of machine tools, $t=\{t_1,t_2,\cdots,t_p\}$ the set of cutting tools, $f=\{f_1,f_2,\cdots,f_q\}$ the set of fixtures, and o, p, and q the total number of machines, cutting tools, and fixtures, respectively. R_u can be expressed as $R_u=\{m_s,t_k,f_r\}$, where $1\leq s\leq o$, $1\leq k\leq p$, $1\leq r\leq q$.

The machining element set of a component can be written as:

$$ME = \{me_1, me_2, \cdots, me_n\}$$

where me_n is the set of all the machining elements of F_n.

For a component, a process route is a certain combination of all elements in machining element set. For example, if a process route is written as $x=\{me_{a1},me_{a2},\cdots,me_{a'n}\}$, this process route x begins at me_{a1} and end with $me_{a'n}$. Hence, the process route planning problem can be summarized as a problem of feature element analyzing and machining element sequencing.

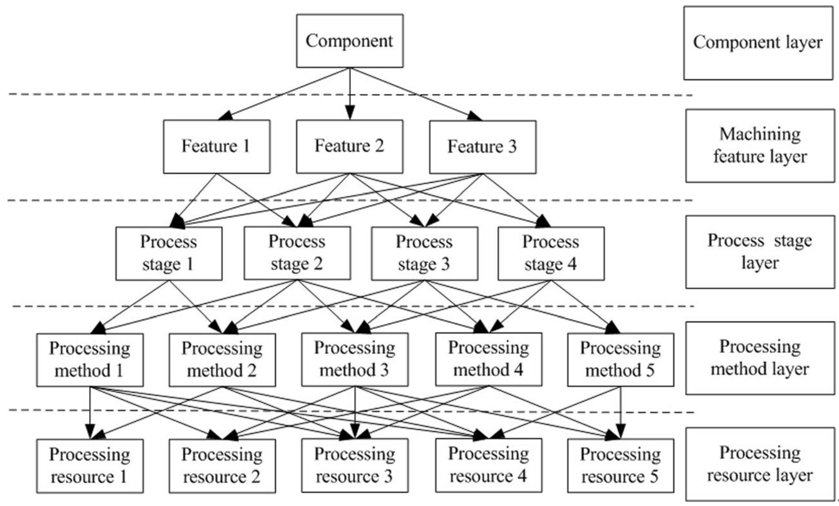

Fig. 1 The processing hierarchy chart of mechanical parts

3.2 Framework of carbon emission and efficiency estimation model

A framework of carbon emission and efficiency estimation model is developed to evaluate the performances of the process route plans. This model includes categorizing and calculating the total carbon emission of a process route as well as processing time and defines a set of functions to support the relevant calculations.

3.2.1 Carbon emission function

In process route planning, minimizing the total carbon emission from all processing method during the whole machining process is proposed as an objective. In order to provide a simple and effective way to calculate the carbon emission, the processing methods are classified into two categories: cold and hot processing, and general calculation functions are proposed to estimate the carbon emission during machining process.

1. Carbon emission from cold processing

Cold processing is the major component of machining process. Carbon emission from a cold processing method is generated by electric consumption, cutting fluid consumed, and cutting tool wear and tearing [20]. For a cold processing method i, during processing, its carbon emission can be calculated as:

$$CE_i = CE_i^e + CE_i^f + CE_i^t \tag{1}$$

where CE_i^e is the carbon emission from electric consumption the processing machine during i; CE_i^f is the carbon emission from cutting fluid consumption in i; CE_i^t is the carbon emission from cutting tools using and wearing in i. If i is the dry-type processing that do not need cutting fluid during processing, then the CE_i^f is set as zero.

a. Calculation of CE_i^e

Energy consumption of mechanical processing equipment mainly includes cutting energy consumption and auxiliary energy consumption. Cutting energy consumption refers to the energy consumed by cutting tool driving systems (main drive system and feed drive system); auxiliary energy consumption is the energy used to support auxiliary systems (illuminating system, lubricating and cooling system, and stamping system) in processing. CE_i^e can be calculated as:

$$CE_i^e = CEF_{\text{elec}} \times \left(EC_i^{\text{cut}} + EC_i^{\text{au}}\right) \tag{2}$$

where CEF_{elec} is carbon emission factor of electrical energy, EC_i^{cut} is cutting energy consumption of i, and can be calculated via some mathematical methods, such as theoretical calculation method [20, 21], energy density method [22], average process energy method [23], and so on. In this paper, a simplified theoretical calculation method is employed, and the cutting energy consumption can be estimated as:

$$EC_i^{\text{cut}} = \left(P_i^{\text{unload}} + P_i^{\text{cut}} + P_i^{\text{add}}\right) \times t_i \tag{3}$$

where P_i^{unload} is the unload power, P_i^{cut} is the cutting power, and P_i^{add} is the additional load loss power during machine processing of method i. t_i is the machining time.

