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RESEARCH ARTICLE

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Optimization of remanufacturing process routes oriented toward eco-efficiency

Abstract Remanufacturing route optimization is crucial in remanufacturing production because it exerts a considerable impact on the eco-efficiency (i.e., the best link between economic and environmental benefits) of remanufacturing. Therefore, an optimization model for remanufacturing process routes oriented toward eco-efficiency is proposed. In this model, fault tree analysis is used to extract the characteristic factors of used products. The ICAM definition method is utilized to design alternative remanufacturing process routes for the used products. Afterward, an eco-efficiency objective function model is established, and simulated annealing (SA) particle swarm optimization (PSO) is applied to select the manufacturing process route with the best eco-efficiency. The proposed model is then applied to the remanufacturing of a used helical cylindrical gear, and optimization of the remanufacturing process route is realized by MATLAB programming. The proposed model's feasibility is verified by comparing the model's performance with that of standard SA and PSO.

Keywords remanufacturing, process route optimization, eco-efficiency, simulated particle swarm optimization algorithm, IDEF0

1 Introduction

China's equipment assets amount to several trillions of RMB. Applying remanufacturing technology to 10% of scrapped equipment to form new products can provide numerous economic and social benefits. Large amounts of waste resources cause unpredictable damage to the ecological environment. These conditions have resulted in a broad market space for the emerging remanufacturing industry [1]. Compared with new product manufacturing, remanufacturing can prolong the service life of products by multiple times, maximize the available value of used products, produce nearly no solid waste, and reduce atmospheric pollutant emissions by more than 80% [2]. Moreover, the development of the remanufacturing industry has been conducive to reducing the intensity of greenhouse gas emissions [3–5]. However, the realization of these advantages largely depends on the optimization of the remanufacturing process route.

The remanufacturing process route refers to the process of reconditioning used products. Optimization of the process route is important in improving the environmental benefits, economic benefits, eco-efficiency, and performance of remanufactured products [6,7]. Li et al. [8] constructed an optimization model for the remanufacturing process route; the model is based on an improved fuzzy neural network. Golinska-Dawson et al. [9] used a grey decision-making evaluation method to assess the sustainability of remanufacturing process routes. Subramoniam et al. [10] established an optimization model of the remanufacturing process route on the basis of an extensive literature review and verified that the optimization model can also be applied to other industries. These methods have provided vital contributions to the research on remanufacturing process route optimization (e.g., those on fuzzy neural networks and grey decision-making evaluation), but few scholars have studied the uncertainty of the remanufacturing process route.

Given that the qualities of recycled used products differ, the remanufacturing process is full of uncertainty; consequently, the eco-efficiency of remanufacturing is also uncertain. The uncertainty of a process route considerably increases the difficulty of remanufacturing process route optimization. Wang et al. [11] overcame the uncertainty of

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a process route based on failure characteristics, but the quality status of used products was not fully expressed by the failure characteristics. Aside from failure characteristics, other characteristic factors, such as material characteristics, surface hardness, and processing accuracy, exist [12]. Therefore, these characteristic factors can be used to characterize the quality status of used products comprehensively.

Fault tree analysis (FTA) and the ICAM definition method (IDEF0) are utilized in this study to analyze the characteristic factors of used products, establish the relationship between the characteristic factors of such products and the process route, and adapt to the uncertainty of the remanufacturing process route. FTA can directly and clearly express the direct and indirect basic causes of events in systems engineering and natural sciences with logic diagrams [13]. Hence, it is used to extract the characteristic factors of used products. IDEF0 can accurately describe the functional activities of systems and the relationship between them by using simple graphical symbols and natural language [14]. This capability enables remanufacturing enterprises to generate remanufacturing process routes accurately by using IDEF0. Therefore, optional process routes can be obtained based on IDEF0 after the characteristic factors of the used products are determined. Afterward, an appropriate objective function is needed to optimize the acquired process routes.

