Front. Mech. Eng. 2020, 15(2): 338–350
https://doi.org/10.1007/s11465-019-0572-8

RESEARCH ARTICLE

Shuo ZHU, Hua ZHANG, Zhigang JIANG, Bernard HON

A carbon efficiency upgrading method for mechanical machining based on scheduling optimization strategy

Abstract Low-carbon manufacturing (LCM) is increasingly being regarded as a new sustainable manufacturing model of carbon emission reduction in the manufacturing industry. In this paper, a two-stage low-carbon scheduling optimization method of job shop is presented as part of the efforts to implement LCM, which also aims to reduce the processing cost and improve the efficiency of a mechanical machining process. In the first stage, a task assignment optimization model is proposed to optimize carbon emissions without jeopardizing the processing efficiency and the profit of a machining process. Non-dominated sorting genetic algorithm II and technique for order preference by similarity to an ideal solution are then adopted to assign the most suitable batch task of different parts to each machine. In the second stage, a processing route optimization model is established to plan the processing sequence of different parts for each machine. Finally, niche genetic algorithm is utilized to minimize the makespan. A case study on the fabrication of four typical parts of a machine tool is demonstrated to validate the proposed method.

Received March 24, 2019; accepted September 10, 2019

Shuo ZHU (✉), Hua ZHANG, Zhigang JIANG
Key Laboratory of Metallurgical Equipment and Control Technology (Ministry of Education), Wuhan University of Science and Technology, Wuhan 430081, China
E-mail: tczswilly@163.com

Shuo ZHU, Hua ZHANG, Zhigang JIANG
Hubei Key Laboratory of Mechanical Transmission and Manufacturing Engineering (Ministry of Education), Wuhan University of Science and Technology, Wuhan 430081, China

Shuo ZHU
Engineering Research Center for Metallurgical Automation and Detecting Technology (Ministry of Education), Wuhan University of Science and Technology, Wuhan 430081, China

Bernard HON
School of Engineering, University of Liverpool, Liverpool L69 3BX, UK

Keywords Low-carbon manufacturing, carbon efficiency, multi-objective optimization, two-stage scheduling, job shop

1 Introduction

With rapid economic and technological development, the contradiction between environmental pressure (e.g., energy shortage and carbon emissions) and economic growth has become more severe. In 2014, the energy consumption of China's manufacturing industry was 2.45 billion tons of standard coal, accounting for 57% of the total annual CO_2 emissions [1]. The environment has raised higher requirements for the manufacturing industry. The low carbonization of manufacturing processes can improve the social benefits and product competitiveness of manufacturers and will bring about new opportunities for the machinery manufacturing industry [2].

In mechanical manufacturing, job shop scheduling is key to realizing the high efficiency, flexibility, and reliability of the mechanical manufacturing system. Scheduling optimization is a core technology of advanced manufacturing and modern management [3]; it not only allocates processing tasks but also affects the utilization level of resources and energy of the job shop. Therefore, adopting a scheduling strategy and considering the collaborative optimization between traditional economic indicators and low-carbon indicators are significant means for manufacturers to realize low-carbon manufacturing (LCM) [4].

In recent times, many attempts have been made to solve the scheduling optimization problems for low-carbon mechanical machining. In terms of energy saving, Mouzon et al. [5,6] considered the energy consumption caused by the unloading operation of machines and proposed a multi-objective scheduling optimization model to minimize the total energy consumption and makespan. Giglio et al. [7] presented a mixed-integer programming formulation with the aim of defining and solving an integrated lot sizing and energy-efficient job shop scheduling. Their proposed method diminishes the energy consumption and idle times of machines and reduces the overall cost of the job shop. Salido et al. [8] applied job shop scheduling to optimize energy efficiency and makespan and, consequently, realize high energy efficiency of the machining process. Li et al. [9] proposed a job shop scheduling approach by integrating alternative routing assignment and machine resource dispatching. They also introduced a colored timed Petri net to model the dynamics of the remanufacturing process. To diminish total carbon emissions, Piroozfard et al. [10] established a low-carbon scheduling model of a flexible mechanical job shop and used an improved genetic algorithm (GA) to obtain the optimal plan. Zhang et al. [11] focused on the carbon footprint of the machining process and proposed a low-carbon scheduling method to reduce the carbon emissions of a mechanical job shop. Zhang et al. [12] considered the relationship between among the parameters, carbon emissions, and makespan of a manufacturing process and put forward an integrated optimization model to find a low-carbon scheduling scheme with fluctuation of cutting parameters. Lei [13] presented a teaching-learning-based optimization algorithm to minimize the total carbon footprint and average tardiness of a flexible mechanical job shop. Zhou et al. [14] proposed a low-carbon process route optimization model based on process bill of material and designed a multi-objective ant colony algorithm to solve the proposed model.

A significant amount of research has been conducted in the above areas, yet relatively few attempts have been made to sufficiently analyze the scheduling correlation between different levels of the job shop during the mechanical machining process. Moreover, some studies have not considered the effect of dividing sub-batches of each processing machine on the final makespan under multi-batch, multi-machine, and multi-process circumstances of the mechanical job shop. As a result, optimization effectiveness and efficiency are usually restricted. Given that processing cost, processing efficiency, makespan, and carbon emissions are directly affected by the scheduling scheme, determining how to comprehensively utilize the scheduling optimization that considers these performance indicators and realize low carbonization of the mechanical machining process is rarely reported as well. Thus, a more suitable low-carbon scheduling strategy is urgently needed.

In this paper, a two-stage scheduling method with multi-objective optimization of the job shop is presented to enhance the carbon efficiency of a mechanical machining process. Compared with previous works, the novelty of this study is mainly manifested in three aspects. (1) The study presents a novel low-carbon scheduling optimization strategy framework that investigates the effect of the scheduling process on carbon emissions and the scheduling relationship of the mechanical job shop on each level. (2) Economy carbon efficiency (ECE^u) and processing carbon efficiency (PCE^u) of the process unit are defined, which effectively integrates the processing performance indicators with carbon emissions. This development has not been achieved in prior works on low-carbon scheduling. (3) Multi-objective two-stage scheduling optimization models and their corresponding algorithms are proposed, which maximize the division of batch task to ensure optimal scheduling results and simplify the difficulty of obtaining the optimal scheduling scheme.

The rest of the paper is organized as follows. Section 2 states the methodological framework for the two-stage carbon efficiency scheduling optimization of the mechanical machining process. Section 3 outlines the idea of the carbon efficiency upgrading method, which contains the definition of ECE^u and PCE^u, the low-carbon scheduling optimization models, and their corresponding algorithms. Section 4 presents the case study to demonstrate the effectiveness and practicability of the method. Section 5 concludes with our work summary and future research direction.

2 Statement of methodological framework

The machining process has multi-batch, multi-machine, and multi-processing route characteristics, among many others, and its job shop scheduling is to achieve the optimal production objectives through the reasonable allocation of resources and tasks under certain constraints, such as processing craft, delivery time, and resources of job shop. Low-carbon scheduling optimization of the job shop aims to solve two problems: (1) Task assignment problem, or how to reasonably choose the processing machines from each process unit and assign tasks to each machine; and (2) processing route arrangement problem, or how to optimize the processing sequence arrangement of batch tasks on each machine. The above analysis indicates that the essence of this research is to solve the multi-batch low-carbon scheduling of flexible mechanical job shop.

Compared with general scheduling optimization, low-carbon scheduling of the mechanical job shop must be considered seriously because of the following reasons. (1) The processing efficiency and carbon emissions of each machine are different even if these machines manufacture the same parts. The machine with high processing efficiency may also produce high carbon emissions, such that the existing scheduling that considers processing efficiency as the only objective may lead to increased carbon emissions. (2) The carbon emissions of some machines are several times higher than those of other machines. However, due to the strong processing capacity of these machines, such as the capability to process more than one part at the same time, the processing costs are low. Therefore, the scheduling that considers only the economic objective will result in increased carbon emissions. (3) As the scrap rate of each machine is different and defective parts influence the indirect carbon emissions of raw material waste, total carbon emissions can be increased without considering the processing qualification rate.