EC_i^{au} is auxiliary energy consumption of i and can be calculated as:

$$EC_i^{\text{au}} = P_i^{\text{au}} \times T_i \tag{4}$$

where P_i^{au} is the total power consumption of all auxiliary system of the machine used for processing method i, and T_i is the processing time (including machining time and idling time).

b. Calculation of CE_i^f

In general, different types of cutting fluid are required based on processing method types. When the carbon emission factors and change interval of each cutting fluids vary considerably, it leads to a big difference in carbon emission when varieties alternative processing methods are available. The carbon emission of cutting fluid in processing method i can be calculated as:

$$CE_i^f = \frac{T_i}{T_i^f} \times \left[CEF_i^{\text{oil}} \times (CC_i + AC_i) + CEF_i^{wf} \times \frac{(CC_i + AC_i)}{\delta_i} \right] \tag{5}$$

where T_i^f is the cutting fluid change interval, which is set between 1 month and 3 months in general. CEF_i^{oil} is the carbon emission factor of cutting fluid, CEF_i^{wf} is the carbon emission factor of cutting fluid disposal. CC_i and AC_i represent the initial dosage and the additional consumption of cutting fluid. δ_i is the concentration of cutting fluid.

c. Calculation of CE_i^t

Similar as the cutting fluid we discuss above, the cutting tools are diverse used in different kind of processing method types. Even in the same processing method, there is usually more than one kind of cutting tool can be used. Thus, carbon emission generated from cutting tools using and wearing appears different due to different carbon emission factors and cutting tool lifecycles. It can be calculated as:

$$CE_i^t = \frac{t_i}{T_i^t} \times CEF_i^t \times W_i^t \tag{6}$$

where T_i^t is the cutting tool's lifecycle, CEF_i^t is the carbon emission factor of the cutting tool and W_i^t is the quality of the cutting tool.

2. Carbon emission from hot processing method

In the machining process, while cold working process plays the major role, it also involves some hot processing methods like thermal treatment, weld, and so on. Our research only discusses the heat treatment here, which is common in mechanical machining process. For metal heat treatment, the most frequently used heating method is electric furnace heating. The furnace runs using electricity as its main power source to both generate heat and push the air through the central heating system. The carbon emission generated can be determined as:

$$CE_j^{ht} = CEF_{\text{elec}} \times EC_j^{ht} \tag{7}$$

where j is the j^{th} process stage that heating method is used. CEF_{elec} is the carbon emission factor of electric energy. EC_j^{ht} is the electric consumption of the j^{th} process stage, which can be estimated according to heat treatment process power consumption quota:

$$EC_j^{ht} = N_b \times K_1^j \times K_2^j \times K_3^j \times K_4^j \times K_5^j \tag{8}$$

N_b is standard process power consumption of heat treatment, and its value is set as 1.08×10^6 J/kg. K_1^j, K_2^j, K_3^j, K_4^j, K_5^j respectively represent the technology conversion factor, the heating mode factor, the production mode factor, the workpiece material factor, and the load factor of process stage j. The values of these factors are available in standards literature [24].

Then, the calculation function of hot processing method can be written as:

$$CE_j^{ht} = CEF_{\text{elec}} \times N_b \times K_1^j \times K_2^j \times K_3^j \times K_4^j \times K_5^j \tag{9}$$

To sum up, if a process route contains n process stages that use the cold processing method and m process stages of hot processing method, the total carbon emission of the machining process can be calculated as:

$$\begin{aligned} CE &= \sum_{i=1}^{n} \left(CE_i^e + CE_i^c + CE_i^t \right) \\ &\quad + \sum_{j=1}^{m} \left(CEF_{\text{elec}} \times EC_j^{ht} \right) \\ &= \sum_{i=1}^{n} \Big\{ CEF_{\text{elec}} \times \left(P_u t_{\text{idle}} + P_i t_i + P_i^{au} T_i \right) + \frac{T_i}{T_i^f} \\ &\quad \times \left[CEF_i^{\text{oil}} \times (CC_i + AC_i) + CEF_i^{wf} \times \frac{(CC_i + AC_i)}{\delta_i} \right] \\ &\quad + \frac{t_i}{T_i^t} \times CEF_i^t \times W_i^t \Big\} \\ &\quad + \sum_{j=1}^{m} \left(CEF_{\text{elec}} \times N_b \times K_1^j \times K_2^j \times K_3^j \times K_4^j \times K_5^j \right) \end{aligned} \tag{10}$$

3.2.2 High efficiency function

To ensure the efficiency of our low carbon processing model, we take the total process time of process route as another optimization objective, which include machining processing time (*MPT*), machine change time (*MCT*), cutting tool change time (*TCT*), and fixture change time (*FCT*). They are described in detail as followed.

1. Machining processing time (*MPT*)

Let t_i be the processing time of the processing method used in stage i, and there are n process stages in the process route. The total machining processing time can be calculated as:

$$MPT = \sum_{i=1}^{n} t_i \tag{11}$$

2. Machine change time (*MCT*)

Machine change is defined as two adjacent process stages used different machines. The total machine change time can be calculated as:

$$MCT = MCTI \times \sum_{i=1}^{n-1} \Psi_m(M_{i+1} - M_i) \tag{12}$$

$$\Psi_m(M_{i+1} - M_i) = \begin{cases} 1 & if \quad M_i \neq M_{i+1} \\ 0 & if \quad M_i = M_{i+1} \end{cases} \tag{13}$$

where *MCTI* is machine change time factor (time for one change), M_i is the machine that the i^{th} stage used. Ψ_m is the machine change indicator.

3. Cutting tool change time (*TCT*)

Cutting tool change is two adjacent process stages use different cutting tools. It can be calculated as:

$$TCT = TCTI \times \sum_{i=1}^{n-1} \Psi_t(T_{i+1} - T_i) \tag{14}$$

$$\Psi_t(T_{i+1} - T_i) = \begin{cases} 1 & if \quad T_i \neq T_{i+1} \\ 0 & if \quad T_i = T_{i+1} \end{cases} \tag{15}$$

where *TCTI* is cutting tool change time factor (time for one change), T_i is the cutting tool that i^{th} stage used. Ψ_t is the cutting tool change indicator.