Many scholars have studied the objective function selection of remanufacturing process route optimization to address different needs. For example, Jiang et al. [15] established a remanufacturing process route optimization theory by evaluating the failure type, failure location, and failure degree of used components to optimize reliability and cost. Given that countries pay increasing attention to environmental issues, setting cost, time, and other factors as objective functions does not meet the current requirements of environmental protection. Environmental and economic benefits were considered in process route optimization in Ref. [16]; however, a weighting method was used to transform multiple objectives into a single objective, thereby considerably increasing the subjectivity in process route optimization. The concept of eco-efficiency was proposed to reduce such subjectivity. In 1990, Schaltegger and Krähenbühl [17] introduced the concept of eco-efficiency, which is the ratio of added value to increased environmental impact. The concept of eco-efficiency has been widely recognized and accepted through the book "*Changing Course: A Global Business Perspective on Development and the Environment*" that was published by the World Business Council for Sustainable Development (WBCSD) in 1992 [18]. Eco-efficiency can link three indicators, namely, resources, economy, and environment, and establish an optimal link between the best economic objectives and the best environmental objectives [19–22]. Therefore, optimizing the eco-efficiency of remanufacturing can not only improve the economic and environmental benefits of remanufacturing but also reduce the subjectivity of multi-objective optimization. The eco-efficiency function can thus be set as the objective function of process route optimization after being established.

What algorithm should be used to optimize the remanufacturing process route after the objective function is determined? The optimization algorithms currently used to optimize remanufacturing process routes include genetic algorithm, particle swarm optimization (PSO), evolutionary programming, and artificial bee colony. PSO is widely implemented to solve various optimization problems due to its advantages of easy implementation, high precision, and fast convergence [23,24]. For example, Li et al. [25] used multi-objective PSO to optimize the total cost and carbon emissions in a remanufacturing process route. Chen and Liu [26] proposed a modified PSO to optimize the remanufacturing reverse logistics model.

These attempts to introduce PSO into remanufacturing process route optimization have led to in-depth research on process route optimization. However, PSO tends to fall into local optima when handling complex problems [27]. The simulated annealing (SA) algorithm accepts new solutions with probabilities [28], thus avoiding local optima to some extent. Therefore, PSO and SA are integrated into SAPSO in this study to optimize the remanufacturing process route and effectively avoid falling into local optima. Compared with other optimization algorithms, SAPSO can comprehensively combine the advantages of PSO and SA. This integrated algorithm can be used to solve many optimization problems due to its easy implementation, high accuracy, and acceptance of new solutions with probabilities.

Previous research on remanufacturing process route optimization has revealed the following main difficulties in optimization: Dealing with the uncertainty of process routes and determining the appropriate optimization objectives. The innovations of this study are the following points:

1) The quality uncertainty of used products is represented by characteristic factors instead of failure characteristics. Compared with single failure characteristics, characteristic factors can more comprehensively express the quality conditions of used products.

2) Optional process routes are generated by the characteristic factors of used products. FTA and IDEF0 are utilized to establish the relationship between characteristic factors and process routes, thereby enabling adaptation to the uncertainty of remanufacturing process routes.

3) The objective function of eco-efficiency is established. Compared with traditional multi-objective optimization, the optimization of the eco-efficiency function can

not only improve economic and environmental benefits but also significantly reduce the subjectivity in process route optimization.

4) SAPSO is used to optimize the objective function and solve the single-objective optimization problem while overcoming the limitations of PSO and SA.

2 Construction of a remanufacturing process route optimization model

The manufacturing process route optimization model oriented toward eco-efficiency consists of designing the optional process routes and selecting the process route with the best eco-efficiency. The specific process is shown in Fig. 1.

In this flowchart, $EE(x)$ represents the eco-efficiency objective function. This optimization model is built through the following steps:

Step 1: Obtaining the characteristic factors of the used products. FTA is used to extract the characteristic factors of the used products.

Step 2: Designing the optional process routes. IDEF0 is used to design the optional process routes after the characteristic factors of the used products are determined.

Step 3: Establishing the objective function. The objective function of eco-efficiency is constructed in accordance with the definition of eco-efficiency, and the constraint function is established according to the constraints.

Step 4: Generating the optimal process route. SAPSO is used to select the process route with the optimal eco-efficiency.