Therefore, systematic indicators to simplify the low-carbon scheduling problem are required. In this paper, the ECE^u and PCE^u of a process unit (i.e., a set of machine tools that processes the same or similar process types, such as cutting, grinding, and milling), as two effective indicators to take systematic consideration of processing efficiency, processing cost, processing qualification rate, and carbon emissions in low-carbon scheduling, are defined on the basis of Refs. [15–17] as follows:

$$ECE^u = \frac{VP}{CP}, \tag{1}$$

$$PCE^u = \frac{Q}{CP \cdot T}, \tag{2}$$

where VP represents the machining profit of the process unit (unit: CNY), CP is defined as the carbon emissions of the process unit (unit: kg CO_2e), ECE^u reflects the processing increment of the carbon emissions' dynamic change of the process unit (unit: CNY/(kg CO_2e)), Q refers to the amount of qualified parts of the process unit (unit: piece), T is the processing time of the process unit (unit: s), and PCE^u describes the processing efficiency changes with the carbon emissions of the process unit.

Three levels can be identified according to the organization of the mechanical machining system. The process chain level (top level) mainly receives production tasks according to customer orders and consists of part set (W_i, $i = 1, 2, ..., n$), process chain set ($P_{i,s}$, $s = 1, 2, ..., f$), and batch task set (H_i). In actual situations, the process unit level (transition level) usually divides the various processing machines (M_l, $l = 1, 2, ..., m$) into multiple specific process units to accomplish machining tasks with similar or same processes of parts according to the process chain set. The machine level (bottom level) is mainly responsible for the activities of processing machines, including the states of standby, unload, and load of machines. Figure 1 shows the two-stage low-carbon scheduling framework associated with the carbon efficiency indicators.

In the two-stage low-carbon scheduling framework, the scheduling activities of each stage must be considered the overall mechanical job shop system. Once the processing craft of each part is determined in the process chain level (top level), the information and data of process chains and process units during low-carbon scheduling activities are represented as the transfer or accumulation of the machine

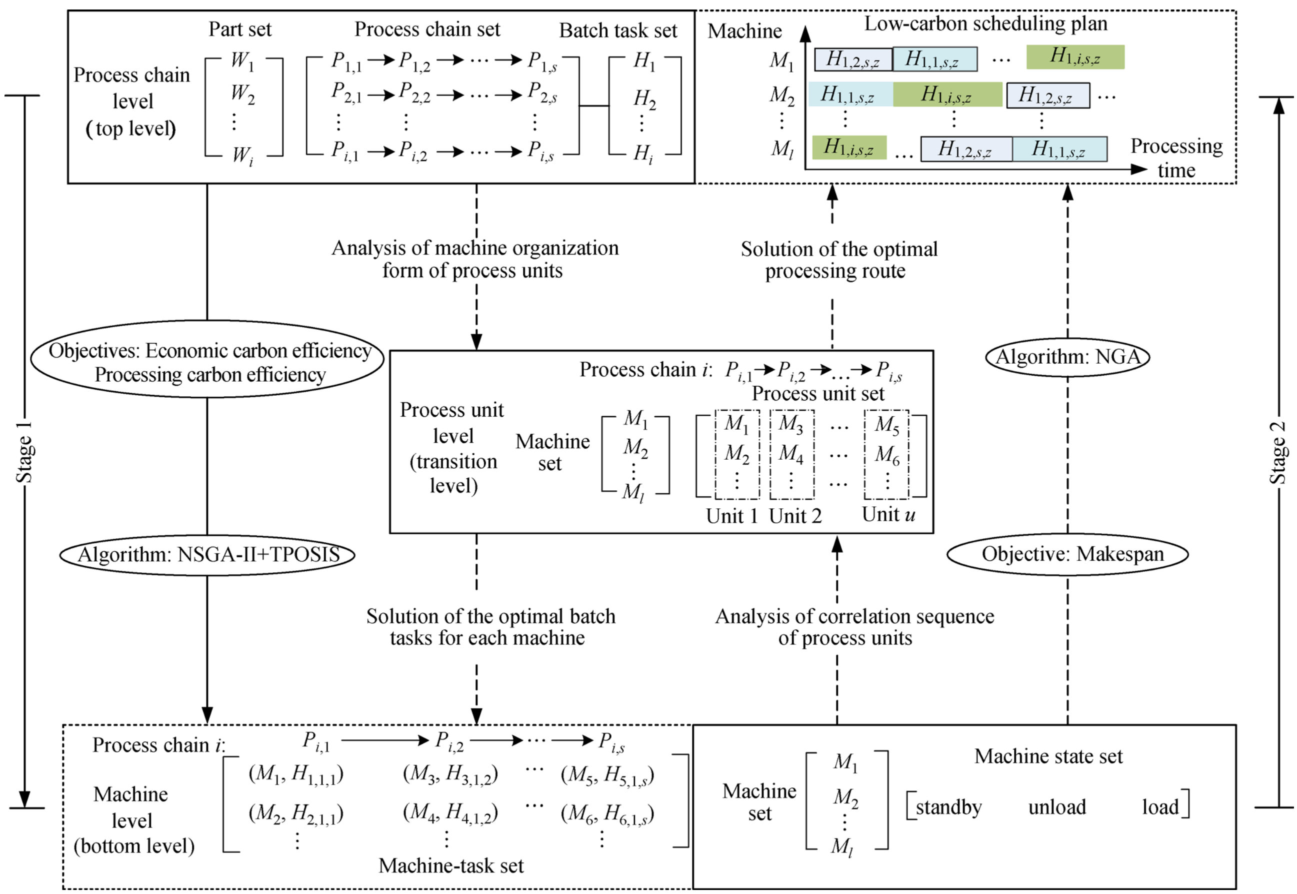

Fig. 1 Two-stage low-carbon scheduling framework.

level (bottom level). Therefore, the key to improving the carbon efficiency of mechanical job shop is to measure whether the scheduling activities in different stages will affect the operation activities of machine tools. According to the state set of machine tools in the bottom level, the total processing task assignment of the job shop changes the running time of the machine tools in different states, which correspondingly results in the variation of carbon efficiency parameters, including economic benefit, output, and carbon emissions. In particular, the total processing task assignment of the job shop in the top level acts on the low-carbon optimization of machine tools on the bottom level. Based on this outcome, the processing route optimization for the batch task of each machine in the bottom level acts on the makespan of the top level. Such route optimization aims to change the sequence of assigned batch tasks rather than the running state and time of the machine tools. Thus, it can ensure the optimal carbon efficiency of the job shop and further shorten the production cycle. The method flow for the two-stage low-carbon scheduling strategy is presented as follows:

(1) In the first stage, the ECE^u and PCE^u of the process unit are regarded as the optimization objectives to integrate the performance indicators of processing efficiency, processing cost, processing qualification rate, and carbon emissions. In addition, a task assignment optimization model is established to select the suitable processing machines from the process unit level and assign the optimal batch task ($H_{l,i,s}$) to the machine level by using non-dominated sorting genetic algorithm II (NSGA-II) and technique for order preference by similarity to an ideal solution (TOPSIS).

(2) In the second stage, a processing route optimization model is presented to further divide the assigned batch task $H_{l,i,s}$ in the first stage into z sub-batches $H_{l,i,s,z}$, $z = 1, 2, ..., y$. The processing sequence of parts for each machine is also planned to minimize the makespan. Niche genetic algorithm (NGA) is utilized to finally obtain the task schedule Gantt chart with the optimal carbon efficiency performance.