4. Fixture change time (*FCT*)

Fixture change is two adjacent process stages use different fixtures. It can be calculated as:

$$FCT = FCTI \times \sum_{i=1}^{n-1} \Psi_f(F_{i+1} - F_i) \tag{16}$$

$$\Psi_f(F_{i+1} - F_i) = \begin{cases} 1 & if \quad F_i \neq F_{i+1} \\ 0 & if \quad F_i = F_{i+1} \end{cases} \tag{17}$$

where *FCTI* is fixture change time factor (time for one change), F_i is the fixture that i^{th} stages used. Ψ_f is the fixture change indicator.

In sum, the total process time of process route can be calculated as:

$$\begin{aligned} TPT &= MPT + MCT + TCT + FCT \\ &= \sum_{i=1}^{n} t_i + +MCTI \times \sum_{i=1}^{n-1} \Psi_m(M_{i+1} - M_i) + TCTI \\ &\quad \times \sum_{i=1}^{n-1} \Psi_t(T_{i+1} - T_i) + FCTI \\ &\quad \times \sum_{i=1}^{n-1} \Psi_f(F_{i+1} - F_i) \end{aligned} \tag{18}$$

3.3 Process route optimization problem

3.3.1 Constraints

In process route planning, the geometric and manufacturing constraints between manufacturing features should be considered when determining or optimizing the operation sequence. We summarized the related research by Li et al. [18] and Qiao et al. [25] and divide these constraints into two mandatory categories: rationality and optimal constraints. One optimal solution of process route optimization must satisfy rationality constraints and try to gratify optimal constraints. Thus, the basic idea of process route planning optimization is first to find out the set of all rationality process routes that meet rationality constraints and then evaluate them according to the optimal constraint standards in order to find out the optimal or near-optimal process route of the component.

Currently, rationality constraints in machining process include primary surfaces prior to secondary surfaces, rough machining operation prior to finish machining operation, planes prior to its associated features, and clamping or supporting faces should be machined later. Other constraints such as less carbon emission, less machine change, less cutting tool change, and less clamping times are considered as optimal constraints.

3.3.2 Optimization problem

The process route planning problem is defined as machining element scheduling optimization problem that aims to reduce carbon emission and improve efficiency, with different restricted conditions. Therefore, the process route planning problem can be treated as a constraint combinatorial

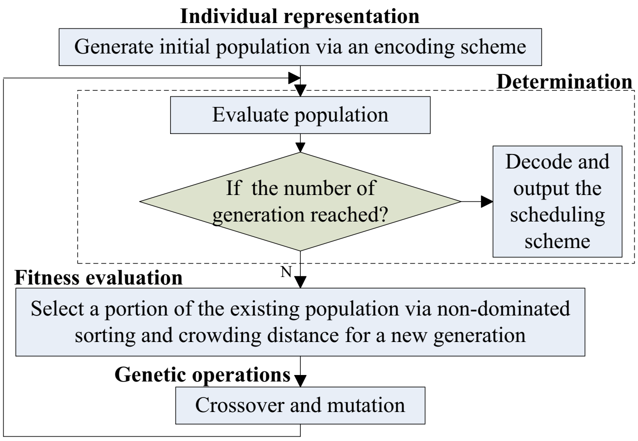

Fig. 2 The flow chart of the evolution process

optimization problem mathematically which considers the order of machining elements as optimization variable. The mathematical model is:

$$\begin{aligned} &\min f\ (x) = F\ (CE,\ TPT) \\ &x = (me_{a1}, me_{a2}, \cdots, me_{a'n}) \\ &S.\ T. \begin{cases} h_j(x) = 0, & j = 1,\ 2,\ \cdots, l \\ g_i(x) \le 0, & i = 1,\ 2,\ \cdots,\ m \\ x \in \Omega, & \Omega = (x_1, x_2, \cdots, x_{n!}) \end{cases} \end{aligned} \tag{19}$$

where $f(x)$ is the objective function and it refers to minimizing the carbon emission and total processing time. $h_j(x)$, $g_i(x)$ are the rationality constraints and the optimal constraints discussed above. Ω is the set of all different sequence of machining elements of the component, and x is one particular solution in Ω. Theoretically, there are $n!$ elements in Ω, while in fact the number is far less than $n!$ because of the constraints in process route planning.

4 Solving optimization model based on NSGA-II

GA is a heuristic algorithm that mimics the process of natural selection, such as inheritance, crossover, mutation, and selection. It has been used in a variety of applications such as tactical asset allocation [26], job scheduling [27], machine-part assemble and disassemble [28, 29], and other engineering fields. Among the existing GA, NSGA-II [30] is one of the most prominent algorithms for solving multi-objective optimization problems. In our research, this algorithm is employed and adapted to solve the process route planning optimization problem, with two objectives on minimizing carbon emission and total processing time. To satisfy the actual problem proposed above, a representation scheme based on machining feature, with corresponding genetic operations and fitness evaluation functions, is introduced and described in detail as follows. The key components and the evolution process of the adapted NSGA-II are shown in Fig. 2.