2.1 Characteristic factors of extracting used products

FTA is a top-down deductive failure analysis method that combines low-order events with Brin logic to analyze unwanted states in a system. It is mainly used to understand the causes of system failure. Hence, FTA is applied to analyze the failure causes of used products and extract the characteristic factors leading to such failure. Figure 2 shows the extraction of the characteristic factors of used products by FTA.

In Fig. 2, X_1, X_2, ..., X_n denote the characteristic factors corresponding to the failure form, i.e., Characteristic factor 1, Characteristic factor 2, ..., Characteristic factor n. The failure of the used products represents an accident in FTA. The various failure forms leading to the failure of the used products denote the direct cause of the accident, and the characteristic factors corresponding to each failure form represent the basic event.

2.2 Optional process route generation

IDEF0 can be adopted to design optional process routes after the characteristic factors of the used products are obtained. At the beginning of the modeling, IDEF0 uses a box and its interface arrow to represent the origin and development of the whole system, as well as the internal and external relations, as shown in Figure A-0 in Fig. 3. Then the single module of the expression system is decomposed into several sub-modules, which are represented by boxes, and the connections or interfaces between sub-modules are represented by arrows. Each sub-module can be divided into more detailed details, such as A0 shown in Fig. 3.

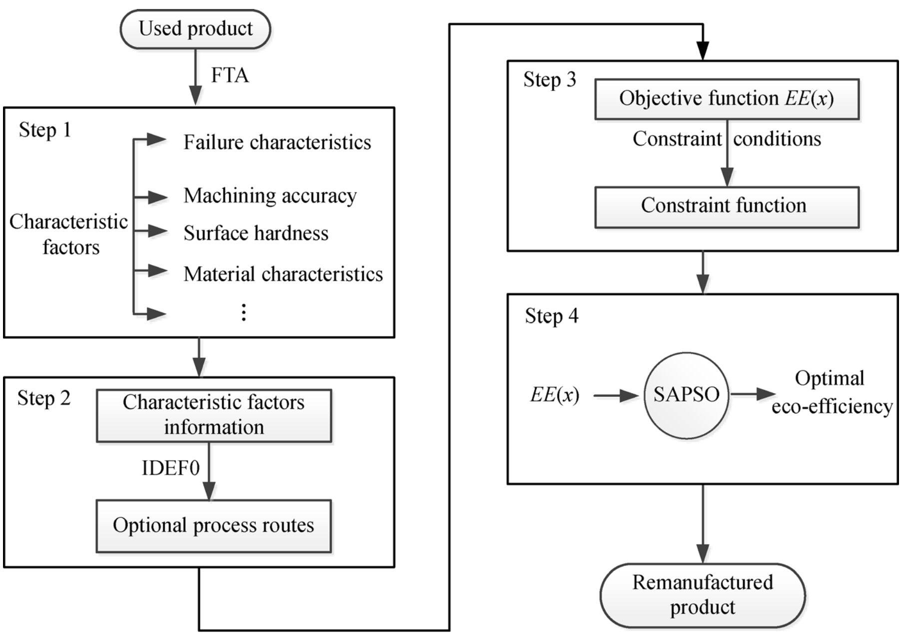

Fig. 1 Remanufacturing process route optimization flowchart.