3 Method and algorithm of carbon efficiency upgrading

3.1 Task assignment model and algorithm

According to Eq. (2), a high PCE^u value indicates less carbon emissions, greater machining efficiency, and better processing qualification rate of the mechanical machining process. When the organizational characteristics of the process unit in the transition level are considered, the processing activities of different process units are found to be relatively independent once the tasks are assigned, and the accumulated carbon efficiency parameter data of each process unit is the process chain data. Therefore, the optimal task assignment result of each process unit ensures the best carbon efficiency of the overall machining process. The objective functions for maximizing ECE^u and PCE^u are formulated respectively as follows:

$$f(1) = \max \frac{VP^u}{CP^u} = \max \sum_{l \in l^u} \sum_{i \in i^u} \sum_{s \in s^u} \left(\frac{V_{l,i,s}^{\mathrm{val}} - V_{l,i,s}^{\mathrm{scr}} - V_{l,i,s}^{\mathrm{art}} - V_{l,i,s}^{\mathrm{depr}} - V_{l,i,s}^{\mathrm{elec}} - V_{l,i,s}^{\mathrm{aux}}}{\sum_{o=1}^{v} CES_{l,i,s,o} + \sum_{h=1}^{q} CEQ_{l,i,s,h} + \sum_{k=1}^{w} CEW_{l,i,s,k} + CEE_{l,i,s}} \right), \tag{3}$$

$$f(2) = \max \frac{Q^u}{CP^u T^u} = \max \sum_{l \in l^u} \sum_{i \in i^u} \sum_{s \in s^u} \frac{Q_{l,i,s}}{CP_{l,i,s} T_{l,i,s}}, \tag{4}$$

where VP^u and CP^u are defined as the processing profit and carbon emissions of process unit u, respectively, l^u, i^u, and s^u are the machine set, part set, and process step set of process unit u, respectively, $V_{l,i,s}^{\mathrm{val}}$, $V_{l,i,s}^{\mathrm{scr}}$, $V_{l,i,s}^{\mathrm{art}}$, $V_{l,i,s}^{\mathrm{depr}}$, $V_{l,i,s}^{\mathrm{elec}}$, and $V_{l,i,s}^{\mathrm{aux}}$ refer to the value added by processing, scrap cost, artificial cost, machine depreciation cost, electric energy cost, and auxiliary resource cost of the machining during process step $P_{i,s}$ of part W_i on machine M_l, respectively, and Q^u is the processing amount of process unit u, when the batch task H_i is determined without considering the random factors, such as unqualified processing, where Q^u will be a constant. Moreover, T^u is the total machining time of process unit u, $Q_{l,i,s}$, $CP_{l,i,s}$, and $T_{l,i,s}$ are defined as the production volume, carbon emissions, and processing time of the machining during process step $P_{i,s}$ of part W_i on machine M_l; and $CES_{l,i,s,o}$, $CEQ_{l,i,s,h}$, $CEW_{l,i,s,k}$, and $CEE_{l,i,s}$ are the carbon emissions generated by the oth solid waste, hth fossil fuel, kth liquid waste, and electricity consumption during process step $P_{i,s}$ of part W_i on the machine M_l. For the quantification of carbon emissions, the common carbon equivalent coefficient method is adopted [18]. According to the Intergovernmental Panel on Climate Change, the carbon equivalent coefficient is defined as the carbon emissions caused by a unit resource, mainly obtained by converting the load energy of the material into the coal equivalent and finally transform it by using the carbon equivalent coefficient of standard coal [19].

The constrains of functions $f(1)$ and $f(2)$ are also under following considerations:

1) The production volume of process step $P_{i,s}$ is the batch task of process step $P_{i,s+1}$, and the batch task must be an integer, where [ ] is the integer notation.

$$Q_{i,s} = H_{i,s+1} = \sum_{l=1}^{m} [H_{l,i,s} \cdot \beta_{l,i,s}], \tag{5}$$

where $\beta_{l,i,s}$ is defined as the qualification rate of the process step $P_{i,s}$ of part W_i on machine M_l.

2) The sum of the batch task assigned to each machine $H_{l,i,s}$ must be in accordance with the task received on process step $P_{i,s}$.

$$H_{i,s} = \sum_{l=1}^{m} H_{l,i,s}. \tag{6}$$

3) Each processing machine M_l can only process one part machining on one process step at a time.

$$TS_{M_{l,i,s}} \neq TS_{M_{l,i^+,s^+}},\ i \neq i^+,\ s \neq s^+, \tag{7}$$

where $TS_{M_{l,i,s}}$ represents the start time of the process step $P_{i,s}$ of part W_i on machine M_l.

4) At least one processing machine M_l can be used to conduct the machining of process step $P_{i,s}$ of part W_i.

$$\{Q_{i,s}\} \neq \varnothing,\ Q_{i,s} \geqslant 0,\ Q_{i,s} \in Z. \tag{8}$$

5) After the machining of process unit u is completed, the quantity of qualified products Q_i^u, machining time PT_i^u, and machining profit VP_i^u should be superior to the expected values of Q_i^{u0}, PT_i^{u0}, and VP_i^{u0}, respectively.

$$Q_i^u \geqslant Q_i^0,\ PT_i^u = TE_i^u - TS_i^u \leqslant PT_i^{u0}, VP_i \geqslant VP_i^0, \tag{9}$$

where TE_i^u and TS_i^u are the machining complete time and start time of process unit u of part W_i, respectively.

Therefore, the task assignment model of the mechanical machining process for carbon efficiency upgrading is defined as follows, and both objectives are considered equally important in this paper.

$$\max[F(H_{l,i,s})] = \Big(\max f(1), \max f(2)\Big). \tag{10}$$

Subject to

$$\begin{cases} H_{i,s} = Q_{l,i,s-1} = \sum_{l=1}^{m} [H_{l,i,s-1} \cdot \beta_{l,i,s-1}], \\ H_{i,s} = \sum_{l=1}^{m} H_{l,i,s}, \\ TS_{M_{l,i,s}} \neq TS_{M_{l,i^+,s^+}},\ i \neq i^+,\ s \neq s^+, \\ TE_{M_{l,i,s}} - TS_{M_{l,i,s}} = T_{M_{l,i,s}}, \\ \{Q_{i,s}\} \neq \varnothing,\ Q_{i,s} \geqslant 0,\ Q_{i,s} \in Z, \\ Q_i^u \geqslant Q_i^0,\ PT_i^u = TE_i^u - TS_i^u \leqslant PT_i^{u0}, VP_i \geqslant VP_i^0. \end{cases} \tag{11}$$

Task assignment optimization is a typical multi-objective optimization problem. In this issue, the main reason for having multiple optimal solutions is that it is impossible to optimize multiple objects simultaneously to find a single optimal solution. Therefore, an algorithm that can give an optimal solution set is of practical value. In this study, NSGA-II is introduced to obtain the solution set. NSGA-II is currently one of the most popular multi-objective GAs because of its fast running speed and good convergence of solution set. Compared with the use of weighted sum to convert multiple objective functions into a single objective function to obtain the unique optimal solution, NSGA-II can find a multi-valued Pareto optimal solution in one operation, a capability that is more in line with actual needs and which has become the benchmark of other multi-objective optimization algorithms. The implementation steps of NSGA-II for this model are shown in Fig. 2.

According to the characteristics of the multi-objective task assignment model, the real number coding mode is chosen for the chromosome coding of the NSGA-II algorithm, which is generally applicable to solve the problem of continuous parameter optimization. On the basis of the determined process and machine sequence, the task assignment solution can be formed into a 2D matrix of machine number and task quantity. The column number of the matrix represents the total number of processes, with the process sequence indicated from left to right. The row number of the matrix is the maximum number of machines in the process unit, with the machine sequence indicated from top to bottom. The elements in the matrix are the processing tasks assigned to each machine for each process, and the element vacancy of the matrix is replaced by 0. When there are f processes in the job shop and the maximum number of machines in each process unit is l, the chromosome of task assignment is coded as a $l \times f$ matrix. On this basis, the algorithm flow shown in Fig. 2 is used to obtain the task assignment solutions. The NSGA-II starts with a random generated initial population, and feasible task allocation solutions as the initial population R_t are obtained by residual calculation of the optional machine number and the assignment quantity of each process. Then, according to the non-dominated sorting, the partial mapped crossover method is adopted for the crossover operation of processing tasks and the mutation probability value P_{m} is set. Consequently, the first population of offspring generation Q_t can be obtained. For the second generation, the populations of parents and offspring generation are combined to execute non-dominated sorting again and calculate the crowding distance of the individual in each non-dominant layer. Hence, a new parent population P_{t+1} is formed by filling the low-level non-dominant individual into the parent population P_t. Iteratively, genetic manipulation is carried out to form a new population of offspring generation Q_{t+1}. Finally, when the termination condition meets $Gen < V$, the optimal solution set of task assignment can be output.