S_i	1	2	2	3	4	4	3	3	5	6	1	1	5	2
M_i	7	7	7	7	1	1	1	2	2	1	1	2	7	7
T_i	1	1	1	1	3	3	2	2	1	1	2	2	3	3

Fig. 3 The encoding scheme of a chromosome

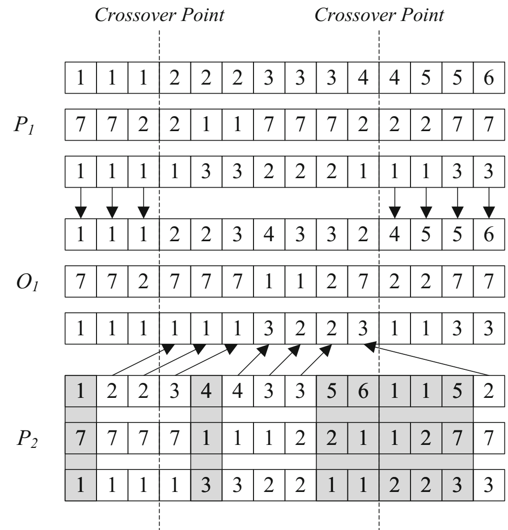

Fig. 4 Improved two-point crossover

4.1 Individual representation

Individual representation in NSGA-II should be natural, clear, and not redundant. In this paper, a representation scheme based on machining feature is presented. Each chromosome represents a complete process route plan, including the sequence of process stages of all machining features, as well as related selection of machines and cutting tools.

As shown in Fig. 3, a complete chromosome is composed of three substrings, the process stages code substring S_i, the machine code substring M_i, and the cutting tool code substring T_i.. The length of each substrings are equal to the total number of process stages of component i.

In S_i, process stages are encoded by features; each gene X stands for a process stage of feature X, and the process stage

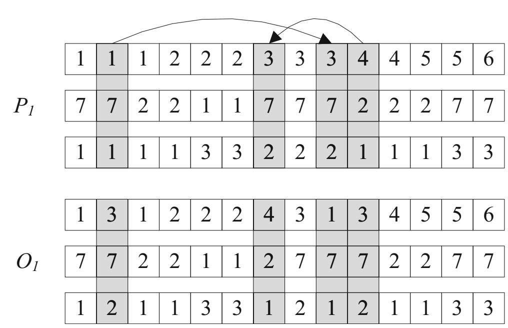

Fig. 5 Mutation operation for the whole chromosome

	1	3	1	2	2	2	4	3	1	3	4	5	5	6
P_1	7	7	2	2	1	1	2	7	7	7	2	2	7	7
	1	2	1	1	3	3	1	2	1	2	1	1	3	3

	1	3	1	2	2	2	4	3	1	3	4	5	5	6
O_1	7	7	2	7	1	1	2	7	7	7	2	2	7	7
	1	2	1	2	3	3	1	2	1	2	1	1	1	3

Fig. 6 Mutation operation for M_i and T_i

physically positioned earlier in string will be processed first. This can be explained as:

The number of gene X appears in S_i is equal to the number of process stages in feature X. For example, in Fig. 3, there are three occurrences of '1' in S_i, which means there are three process stages in feature 1 (F_1).

The first X in S_i represents the first process stage of feature X; the second X represents the second process stage, and so on. All the genes of X in this substring compose the processing route of feature X.

M_i is generated by machine number, where each gene represents the machine used in the process stage of the same location in S_i. For example, in Fig. 3, the first gene in M_i is 7, which refers to the process stage in S_i; the first stage of F_1 is processed by machine 7. Similarly, the cutting tool code is generated by cutting tool numbers with relevant position of process stages. In Fig. 3, the first gene in T_i is 1, which refers to the 1st stage of F_1 is processed by using cutting tool 1.

4.2 Genetic operations

During each successive generation, a proportion of the existing population is selected to breed a new generation through genetic operators: crossover (also called recombination) and mutation. Based on our optimization problem and representation scheme, traditional crossover and mutation methods are modified in order to satisfy the rationality constraints of process route problem.

4.2.1 Crossover

An improved two-point crossover is imported to avoid illegal individuals. As in Fig. 4, the procedure of the crossover can be described as follows:

Step 1 Select two crossover points randomly.

Step 2 Copy the genes of S_i with related M_i and T_i before the first crossover points and after the second crossover points of P_1 to the same positions of the offspring. Delete these genes of S_i with related to M_i and T_i from P_2 sequentially.