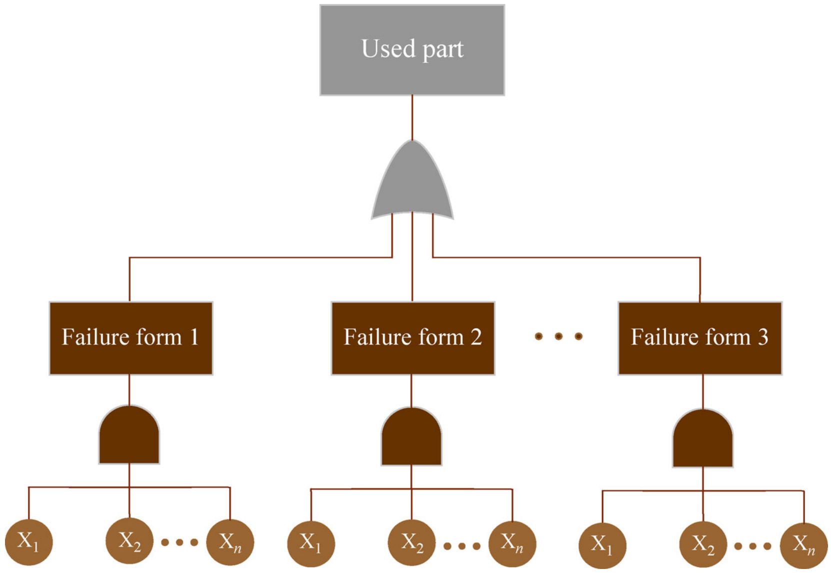

Fig. 2 Characteristic factors of used products.

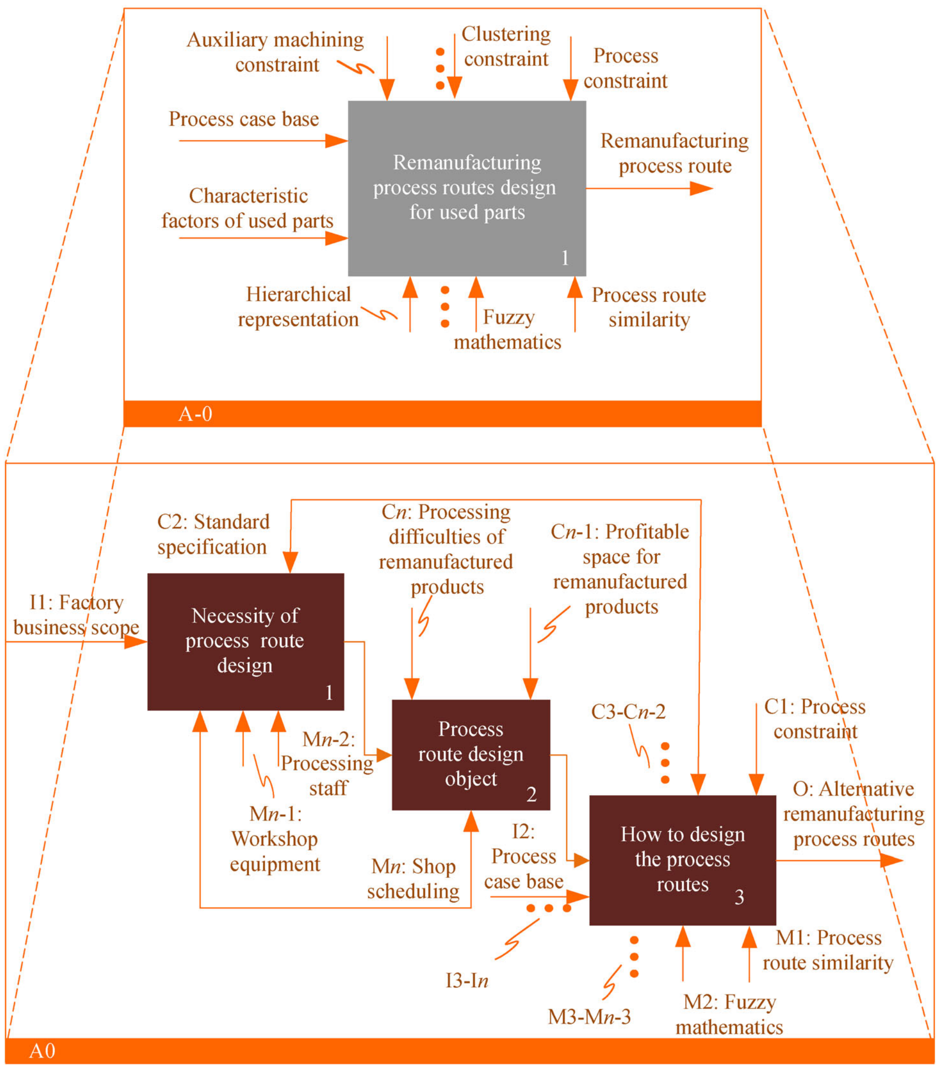

Fig. 3 IDEF0 for the design of remanufacturing process routes.