The main feature of NSGA-II is the elitist strategy of individuals achieved by the steps of non-dominated sorting and crowding distance calculation. This feature improves

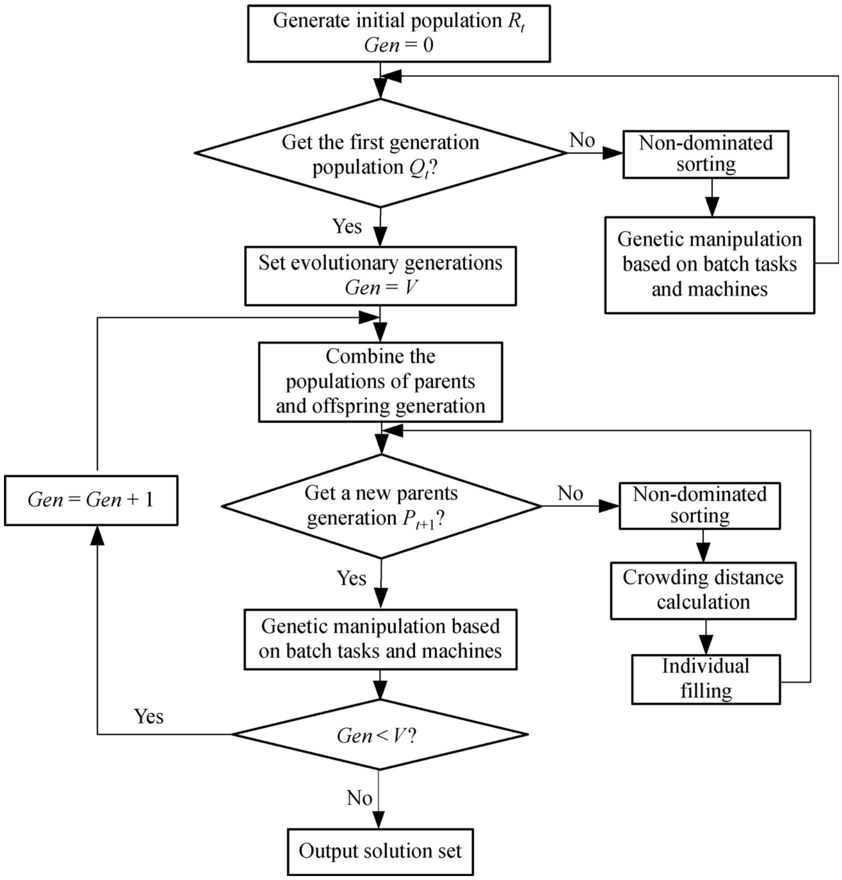

Fig. 2 NSGA-II flowchart for task assignment model.

the diversity and distribution of the Pareto optimal solution set and guarantees prodigious suitability in the multi-objective optimization problem. However, it is difficult for decision makers to directly select one or several of the best solutions on the numerous Pareto fronts. Therefore, an appropriate evaluation criterion or method is needed to evaluate the performance of the Pareto optimal solution set and then select the only optimal solution that meets the practical workshop conditions to guide production. On this basis, TOPSIS is used to further determine the final solution from the approximate optimal solution set. The method flow is expressed as follows [20]:

1) According to the approximate optimal solution set of functions $f(1)$ and $f(2)$, an evaluation decision matrix $\boldsymbol{G} = [g_{o,p}]_{h\times 2}$ is established, where $g_{o,p}$ is the approximate optimal solution, and $o = 1, 2, ..., h$, $p = 1, 2$.

2) $g_{o,p}$ is normalized to build the normalized decision matrix $\boldsymbol{K} = [k_{o,p}]_{h\times 2}$, where $k_{o,p} = g_{o,p} \Big/ \sqrt{\sum_{o=1}^{h} g_{o,p}^2}$.

3) The Euler distance between the normalized index $k_{o,p}$ and the ideal solution (the optimal value for each objective value) k_p^+ as well the negative ideal solution (the worst value for each objective value) k_p^- needs to be calculated by $S_o^+ = \sqrt{\sum_{p=1}^{2} \omega_p (k_{o,p} - k_p^+)^2}$ and $S_o^- = \sqrt{\sum_{p=1}^{2} \omega_p (k_{o,p} - k_p^-)^2}$, where ω_p is the weight of $f(1)$ and $f(2)$. In this study, both objectives are considered equally important, namely, $\omega_1 = \omega_2$.

4) The relative closeness of approximate optimal solutions can be calculated by $C_o = S_o^- / (S_o^+ + S_o^-)$. Owing to the $\omega_1 = \omega_2$, the relative closeness C_o is evaluated between 0 and 1. A C_o value closer to 1 reveals that the task assignment plan is much better.

3.2 Processing route optimization model and algorithm

The primary objective of processing route optimization is to further divide the assigned batch task $H_{l,i,s}$ in the first stage into sub-batch $H_{l,i,s,z}$ and plan the processing sequence of parts for each machine to minimize the makespan of the mechanical machining process. The running time of the machine tools in each state is the fundamental factor affecting the carbon efficiency of the machining process. However, batch task decomposition and processing sorting in processing route optimization do not affect the running time of the machine tools. Specifically, ECE^u, PCE^u, and carbon emissions optimized in the first stage of scheduling can be maintained, and the relationship of two stages in the scheduling strategy is both progressive and independent. The processing route optimization model to minimize the makespan of the mechanical machining process is formulated as follows:

$$T_{\mathrm{p}} = \min(\max TE_{l,i,f}). \tag{12}$$

Subject to

$$\begin{cases} H_{i,s} = Q_{l,i,s-1} = \sum_{l=1}^{m}[H_{l,i,s-1} \cdot \beta_{l,i,s-1}], \\ H_{i,s} = \sum_{l=1}^{m} H_{l,i,s},\ H_{l,i,s} = \sum_{z=1}^{y} H_{l,i,s,z}, \\ TS_{M_{i,s}} \neq TS_{M_{l,i^+,s^+}},\ i \neq i^+,\ s \neq s^+, \\ TE_{M_{l,i,s}} - TS_{M_{l,i,s}} = T_{M_{l,i,s}}, \\ \{Q_{i,s}\} \neq \varnothing,\ Q_{i,s} \geqslant 0,\ Q_{i,s} \in Z, \\ Q_i^u \geqslant Q_i^0,\ PT_i^u = TE_i^u - TS_i^u \leqslant PT_i^{u0}, VP_i \geqslant VP_i^0, \end{cases} \tag{13}$$

where T_{p} is the production time of the mechanical machining process, and $TE_{l,i,f}$ is the completion time of the last process $P_{i,f}$ of part W_i on machine M_l. Except for the need to satisfy the constraints in the task assignment model, the processing route optimization model is necessary to ensure the sum of divided batch task $H_{l,i,s,z}$ is equal to the corresponding batch task $H_{l,i,s}$.

Processing route optimization is a typical multi-peak optimization problem. When GA is used to solve this kind of problem, only a few optimal values can be found and local optimal solutions tend to be obtained. Therefore, the concept of niche is introduced by scholars to help resolve this issue. Niche technology extends the GA by facilitating the formation of stable subpopulations within the neighborhood of multiple optimal solutions, enabling GAs to be applied to problems with multiple local optimal solutions in the search space. The NGA uses a sharing mechanism to set a sharing function that reflects the degree of similarity between individuals to adjust individual fitness and achieve the purpose of maintaining population diversity. It can also more easily find all the local and global optimal solutions because it is the current classical algorithm to solve the optimization problem of complex multi-peak functions. Given the nature and complexity of processing route optimization, the NGA is adopted to derive the optimal solution. Interested readers can refer to Ref. [21] for the full feature of the algorithm. The main implementation steps of NGA for processing route optimization are sketched as follows:

1) Population initialization: Randomly generate a set of process routing, and then randomly divide the batch tasks $H_{l,i,s,z}$ for each process step on each machine.