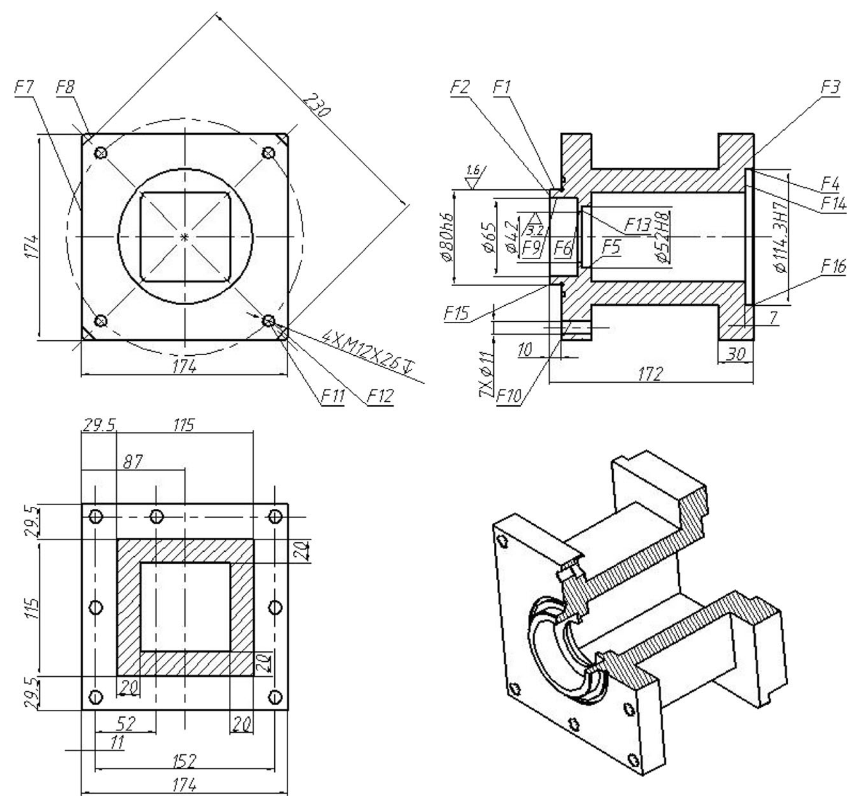

Fig. 7 The three basic orthographic views of machine motor seat

Table 1 machining features and corresponding process stages

Feature ID	Feature type	Process stages	Remark
F1	Excircle	Rough turning–half finish turning–finish turning	
F2	The left face	Rough turning–half finish turning–finish turning	
F3	The right face	Rough turning–half finish turning–finish turning	
F4	Hole	Rough turning–finish turning	ϕ114.3
F5	Hole	Rough turning–finish turning	ϕ52
F6	Hole	Rough turning–finish turning	ϕ42
F7	4 sides	Rough milling–finish milling	174×174
F8	4 steps	Rough milling–finish milling	230×230
F9	Hole	Finish turning	ϕ65
F10	Hole	Drilling	ϕ11×7
F11	Hole	Drilling	ϕM12×4
F12	Hole	Tapping	ϕM12×4
F13	Step face of inner hole	Finish turning	ϕ52
F14	Step face of inner hole	Finish turning	ϕ114.3
F15	Chamfer	Finish turning	
F16	Hole chamfer	Finish turning	

Step 3 Copy the remaining genes of P_2 to the undetermined positions of the offspring sequentially as they appear in P_2.

4.2.2 Mutation

For the whole chromosome, two-point insert is implemented as mutation operation, as illustrated in Fig. 5. In the parent string, two genes are randomly chosen and are inserted to other two randomly selected positions.

Then, single-point mutation is used only in M_i and T_i, as shown in Fig. 6. For M_i, one gene is randomly chosen first and alternated it with another available machine for this process stage. Then, the related gene in T_i is replaced with available cutting tool number. For T_i, one gene was randomly chosen and alternated it with another available cutting tool for this process stage.

Table 2 Machine information list

Machine ID	Machine name	Power (kw)
M01	Lathe	10
M02	CNC lathe	22
M03	CNC vertical miller	15
M04	Vertical miller	11
M05	Radial drill	4
M06	Radial drill	3
M07	CNC lathe	18.5

4.3 Fitness evaluation

In GA-based algorithms, the fitness evaluation scheme should be designed so that a wide spread of solutions close to the Pareto optimal solutions can be searched. In NSGA-II, a fast non-dominated sorting approach is used to reduce computational complexity and crowding distance calculation is introduced to maintain diversity among population [30]. Individual solutions can be evaluated through the non-dominated level and crowding distance.

1. Non-dominated sorting approach

In this paper, we adopt a fast non-dominated sorting approach presented by Deb et al. [30]. The carbon emission and total processing time are chosen as fitness functions, and each individual solution in the current population is compared through the measure of fitness in order to categorize them into different non-dominated fronts. The members with lower non-dominated level with better fitness values are more likely to be chosen to breed a new generation.

2. Crowding distance calculation

To preserve the population's diversity, crowded-comparison approach was introduced in the process of individual evaluation. For an individual i, crowding distance di can be calculate by sum up all the distance of the left and right neighbors of i along each of the fitness function. In our paper, it can be represented as:

Table 3 Cutting tool information list

Cutting tool ID	Cutting tool name	Lifecycle (min)	Quality (g)	Main application
T01	Lathe tool 1	60	9.5	Turning
T02	Lathe tool 2	100	10	Turning
T03	Lathe tool 3	90	9	Turning
T04	Milling tool 1	240	7.5	Milling
T05	Milling tool 2	180	5	Milling
T06	Drill 1	60	375	Drilling
T07	Drill 2	75	475	Drilling
T08	Screw tap	75	275	Tapping

$$d(i) = |f_{CE}(i+1) - f_{CE}(i-1)| + |f_{TPT}(i+1) - f_{TPT}(i-1)| \tag{20}$$

where $f_{CE}(i)$ and $f_{TPT}(i)$ are the values of carbon emission and total processing time of i.

The fitness value of i can be calculated as:

$$\text{eval}_i = r(i) + \frac{1}{1 + d(i)} \tag{21}$$

where $r(i)$ and $d(i)$ represent the non-dominated level and crowding distance in this level of individual i respectively. The one with lower fitness value is regarded as relatively good and more suitable for inheritance.

5 Case study

To validate our model and algorithm, we conducted a simulation-based case study on manufacturing a machine motor seat. Figure 7 shows the three basic orthographic views of the machine motor seat. In this section, we first analyze the machining features of the component. Then, the simulation study is introduced. Finally, we present and discuss the results of the experiment.

5.1 Machining feature analysis

The machine motor seat contains as many as 16 main machining features, such as excircle, face, hole, step, step face of inner hole, chamfer, and hole chamfer. The machining features with their corresponding process stages are detailed in Table 1.

Tables 2 and 3 show the machine information and cutting tool information, including machine power, lifecycle, and quality of cutting tool [31]. In this research, the carbon emission factor of electricity is 0.7125 $kgCO_2/kWh$ based on the reference data from development and reform commission of China [32]. Cemented carbide cutting tools are chosen during the whole machining process, of which the emission factor is 30.153 $kgCO_2/kg$ [33]. For the convenience of calculation, we unify the parameters of the cutting fluids used in all machines. The emission factor of cutting fluid making and disposal are 500 $kgCO_2/m^3$ and 200 $kgCO_2/m^3$. The initial and additional dosages of cutting fluid are 0.0085 and 0.0045 m^3, the concentration is 0.5 and the cutting fluid change interval is 2 months.