In Fig. 3, the content of the box is the function activity of IDEF0. The arrow on the left side of the box is the input required to complete the function activity. The arrow on the right side of the box is the output after the function activity is completed. The arrow on the top of the box is the constraint in the process of implementing the function activity, and the arrow on the bottom of the box is the mechanism of the function activity (i.e., what is the function activity accomplished by?). IDEF0 introduces the ICOM code into the subgraphs to show the corresponding relationship between the parent graphs and subgraphs clearly. The specific methods are as follows. The beginning of each boundary arrow in the subgraphs is represented by the letters I (input), C (control), O (output), and M (mechanism), and the relative position of the arrows in the parent graph is represented by a number. The numbering order is from top to bottom and from left to right. For example, the control C1 represents the first control of the A0 subgraph.

In this regard, IDEF0 is used to design the remanufacturing process routes of the used products. The process is shown in Fig. 3.

As shown in Fig. 3, the function activity of this IDEF0 model is the design for the remanufacturing process route of used products; the input needed to complete the function activity includes the characteristic factors of the used products and the process case base; the output after the function activity includes the process route of remanufacturing; the constraint in the realization of the function activity includes process and clustering constraints; and the mechanism of functional activities includes process route similarity and fuzzy mathematics.

2.3 Construction of the objective function

The objective function should be established as the basis for selecting the best process route after feasible process routes are obtained. The definition of eco-efficiency varies slightly according to the level of the research object and the research purpose. The WBCSD stated that the purpose of studying eco-efficiency is to minimize environmental impact and maximize value, and it defines eco-efficiency as the separation between economic growth and environmental pressure [29]. According to the characteristics of remanufacturing, the economic benefits of remanufacturing per unit environmental impact are defined as the eco-efficiency of remanufacturing. A high index value signifies considerable economic benefit of remanufacturing per unit environmental impact. According to the definition of eco-efficiency, the economic benefit and environmental impact functions should be established before the eco-efficiency function.

1) Construction of the economic benefit function

The economic benefit of remanufactured products is equal to the price of products minus the cost of recycling used products and the cost of the remanufacturing process. Therefore, the economic benefit of remanufactured products can be expressed by Eq. (1):

$$EB = S - C - R, \tag{1}$$

where EB represents the economic benefit function, S denotes the price of remanufactured products, C denotes the cost of remanufacturing process route, and R denotes the cost of recycling used products.

The cost of the remanufacturing process route for used products usually consists of the costs of machine tools, cutting tools, and labor [30]. Therefore, the cost of the process route can be calculated with Eq. (2). The total time of the process route includes the time of mending and cutting operations, and it can be calculated as Eq. (3):

$$C = \sum_{i=1}^{m} K_i t_i + \sum_{j=1}^{n} (L_j + T_j)\ t_j + C_1 t, \tag{2}$$

$$t = \sum_{i=1}^{m} t_i + \sum_{j=1}^{n} t_j, \tag{3}$$

where i and j indicate the ith mending operations and the jth cutting operations respectively, t_i indicates the processing time of the ith mending operation, t_j indicates the processing time of the jth cutting operation, t represents the total processing time of the process route, K_i represents the processing cost of the ith mending operation per unit time, T_j denotes the corresponding cutting operation processing cost, C_1 indicates the unit labor cost, and m and n represent the numbers of mending and cutting operations, respectively.

2) Construction of the environmental impact function

Liao et al. [31,32] believed that carbon emissions are important in environmental impact assessment and used them to assess the environmental impact of remanufacturing. On this basis, carbon emissions are utilized to represent the environmental impact of the remanufacturing process route. The carbon emissions of the remanufacturing process route can be expressed by the energy consumption of remanufacturing multiplied by the carbon emission coefficient. The energy consumption of the reconditioning process of used products is mainly caused by general equipment (e.g., equipment for mending and cutting operations). Here, to simplify the calculation procedure, the energy consumption of accessory equipment (e.g., workbench and tool holder) is disregarded. Thus, the environmental impact can be expressed as follows:

$$EI = \sum_{i=1}^{m} P_i t_i \chi + \sum_{j=1}^{n} P_j t_j \chi, \tag{4}$$

where EI denotes the environmental impact function, χ represents the carbon emission coefficient, which is 875 g/(kW·h) [33], and P_i and P_j are the device power of the ith mending and the jth cutting operations, respectively.