2) Fitness function determination: The sharing mechanism is used to adjust the fitness of individuals in the population and assume the niche radius is σ_{sh}, the sharing function is $sh(d_{i,j})$, and the niche number of individual X_i is m_i. The calculation formulas are as follows:

$$sh(d_{i,j}) = \begin{cases} 1 - \dfrac{d_{i,j}}{\sigma_{\mathrm{sh}}}, & d_{i,j} \leqslant \sigma_{\mathrm{sh}}, \\ 0, & d_{i,j} > \sigma_{\mathrm{sh}}, \end{cases} \tag{14}$$

$$\sigma_{\mathrm{sh}} = \frac{\sqrt{k}}{2\sqrt[k]{m}}, \tag{15}$$

$$m_i = \sum_{j=1}^{n} sh(d_{i,j}), \tag{16}$$

where k is the number of decision variables, m is the number of obtained relative optimal solutions, n means the population size, and $d_{i,j}$ is the Euclidean distance between individuals X_i and X_j. To ensure population diversity and inhibit the infinite proliferation of similar individuals, the fitness function $f(X_i)$ (objective function) of individual X_i should be adjusted to $f_{\mathrm{sh}}(X_i) = f(X_i)/m_i$.

3) Selection of operator determination: According to the fitness value of the adjusted individual, the selection operator p_i can be calculated as follows:

$$p_i = \frac{f_{\mathrm{sh}}(X_i)}{\sum_{i=1}^{n} f_{\mathrm{sh}}(X_i)}. \tag{17}$$

4) Crossover operation: the crossover method for parent and offspring individuals is used to generate a new individual with the following calculation formulas:

$$\begin{cases} X_i^{t+1} = \alpha X_j^t + (1-\alpha) X_i^t, \\ X_j^{t+1} = \alpha X_i^t + (1-\alpha) X_j^t, \end{cases} \tag{18}$$

where α is the scaling factor, $\alpha = \exp(-\alpha_0 t/T)$, α_0 is the preset coefficient within the range of [0, 1], t is the current evolutionary generation, and T represents the largest evolutionary generation.

5) Mutation operation: Assume the mutation step size is Δ and the value range of genes at mutation point x_k on the tth generation is $[U_{\min}^k, U_{\max}^k]$. The new gene value x_k' can be obtained as follows:

$$x_k' = \begin{cases} x_k + \Delta(t, U_{\max}^k - x_k), & \alpha = 0, \\ x_k - \Delta(t, x_k - U_{\min}^k), & \alpha = 1, \end{cases} \tag{19}$$

$$\Delta(t, y) = y\left(1 - r^{(1-t/T)}\right), \tag{20}$$

where r is the random number within the range of [0, 1].

4 Case study

A case study is conducted on machining four typical parts of a machine tool factory to obtain the scheduling scheme with the optimal carbon efficiency performance. The total production cycle is limited to 74 hours according to delivery time, and 11 processing machines divided into five process units are organized in the factory. The relevant information and data of parts, processing steps, and processing machines are shown in Tables 1 and 2.

To quantify the economy and PCE^u of the process units of Eqs. (3) and (4), the related indicator elements (i.e., processing profit, processing time, and carbon emissions) need be measured and calculated. Among them, the power on different states and the corresponding time of machine are measured by the high precision power tester WT1800 [22]. In addition, the average labor cost, depreciation cost of machine, and machining profit are provided by the accounting department of the enterprise in accordance with relevant standards, while the qualification rate of parts is obtained by statistical analysis according to the quality inspection records of the enterprise [23]. The amount of solid waste is also counted by collecting and weighing, and the waste hydraulic oil and waste cutting fluid are converted and calculated according to the actual consumption as well as average replacement cycle. The relevant processing information of carbon efficiency indicator elements of each part are shown in Tables 3 to 6.

During the two-stage scheduling optimization of the mechanical machining process of the four types of machine tool parts, the batch task assignment for each process unit and the machine selection for processing should be first determined. With the use of the task assignment model and NSGA-II, the Pareto optimal solution set of task assignment can be obtained under the circumstance that ECE^u is as important as PCE^u. TOPSIS is then adopted to select the final ideal solution from the Pareto set. Figure 3 illustrates the solutions with the optimal carbon efficiency of process unit obtained via Matlab 7.11.0 (MathWorks, USA).

Figure 3 reflects the ECE^u and PCE^u values of each relatively optimal assignment solution of different process units. As process unit 2 (heat treatment unit) contains three same-type machines that have the same machining activities and process unit 3 (milling unit) contains only one machine, the optimal task assignment solution of these two process units is unique. Furthermore, the corresponding PCE^u and ECE^u of process units 2 and 3 are 1.327×10^{-7} piece/(kg CO_2e·s) 2.33 CNY/(kg CO_2e)

Table 1 Relevant information and data of parts and processing steps

Part number	Batch task	Process step 1	Process step 2	Process step 3	Process step 4	Process step 5	Process step 6	Process step 7
Tailstock spindle W_1	60	Rough turning $P_{1,1}$	Heat treatment $P_{1,2}$	Finish turning $P_{1,3}$	Slotting $P_{1,4}$	Heat treatment $P_{1,5}$	Finish grinding $P_{1,6}$	Grinding taper hole $P_{1,7}$
Tailstock body W_2	80	Heat treatment $P_{2,1}$	Planing plane $P_{2,2}$	Milling $P_{2,3}$	Grinding $P_{2,4}$	Heat treatment $P_{2,5}$	–	–
Under plate W_3	50	Rough planing $P_{3,1}$	Heat treatment $P_{3,2}$	Finish planning $P_{3,3}$	Finish milling $P_{3,4}$	–	–	–
Worktable W_4	50	Rough planing $P_{4,1}$	Milling plane $P_{4,2}$	Finish planing $P_{4,3}$	Milling step $P_{4,4}$	–	–	–

Table 2 Relevant information and data of process units and machines

Process unit number	Process unit name	Machine type and number	Processing capacity/(piece·time^{-1})
1	Turning unit	CA6140 (M_1)	1
		CA6150 (M_2)	1
2	Heat treatment unit	RJX-45-9 (M_3)	5
		RJX-45-9 (M_4)	5
		RJX-45-9 (M_5)	5
3	Milling unit	TX6111D (M_6)	1
4	Grinding unit	M13328X1500 (M_7)	1
		C-600CNC (M_8)	1
		MA1420/500 (M_9)	1
5	Planing unit	BY60100C (M_{10})	1
		BM2020 (M_{11})	1

Table 3 Processing information of carbon efficiency indicator elements of W_1

Process step number	Process unit number	Machine number	Machining profit per time/CNY	Carbon emissions per time/(kg CO_2e)	Processing time per time/s	Qualification rate/%
$P_{1,1}$	1	M_1	41.0	0.24	434	96
		M_2	40.0	0.23	421	96
$P_{1,2}$	2	M_3	148.8	53.40	10980	98
		M_4	148.8	53.40	10980	98
		M_5	148.8	53.40	10980	98
$P_{1,3}$	1	M_1	85.0	1.30	552	95
		M_2	87.0	1.20	533	95
$P_{1,4}$	3	M_6	47.5	0.21	363	95
$P_{1,5}$	2	M_3	146.0	66.90	12780	98
		M_4	146.0	66.90	12780	98
		M_5	146.0	66.90	12780	98
$P_{1,6}$	4	M_7	48.5	0.65	325	95
		M_8	48.8	0.58	310	98
		M_9	44.0	0.48	320	98
$P_{1,7}$	4	M_7	51.0	0.68	344	98
		M_8	52.0	0.59	326	98
		M_9	52.2	0.49	337	98

Table 4 Processing information of carbon efficiency indicator elements of W_2

Process step number	Process unit number	Machine number	Machining profit per time/CNY	Carbon emissions per time/(kg CO_2e)	Processing time per time/s	Qualification rate/%
$P_{2,1}$	2	M_3	82.4	40.90	7200	99
		M_4	82.4	40.90	7200	99
		M_5	82.4	40.90	7200	99
$P_{2,2}$	5	M_{10}	51.5	2.10	401	100
		M_{11}	55.5	2.30	420	100
$P_{2,3}$	3	M_6	49.6	0.42	482	98
$P_{2,4}$	4	M_7	55.0	0.88	421	100
		M_8	53.0	0.68	443	100
		M_9	57.0	0.74	398	100
$P_{2,5}$	2	M_3	124.3	51.20	10200	93
		M_4	124.3	51.20	10200	100
		M_5	124.3	51.20	10200	100