Based on Tables 1, 2, and 3, the alternatives of machine and cutting tool for each process stage are listed in Table 4, where columns 1 and 5, columns 2 and 6 show the features and the related process stages. The machine and cutting tool alternatives are shown in columns 3 and 7, with their processing time in columns 4 and 8. In practice, the machine change time and cutting tool change time are uncertain and varies greatly in different situations. In this case, a series of statistics data are collected in advance, and the average values are chosen as the unit machine change time and cutting tool change time, which are 3 min and 2 min, respectively.

5.2 Simulation experiments

5.2.1 Encode

Before the algorithm is implemented, process stages as well as machines and cutting tools should be encoded first. As shown in Table 4, there are 16 features and 27 process stages in the machine motor set. Each process stage is identified by process stage ID shown in Table 5. It includes two parts of information of the features and processing orders. For example, the process state O0102 represents the second process stage of feature 1. Machine code and cutting tool code are listed in Table 6.

5.2.2 Optimizations based on different evaluation criteria

To test the performance of the algorithm and validate the effectiveness of the low carbon emission and high efficiency optimization model we conducted, simulations were based on different evaluation criteria. Criterion 1 meets the requirements of our low carbon emission and high efficiency model, while criteria 2 and 3 are set as contrasts:

Criterion 1 Minimizing both carbon emission and total processing time.

Table 4 Alternative machines, cutting tools, and processing time of each process stage

Feature ID	Process stage	Machine and cutting tool	Processing time (min)	Feature ID	Process stage	Machine and cutting tool	Processing Time (min)
F1	Rough turning	M02T01	2	F6	Rough turning	M02T01	1
		M02T03	2.1			M02T03	1.1
		M07T01	2.1			M07T01	1.05
		M07T03	2.1			M07T03	1.1
	Half finish turning	M02T01	2		Finish turning	M02T01	1
		M02T03	2.1			M02T03	1.1
		M07T01	2.2			M07T01	1.1
		M07T03	2.2			M07T03	1.15
	Finish turning	M02T01	2	F7	Rough milling	M03T04	1
		M02T03	2.2			M03T05	1
		M07T01	2.1			M04T04	1.2
		M07T03	2.1			M04T05	1.1
F2	Rough turning	M02T01	2		Finish milling	M03T04	1.1
		M02T03	2			M03T05	1
		M07T01	2.1			M04T04	1.2
		M07T03	2			M04T05	1.1
	Half finish turning	M02T01	2	F8	Rough milling	M03T04	2.5
		M02T03	2.1			M03T05	2.5
		M07T01	2.2			M04T04	2.7
		M07T03	2			M04T05	2.6
	Finish turning	M02T01	2		Finish milling	M03T04	2.6
		M02T03	2.1			M03T05	2.6
		M07T01	2.1			M04T04	2.7
		M07T03	2.1			M04T05	2.6
F3	Rough turning	M02T01	2	F9	Finish turning	M02T01	3.2
		M02T03	2			M02T03	3
		M07T01	2.1			M07T01	3.4
		M07T03	2			M07T03	3.3
	Half finish turning	M02T01	2	F10	Drilling	M05T06	2.9
		M02T03	2.1			M05T07	3
		M07T01	2.2			M06T07	2.8
		M07T03	2	F11	Drilling	M05T06	1.7
	Finish turning	M02T01	2			M05T07	1.8
		M02T03	2.1			M06T07	1.6
		M07T01	2.1	F12	Tapping	M05T08	1.5

Table 4 (continued)

Feature ID	Process stage	Machine and cutting tool	Processing time (min)	Feature ID	Process stage	Machine and cutting tool	Processing Time (min)
		M07T03	2.1			M06T08	1.2
F4	Rough turning	M02T01	2.2	F13	Finish turning	M02T01	2.4
		M02T03	2.3			M02T03	2.6
		M07T01	2.2			M07T01	2.5
		M07T03	2.2			M07T03	2.7
	Finish turning	M02T01	2.25	F14	Finish turning	M02T01	2.8
		M02T03	2.2			M02T03	2.9
		M07T01	2.15			M07T01	3.1
		M07T03	2.2			M07T03	3
F5	Rough turning	M02T01	1	F15	Finish turning	M02T01	2.1
		M02T03	1.2			M02T03	2
		M07T01	1.2			M07T01	2.3
		M07T03	1.2			M07T03	2.6
	Finish turning	M02T01	1.1	F16	Finish turning	M02T01	2
		M02T03	1.2			M02T03	2.2
		M07T01	1.1			M07T01	2.4
		M07T03	1.15			M07T03	2.6

Table 5 Operation code

Process stage code	Process stage ID	Description	Process stage code	Process stage ID	Description
1	O0101	Rough turning F1	6	O0602	Finish turning F6
1	O0102	Half finish turning F1	7	O0701	Rough milling F7
1	O0103	Finish turning F1	7	O0702	Finish milling F7
2	O0201	Rough turning F2	8	O0801	Rough milling F8
2	O0202	Half finish turning F2	8	O0802	Finish milling F8
2	O0203	Finish turning F2	9	O0901	Finish turning F9
3	O0301	Rough turning F3	10	O1001	Drilling F10
3	O0302	Half finish turning F3	11	O1101	Drilling F11
3	O0303	Finish turning F3	12	O1201	Tapping F12
4	O0401	Rough turning F4	13	O1301	Finish turning F13
4	O0402	Finish turning F4	14	O1401	Finish turning F14
5	O0501	Rough turning F5	15	O1501	Finish turning F15
5	O0502	Finish turning F5	16	O1601	Finish turning F16
6	O0601	Rough turning F6			

Criterion 2 Minimizing carbon emission only
Criterion 3 Minimizing total processing time only.