3) Construction of the eco-efficiency function

In accordance with the definition of remanufacturing eco-efficiency and the previously established economic benefit and environmental impact functions, the eco-efficiency function can be expressed as follows:

$$EE = \frac{EB}{EI} = \frac{S - \sum_{i=1}^{m} K_i t_i - \sum_{j=1}^{n} (L_j + T_j) t_j - C_1 t - R}{\sum_{i=1}^{m} P_i t_i \chi + \sum_{j=1}^{n} P_j t_j \chi}. \tag{5}$$

4) Constraint function

In general, if reconditioning of used products can be performed, then the machine must be in a stable state. The operating state of the machine can be reflected by the output power of the machine. The following constraints apply:

$$P_{i\min} \leqslant P_i \leqslant P_{i\max}, \tag{6}$$

$$P_{j\min} \leqslant P_j \leqslant P_{j\max}, \tag{7}$$

where $P_{i\max}$ and $P_{i\min}$ represent the maximum and minimum power, respectively, of mending process equipment when the equipment is in a stable operation, and $P_{j\max}$ and $P_{j\min}$ are the maximum and minimum power, respectively, of cutting process equipment when the equipment is in a stable state.

2.4 Process route optimization based on SAPSO

SAPSO is needed to determine the optimal process route of the objective function once the objective function of eco-efficiency is established. SAPSO has the merits of SA and PSO, thereby guaranteeing global search capability and improving calculation accuracy. The implementation process of SAPSO is shown in Fig. 4.

P_{i} and P_{g} represent individual and global extremes of particles, respectively. In SAPSO, first, a group of particles is coded. Second, a group of particles is initialized in the solvable space. Third, the fitness function is used to calculate the fitness value of particles, and P_{i} and P_{g} are updated in accordance with the fitness value. Fourth, the particle velocity and position are updated, and the SA mechanism is introduced to the algorithm. Finally, whether the maximum number of iterations has been reached or not is determined. The details of SAPSO are shown in Fig. 5.

The SAPSO-based remanufacturing process route optimization procedure is divided into 12 steps:

Step 1: Process operation coding: The remanufacturing process operation is coded with numbers.

Step 2: Parameters and population initialization: The following parameters are set: Inertia weight $\omega = 0.9$, acceleration constants $c_1 = c_2 = 2$. The initial population is generated randomly after parameter initialization. The dimension of particles is set as the number of variables in the eco-efficiency function, and the population size represents the optimal range of remanufacturing process routes.

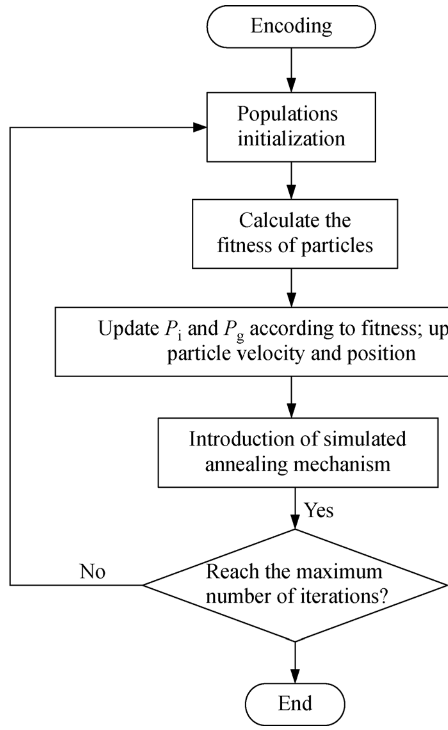

Fig. 4 Implementation of SAPSO.

Step 3: Setting simulated annealing parameters: Initial annealing temperature $T = 10000$ °C, lower temperature limit $T_0 = 0.01$ °C, and temperature attenuation coefficient $\alpha = 0.9$.