Table 5 Processing information of carbon efficiency indicator elements of W_3

Process step number	Process unit number	Machine number	Machining profit per time/CNY	Carbon emissions per time/(kg CO_2e)	Processing time per time/s	Qualification rate/%
$P_{3,1}$	5	M_{10}	79.5	2.20	549	100
		M_{11}	74.5	2.30	542	100
$P_{3,2}$	2	M_3	136.3	59.20	12600	99
		M_4	136.3	59.20	12600	99
		M_5	136.3	59.20	12600	99
$P_{3,3}$	5	M_{10}	82.6	1.90	552	100
		M_{11}	80.0	1.70	549	100
$P_{3,4}$	3	M_6	42.5	0.64	325	98

Table 6 Processing information of carbon efficiency indicator elements of W_4

Process step number	Process unit number	Machine number	Machining profit per time/CNY	Carbon emissions per time/(kg CO_2e)	Processing time per time/s	Qualification rate/%
$P_{4,1}$	5	M_{10}	98.3	2.5	605	100
		M_{11}	99.6	2.1	612	100
$P_{4,2}$	3	M_6	94.6	1.5	582	99
$P_{4,3}$	5	M_{10}	93.9	2.1	578	100
		M_{11}	97.4	1.8	600	100
$P_{4,4}$	3	M_6	74.1	1.1	456	99

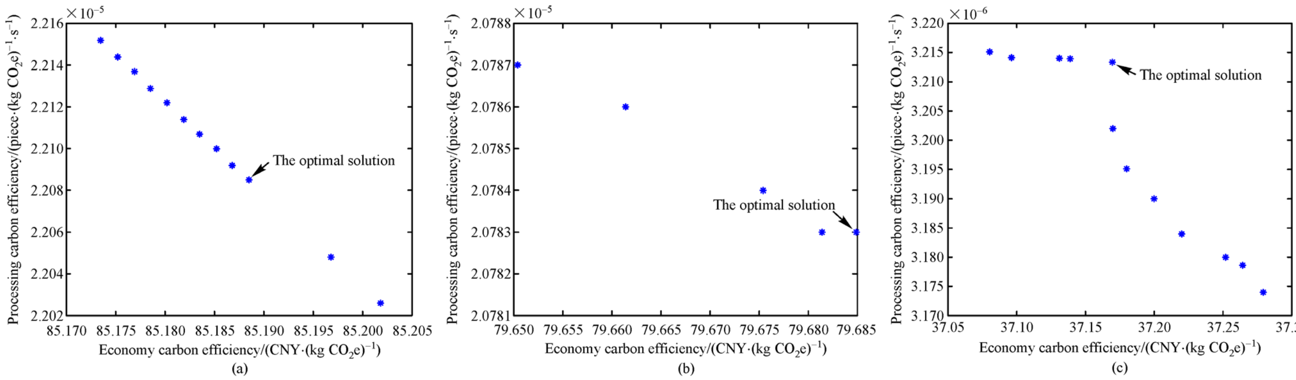

Fig. 3 Solution with the optimal carbon efficiency of (a) process unit 1 (turning unit), (b) process unit 4 (grinding unit), and (c) process unit 5 (planing unit).

and 1.0593×10^{-5} piece/(kg CO_2e·s), 83.4678 CNY/(kg CO_2e), respectively. However, process units 1, 4, and 5 include multiple different-type processing machines and many relative optimal solutions coexist under constraint conditions and have different levels of performance on both ECE^u and PCE^u. Therefore, TOPSIS is used to carry out a final determination of the comprehensive optimal solution, which is 2.2085×10^{-5} piece/(kg CO_2e·s), 85.1885 CNY/(kg CO_2e) (process unit 1); 2.0783×10^{-5} piece/(kg CO_2e·s), 79.6849 CNY/(kg CO_2e) (process unit 4); and 3.2133×10^{-6} piece/(kg CO_2e·s), 37.1696 CNY/(kg CO_2e) (process unit 5). The corresponding task assignment plan of each machine with the optimal carbon efficiency is shown in Table 7.

The above analysis reveals that carbon efficiency scheduling optimization mainly works on the process units consisting of machine tools with different low-carbon performance, namely, the premise of improving carbon efficiency is that machine tools in the process unit have different resource and energy consumption behaviors. In this case, the process units meet the prerequisite conditions, including turning process unit, grinding process unit, and planing process unit. Comparing and analyzing the task assignment solutions of each process unit with the processing efficiency objective (PEO), economic benefit objective (EBO), and carbon efficiency objective (CEO) can obtain the carbon emission reduction effect of carbon efficiency optimization, as shown in Table 8.

Thus far, the first-stage scheduling optimization is accomplished, though the batch task still needs to be divided further, and the processing route should be developed for the purpose of minimizing the makespan. Hence, the processing route optimization model shown in Eqs. (12) and (13) is applied to plan the processing sequence of different parts for each machine, and the NGA is utilized to minimize the makespan. Figures 4 and 5 show the result variation curves and Gantt chart for processing route planning, respectively, obtained via Matlab 7.11.0 (MathWorks, USA). In Fig. 4, the curve of average fitness value of populations converges exponentially at almost 5 generations prior, and between 5 and 10 generations, the change slows down. This outcome shows that the solution process has good performance in maintaining the population diversity and the computational efficiency. After 10 generations of evolution, the curves of average fitness value and optimal fitness value of populations tend to stabilize, and the optimal makespan is maintained in 66.5 hours.

The scheduling scheme shown in Fig. 5 is the optimal solution for carbon efficiency upgrading under production constraints. In the figure, rectangular blocks with different colors represent different parts, and the symbols on rectangular blocks reflect the process step number (e.g.,

Table 7 Task assignment of each machine with the optimal carbon efficiency

Machine number	Process step number, processing task/piece, processing time/h				
	Task 1	Task 2	Task 3	Task 4	Task 5
M_1	$P_{1,1}$, 32, 3.86	$P_{1,3}$, 30, 4.60	–	–	–
M_2	$P_{1,1}$, 28, 3.27	$P_{1,3}$, 30, 4.44	–	–	–
M_3	$P_{1,2}$, 20, 12.20	$P_{1,5}$, 20, 14.20	$P_{2,1}$, 25, 10.00	$P_{2,5}$, 25, 14.10	$P_{3,2}$, 15, 10.50
M_4	$P_{1,2}$, 20, 12.20	$P_{1,5}$, 20, 14.20	$P_{2,1}$, 25, 10.00	$P_{2,5}$, 30, 17.00	$P_{3,2}$, 15, 10.50
M_5	$P_{1,2}$, 20, 12.20	$P_{1,5}$, 20, 14.20	$P_{2,1}$, 30, 12.00	$P_{2,5}$, 25, 14.10	$P_{3,2}$, 20, 14.00
M_6	$P_{1,4}$, 60, 6.05	$P_{2,3}$, 80, 10.71	$P_{3,4}$, 50, 4.51	$P_{4,2}$, 50, 8.08	$P_{4,4}$, 50, 6.33
M_7	$P_{1,6}$, 18, 1.63	$P_{1,7}$, 18, 1.72	$P_{2,4}$, 26, 3.04	–	–
M_8	$P_{1,6}$, 19, 1.64	$P_{1,7}$, 17, 1.54	$P_{2,4}$, 27, 3.32	–	–
M_9	$P_{1,6}$, 23, 2.04	$P_{1,7}$, 25, 2.34	$P_{2,4}$, 27, 2.99	–	–
M_{10}	$P_{2,2}$, 37, 4.12	$P_{3,1}$, 26, 3.97	$P_{3,3}$, 27, 3.37	$P_{4,1}$, 25, 4.20	$P_{4,3}$, 23, 3.69
M_{11}	$P_{2,2}$, 43, 5.02	$P_{3,1}$, 24, 3.61	$P_{3,3}$, 23, 4.27	$P_{4,1}$, 25, 4.25	$P_{4,3}$, 27, 4.50