For criterion 1, NSGA-II was adopted to find the Pareto optimal solutions for both low carbon emission and high efficiency. For criteria 2 and 3, GA was used in optimization to find the best solution with a single objective of minimum carbon emission or total processing time. All the optimization simulation experiments were operated by Matlab. Because the performance of NSGA-II and GA are not guaranteed and can never be assessed on the basis of a single run, in each case, 50 trials were conducted repeatedly.

The parameters for NSGA-II and GA were set as follow: the population size was 60; the iteration number was 200, and crossover and mutation probabilities are 0.85 and 0.05, respectively.

Table 6 Machine code and cutting tool code

Machine code	Machine ID	Cutting tool code	Cutting tool ID
1	M01	1	T01
2	M02	2	T02
3	M03	3	T03
4	M04	4	T04
5	M05	5	T05
6	M06	6	T06
7	M07	7	T07
		8	T08

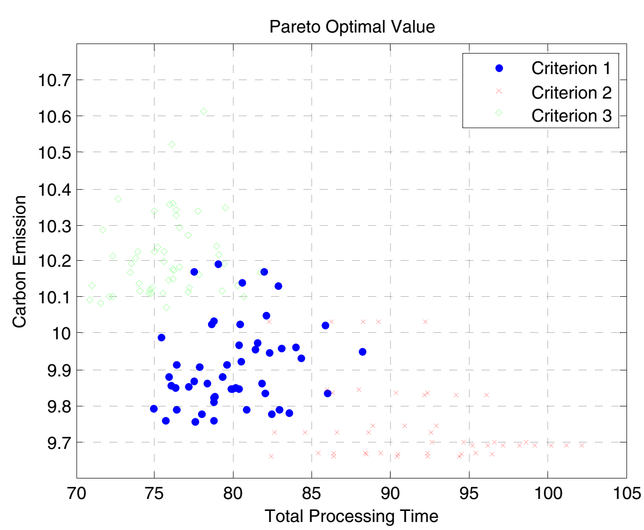

Fig. 8 The results of optimization experiments in three criterions

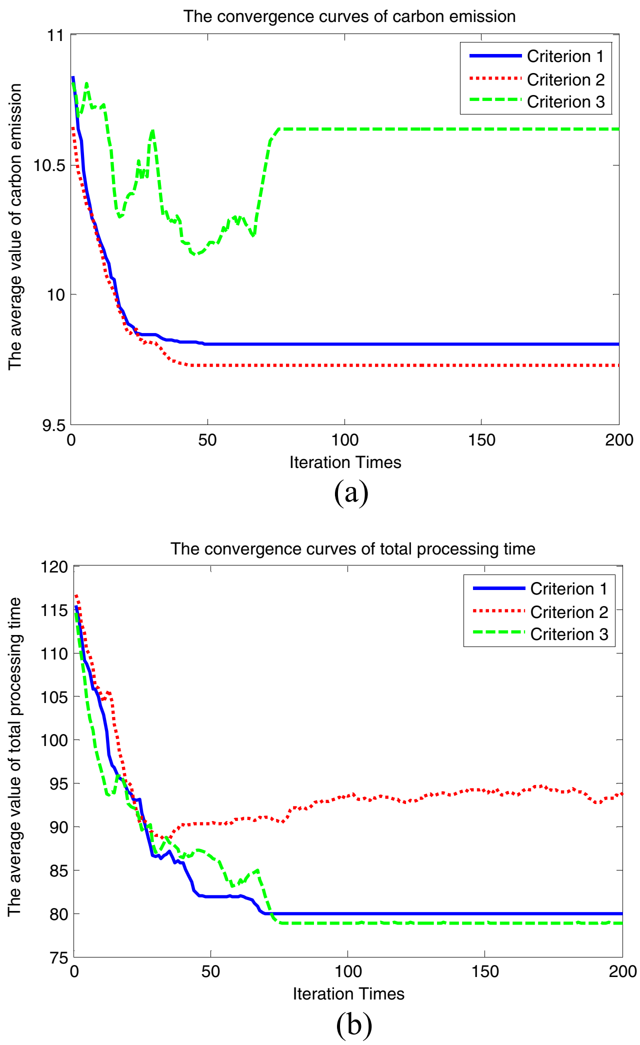

Fig. 9 The convergence curves

5.3 Result analysis

5.3.1 Algorithm performance analysis

Figure 8 shows the result of the three sets of optimization experiments. Simulations with criterion 1 are multi-objective optimization, in which a series of Pareto optimal solutions are obtained with a single run. For the convenience of comparison, the average value of carbon emission and total processing time of these Pareto optimal solutions were calculated as the result of each trial. These results are marked as filled dots in Fig. 8. Simulations with criterion 2 only focus on optimizing the carbon emission objective, after a single run a best solution with minimize carbon emission can be gained. The total processing time for each solution was also calculated, and these results are marked as crosses in Fig. 8. The results of simulations with criterion 3, which aims to minimize total processing time, are marked as diamonds in Fig. 8.