Table 8 Comparative analysis of carbon emissions under different objectives

Process unit	Carbon emissions for PEO/(kg CO_2e)	Carbon emissions for EBO/(kg CO_2e)	Carbon emissions for CEO/(kg CO_2e)	Carbon emission reduction ratio/%
Turning unit	50.38	51.37	46.68	6%–9%
Grinding unit	138.45	141.32	129.77	6%–8%
Planing unit	637.70	563.10	595.90	7%–9%

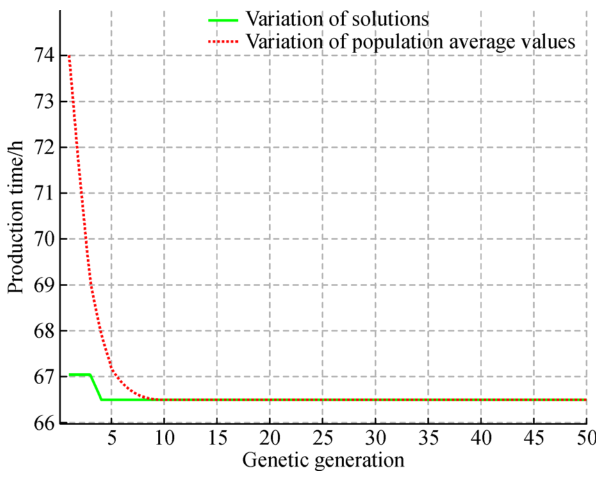

Fig. 4 Variation curve on solving processing route planning.

“p12” means the part W_1 under the processing on process step 1). The position relation of the rectangle block is the processing sequence on different machines. According to Fig. 5, the bottleneck unit is the heat treatment process unit containing machine M_3, M_4, and M_5. However, the optimal scheduling solution obviously improves the machines’ utilization of the bottleneck unit, and the waiting time between each task is eliminated. To further unscramble the Gantt chart, the specification of scheduling results is presented in Table 9. The results reflect the optimality of the current scheduling scheme and verify the applicability of the carbon efficiency upgrading method based on scheduling optimization strategy.

5 Conclusions

Attempts have recently been made to achieve low-carbon mechanical machining through scheduling optimization strategy. However, compared with existing low-carbon scheduling methods, relatively few attempts have been made to investigate the correlation between different levels of the job shop during the low-carbon scheduling process as well as to consider the integration of traditional performance index and carbon emission in multi-objective optimization. As a result, the optimization effectiveness and efficiency are restricted. In this work, three hierarchies, including process chain level (top level), process unit level (transition level), and machine level (bottom level), and their scheduling optimization relationship of job shop were analyzed. On the basis of this analysis, transition level is regarded as the scheduling core, and the ECE^u and PCE^u of the process unit were defined to integrate the indicators of processing cost, processing time, qualification rate, and carbon emission. Additionally, two-stage carbon efficiency scheduling optimization models and corresponding

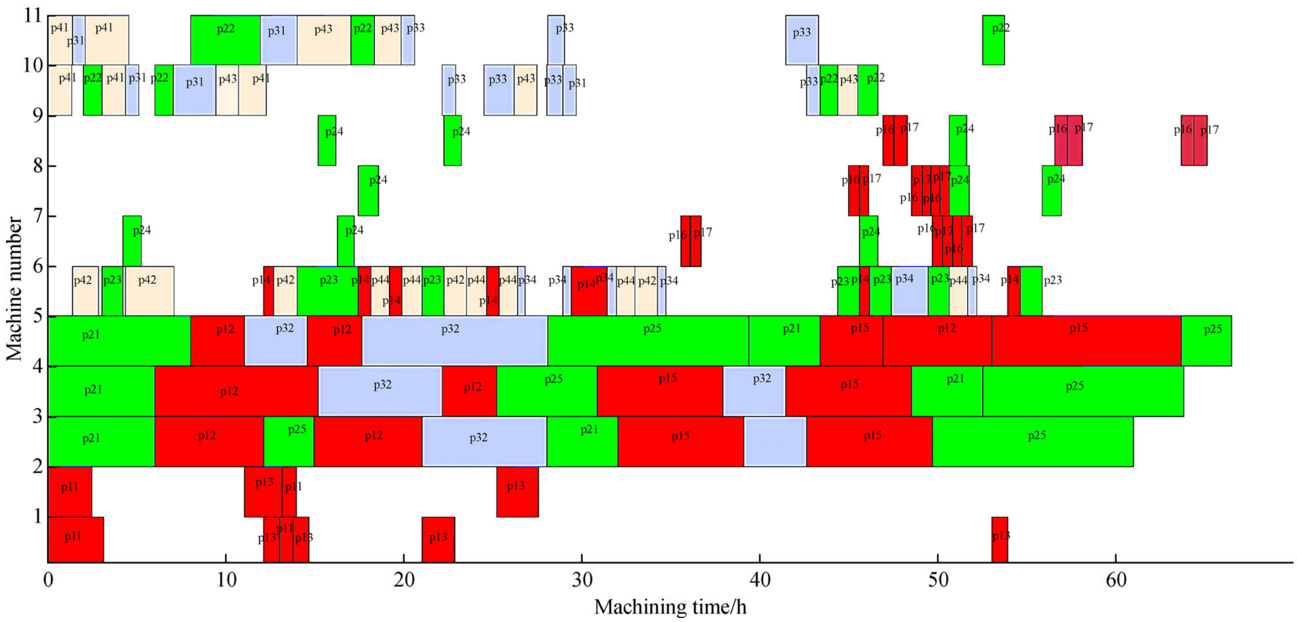

Fig. 5 Gantt chart for processing route planning.

Table 9 Specification of processing route planning

Machine number	Processing route (process step number/divided sub-batch task)
M_1	$P_{1,1}/26 \rightarrow P_{1,3}/6 \rightarrow P_{1,1}/6 \rightarrow P_{1,3}/6 \rightarrow P_{1,3}/12 \rightarrow P_{1,3}/6$
M_2	$P_{1,1}/21 \rightarrow P_{1,3}/14 \rightarrow P_{1,1}/7 \rightarrow P_{1,3}/16$
M_3	$P_{2,1}/15 \rightarrow P_{1,2}/10 \rightarrow P_{2,5}/5 \rightarrow P_{1,2}/10 \rightarrow P_{3,2}/10 \rightarrow P_{2,1}/10 \rightarrow P_{1,5}/10 \rightarrow P_{3,2}/5 \rightarrow P_{1,5}/10 \rightarrow P_{2,5}/20$
M_4	$P_{2,1}/15 \rightarrow P_{1,2}/15 \rightarrow P_{3,2}/10 \rightarrow P_{1,2}/5 \rightarrow P_{2,5}/10 \rightarrow P_{1,5}/10 \rightarrow P_{3,2}/5 \rightarrow P_{1,5}/10 \rightarrow P_{2,1}/10 \rightarrow P_{2,5}/20$
M_5	$P_{2,1}/20 \rightarrow P_{1,2}/5 \rightarrow P_{3,2}/5 \rightarrow P_{1,2}/5 \rightarrow P_{3,2}/15 \rightarrow P_{2,5}/20 \rightarrow P_{2,1}/10 \rightarrow P_{1,5}/5 \rightarrow P_{1,2}/10 \rightarrow P_{1,5}/15 \rightarrow P_{2,5}/5$
M_6	$P_{4,2}/9 \rightarrow P_{2,3}/9 \rightarrow P_{4,2}/17 \rightarrow P_{1,4}/6 \rightarrow P_{4,2}/8 \rightarrow P_{2,3}/26 \rightarrow P_{1,4}/7 \rightarrow P_{4,4}/8 \rightarrow P_{1,4}/7 \rightarrow P_{4,4}/9 \rightarrow P_{2,3}/9 \rightarrow P_{4,2}/8 \rightarrow P_{4,4}/9 \rightarrow P_{1,4}/7 \rightarrow$ $P_{4,4}/8 \rightarrow P_{3,4}/5 \rightarrow P_{3,4}/5 \rightarrow P_{1,4}/20 \rightarrow P_{3,4}/6 \rightarrow P_{4,4}/8 \rightarrow P_{4,2}/8 \rightarrow P_{3,4}/5 \rightarrow P_{2,3}/9 \rightarrow P_{1,4}/6 \rightarrow P_{2,3}/9 \rightarrow P_{3,4}/23 \rightarrow P_{2,3}/9 \rightarrow P_{4,4}/8 \rightarrow$ $P_{3,4}/6 \rightarrow P_{1,4}/7 \rightarrow P_{2,3}/9$
M_7	$P_{2,4}/9 \rightarrow P_{2,4}/8 \rightarrow P_{1,6}/6 \rightarrow P_{1,7}/6 \rightarrow P_{2,4}/9 \rightarrow P_{1,6}/6 \rightarrow P_{1,7}/6 \rightarrow P_{1,6}/6 \rightarrow P_{1,7}/6$
M_8	$P_{2,4}/9 \rightarrow P_{1,6}/7 \rightarrow P_{1,7}/6 \rightarrow P_{1,6}/6 \rightarrow P_{1,7}/5 \rightarrow P_{1,6}/6 \rightarrow P_{1,7}/6 \rightarrow P_{2,4}/9 \rightarrow P_{2,4}/9$
M_9	$P_{2,4}/9 \rightarrow P_{2,4}/9 \rightarrow P_{1,6}/7 \rightarrow P_{1,7}/8 \rightarrow P_{2,4}/9 \rightarrow P_{1,6}/8 \rightarrow P_{1,7}/9 \rightarrow P_{1,6}/8 \rightarrow P_{1,7}/8$
M_{10}	$P_{4,1}/8 \rightarrow P_{2,2}/9 \rightarrow P_{4,1}/8 \rightarrow P_{3,1}/5 \rightarrow P_{2,2}/9 \rightarrow P_{3,1}/16 \rightarrow P_{4,3}/8 \rightarrow P_{4,1}/9 \rightarrow P_{3,3}/5 \rightarrow P_{3,3}/11 \rightarrow P_{4,3}/8 \rightarrow P_{3,3}/6 \rightarrow P_{3,1}/5 \rightarrow P_{3,3}/5 \rightarrow$ $P_{2,2}/9 \rightarrow P_{4,3}/7 \rightarrow P_{2,2}/10$
M_{11}	$P_{4,1}/9 \rightarrow P_{3,1}/6 \rightarrow P_{4,1}/16 \rightarrow P_{2,2}/26 \rightarrow P_{3,1}/18 \rightarrow P_{4,3}/18 \rightarrow P_{2,2}/9 \rightarrow P_{4,3}/9 \rightarrow P_{3,3}/5 \rightarrow P_{3,3}/6 \rightarrow P_{3,3}/12 \rightarrow P_{2,2}/8$

algorithms were proposed to progressively solve the problems of task assignment and processing route planning.

The effectiveness of the proposed method was demonstrated by fabricating four typical parts of a machine tool with the characteristics of multi-machine, multi-task, and multi-process. Results show that in the task assignment stage, the carbon efficiency indicators can effectively diminish the dimension of multi-objective optimization and obtain comprehensive low-carbon promotion effect. In the processing route planning stage, the progressive optimization strategy reduces the difficulty of obtaining the optimal sub-batch and processing sequence and ensures that the makespan is optimized without jeopardizing the carbon efficiency performance. The stochastic factors of the mechanical machining process considered in the scheduling optimization model is likewise worthy of further investigation.

Acknowledgements The work described in this paper was supported by China Postdoctoral Science Foundation (Grant No. 2018M642935), the Plateau Disciplines in Shanghai, and the National Natural Science Foundation of China (Grant Nos. 51905392, 51775392 and 51675388). These financial contributions are gratefully acknowledged.

References

1. Department of Energy Statistics National Bureau of Statistics People's Republic of China. China Energy Statistical Yearbook 2016. Beijing: China Statistics Press, 2016 (in Chinese)
2. Ma F, Zhang H, Hon K K B, et al. An optimization approach of selective laser sintering considering energy consumption and material cost. Journal of Cleaner Production, 2018, 199: 529–537
3. Liu Y, Liu X, Zhao J. Research on job-shop scheduling optimization method with limited resources. International Journal of Advanced Manufacturing Technology, 2008, 38(3–4): 386–392
4. Tang D, Dai M, Salido M A, et al. Energy-efficient dynamic scheduling for a flexible flow shop using an improved particle swarm optimization. Computers in Industry, 2016, 81: 82–95
5. Mouzon G C, Yildirim M B. A framework to minimise total energy consumption and total tardiness on a single machine. International Journal of Sustainable Engineering, 2008, 1(2): 105–116
6. Mouzon G C. Operational methods and models for minimization of energy consumption in a manufacturing environment. Dissertation for the Doctoral Degree. Wichita: Wichita State University, 2008
7. Giglio D, Paolucci M, Roshani A. Integrated lot sizing and energy-efficient job shop scheduling problem in manufacturing/remanufacturing systems. Journal of Cleaner Production, 2017, 148: 624–641
8. Salido M A, Escamilla J, Barber F, et al. Energy efficiency, robustness, and makespan optimality in job-shop scheduling problems. Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 2016, 30(3): 300–312
9. Li L L, Li C B, Li L, et al. An integrated approach for remanufacturing job shop scheduling with routing alternatives. Mathematical Biosciences and Engineering: MBE, 2019, 16(4): 2063–2085
10. Piroozfard H, Wong K Y, Wong W P. Minimizing total carbon footprint and total late work criterion in flexible job shop scheduling by using an improved multi-objective genetic algorithm. Resources, Conservation and Recycling, 2018, 128: 267–283
11. Zhang C, Gu P, Jiang P. Low-carbon scheduling and estimating for a flexible job shop based on carbon footprint and carbon efficiency of multi-job processing. Proceedings of the Institution of Mechanical Engineers. Part B, Journal of Engineering Manufacture, 2015, 229(2): 328–342
12. Zhang Y, Liu Q, Zhou Y, et al. Integrated optimization of cutting parameters and scheduling for reducing carbon emissions. Journal of Cleaner Production, 2017, 149: 886–895
13. Lei D. Novel teaching-learning-based optimization algorithm for low carbon scheduling of flexible job shop. Control and Decision, 2017, 32(9): 1621–1627 (in Chinese)
14. Zhou G, Tian C, Zhang J, et al. Multi-objective process route optimization considering carbon emissions. International Journal of Advanced Manufacturing Technology, 2018, 96(1–4): 1195–1213
15. Verfaillie H A, Bidwell R. Measuring eco-efficiency: A guide to reporting company performance. World Business Council for Sustainable Development, 2000
16. Cao H, Li H, Cheng H, et al. A carbon efficiency approach for life-cycle carbon emission characteristics of machine tools. Journal of Cleaner Production, 2012, 37: 19–28
17. Jiang Z, Ding Z, Zhang H, et al. Data-driven ecological performance evaluation for remanufacturing process. Energy Conversion and Management, 2019, 198: 111844
18. Zhu S, Jiang Z, Zhang H, et al. A carbon efficiency evaluation method for manufacturing process chain decision-making. Journal of Cleaner Production, 2017, 148: 665–680
19. Li C, Tang Y, Cui L, et al. A quantitative approach to analyze carbon emissions of CNC-based machining systems. Journal of Intelligent Manufacturing, 2015, 26(5): 911–922
20. Deb K, Agrawal S, Pratap A, et al. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In: Schoenauer M, Deb K, Rudolph G, et al., eds. Parallel Problem Solving from Nature PPSN VI. PPSN 2000. Lecture Notes in Computer Science, vol 1917. Berlin: Springer, 2000, 849–858
21. Mirjalili S. Genetic algorithm. In: Mirjalili S, ed. Evolutionary Algorithms and Neural Networks. Cham: Springer, 2019, 43–55
22. Ma F, Zhang H, Gong Q, et al. A novel energy evaluation approach of machining processes based on data analysis. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 2019, 1–15
23. Ding Z, Jiang Z, Zhang H, et al. An integrated decision-making method for selecting machine tool guideways considering remanufacturability. International Journal of Computer Integrated Manufacturing, 2018, 1–12