Basically, as shown in Fig. 8, simulations with criteria 2 and 3 show a tendency of better performance in one objective with a great sacrifice of the other one. Optimizations with criterion 1 gain a tradeoff between two objectives, and lower the carbon emission and reduce the total processing time simultaneously. This can also be verified by the convergence characteristic in Fig. 9. Figure 9a, b illustrate the tendency of the average value of carbon emission and total processing time in iteration process. The convergence curves are obtained from statistic data of each 50 trials. It is clear that the optimization algorithm with criterion 1 performs a good property in convergence and optimality. In other words, the NSGA-II we proposed is a promising approach to solve process route optimization problem with low carbon emission and high efficiency consideration.

5.3.2 Effectiveness analysis of high efficiency and low emission optimization model

Table 7 show the average of carbon emission, total processing time, machine change, and cutting tool change of 50 trials with each criterion obtained from simulations. One of the best process routes with each criterion is shown in Table 8.

Comparing the optimization results, we find that optimization target on high efficiency (criterion 3) provides a process route with less change of machine and cutting tool in order to save processing time. However, the selections are concentrated, and machines and cutting tools are more likely to hold on even though there are better alternatives with less emission for the next process stage. Thus the optimal solutions obtained from this optimization model may lead to high carbon emissions. On other hand, the low carbon optimization model (criterion 2) results in a process route with frequently change of machines and cutting tools for the sake of the lowest carbon

Table 7 Optimization results

	Carbon emission (CE)/(kg)	Total processing time (TPT)/(min)	Machine change (MC)/(times)	Cutting tool change (TC)/(times)
Criterion 1	9.91	79.99	4.60	9.48
Criterion 2	9.75	91.75	6.08	13.58
Criterion 3	10.71	75.73	3.38	8.12

Table 8 One of the best process routes with each criterion

Criterion 1			Criterion 2			Criterion 3		
Process stage ID	Machine ID	Cutting tool ID	Process stage ID	Machine ID	Cutting tool ID	Process stage ID	Machine ID	Cutting tool ID
O0701	M03	T05	O0101	M07	T03	O0801	M04	T05
O0101	M07	T03	O0301	M07	T03	O0701	M04	T05
O0102	M07	T03	O0701	M04	T05	O0702	M04	T05
O0301	M07	T03	O0801	M04	T05	O0802	M04	T05
O0801	M04	T05	O0802	M04	T04	O0101	M07	T03
O0702	M04	T05	O0102	M07	T03	O0301	M07	T03
O0802	M04	T04	O0302	M07	T03	O0102	M07	T03
O0302	M07	T01	O0702	M03	T05	O0103	M07	T03
O0303	M07	T03	O0103	M07	T01	O0302	M07	T03
O0103	M07	T03	O0303	M07	T01	O0303	M07	T03
O0501	M07	T03	O0601	M07	T01	O0901	M07	T03
O0502	M07	T03	O0401	M07	T01	O0201	M07	T03
O0901	M07	T03	O0501	M07	T01	O0501	M07	T03
O0601	M07	T03	O0602	M07	T01	O0401	M07	T01
O0602	M07	T03	O0402	M07	T01	O0502	M07	T01
O0201	M07	T03	O0901	M07	T01	O0402	M07	T01
O0202	M07	T03	O0201	M07	T01	O0202	M07	T01
O0401	M07	T03	O0502	M07	T01	O0203	M07	T01
O0203	M07	T03	O0202	M07	T03	O0601	M07	T01
O0402	M07	T03	O0203	M07	T01	O0602	M07	T01
O1301	M07	T01	O1401	M07	T03	O1301	M07	T01
O1401	M07	T01	O1301	M07	T03	O1401	M07	T03
O1601	M07	T01	O1601	M02	T01	O1501	M02	T01
O1501	M07	T01	O1501	M02	T01	O1601	M02	T01
O1101	M06	T07	O1001	M06	T07	O1101	M06	T07
O1001	M06	T07	O1101	M06	T07	O1001	M06	T07
O1201	M06	T08	O1201	M06	T08	O1201	M06	T08
CE=9.82 TPT=78.70 MC=4 TC=9			CE=9.68 TPT=90.20 MC=6 TC=12			CE=10.78 TPT=73.20 MC=3 TC=7		

emission in each process stage, which truly can decrease the carbon emission with an unreasonable long processing time.

On low carbon emission and high efficiency, optimization model (criterion 1) has a better tradeoff between emission and efficiency objectives in process route optimization problem. It reduces 7.47 % of carbon emissions on average, compared with traditional efficiency-based optimization. It saves 12.82 % of processing time on average, compared with optimization only considering carbon emission. As a solution, it provides a set of process routes that reduce the carbon emission without too much loss in efficiency.

6 Conclusions

This article presents an approach of process route optimization to reduce carbon emission and improve efficiency in green manufacturing system. Machining features are introduced, and a carbon emission and efficiency estimation model of process route is established. The total carbon emission and total process time are selected as optimization objectives. We also introduced NSGA-II to solve the problem and used a case to validate the proposed model.

The results of our case studies show that, in the existing manufacturing environment, there is still more energy-saving probability without any change of facilities. The manufacturer can make a lower carbon emission manufacturing mode by optimization the processing route of products. This research also proposes a framework to estimate the carbon emission of processing routes which can be modified and applied to other research.

Our research still has some limitations. First, our method focuses on reducing the carbon emissions by optimizing the process route planning. In manufacturing, process route planning and scheduling are both essential functional modules in product development and manufacturing, and they are usually complementary. Therefore, research on integrating process route planning and scheduling tightly to achieve the global optimization of reduce reducing carbon emission during manufacturing process is necessary and worth proceeding with in the future. Second, the carbon emission in manufacturing system involves many complex factors. Our model only considers a couple of factors. This paper simplified the calculation model to validate the possibility of reducing emission. In the next research step, more practical production conditions should be considered in our model.

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