Step 4: Setting of particle position: The fitness value of each particle is calculated with Eq. (4). P_{i} and P_{g} are set as current and optimal particle positions, respectively.

Step 5: Determining whether the maximum number of iterations has been reached or not: If it has been reached, then Step 12 is implemented; otherwise, the next step is executed.

Step 6: Updating of the position and particle velocity: The position and velocity of the ith particle in the n-dimensional space can be expressed as $\boldsymbol{x}_i = [x_{i1}, x_{i1}, ..., x_{in}]^{\mathrm{T}}$, and $\boldsymbol{v}_i = [v_{i1}, v_{i2}, ..., v_{in}]^{\mathrm{T}}$. During the iteration, the particles update their speeds and positions as follows:

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 (P_{id}^{k} - x_{id}^{k}) + c_2 r_2 (P_{gd}^{k} - x_{id}^{k}), \tag{8}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}. \tag{9}$$

where v_{id}^{k} and v_{id}^{k+1} represent the d-dimensional component of the velocity vector of particle i at the kth and $(k+1)$th iterations, respectively, x_{id}^{k} and x_{id}^{k+1} represent the

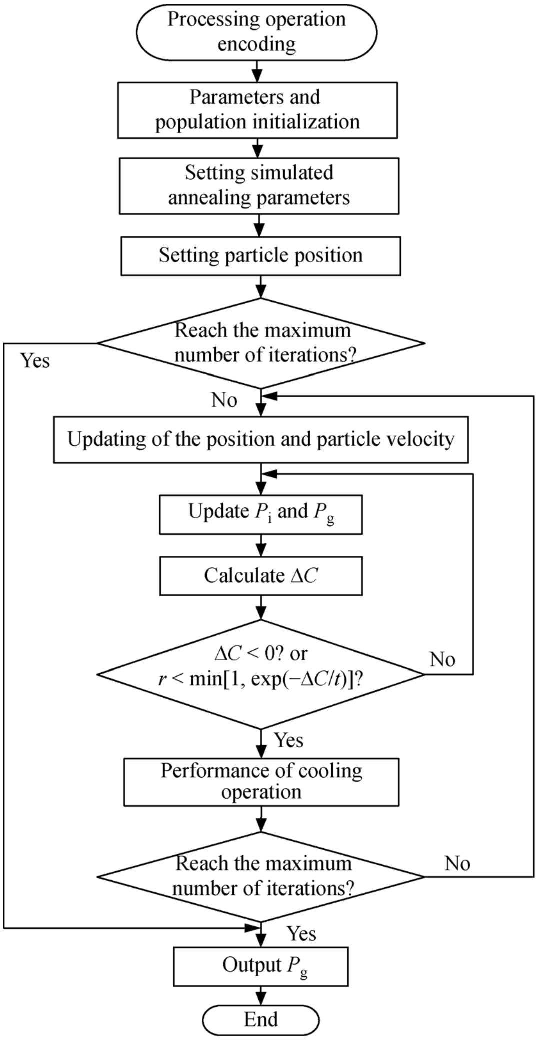

Fig. 5 Flowchart of remanufacturing process route optimization based on SAPSO.

d-dimensional component of the particle i position vector at the kth and $(k+1)$th iterations, respectively, P_{id}^k represents the best position experienced by the d-dimensional component of the particle i position vector at the kth iteration, P_{gd}^k represents the d-dimensional component of the best position experienced by the particle swarm in the solution space at the kth iteration, r_1 and r_2 are random numbers in the range of [0, 1], other parameters (i.e., ω, c_1 and c_2) have been explained in Step 2.

Step 7: Updating of individual and global extrema: The fitness of particles is compared with that of $P_{\rm i}$, and the optimum value is updated to $P_{\rm i}$. The fitness of particles is compared with that of $P_{\rm g}$, and the optimal value is updated to $P_{\rm g}$.

Step 8: Calculation of the difference in fitness values: A new position for a particle is generated randomly, and the difference in fitness values (ΔC) between the old and new positions is calculated.

Step 9: Introduction of the SA mechanism: A random number r in the range of [0, 1] is generated. If $\Delta C < 0$ or $r < \min[1,\exp(-\Delta C/t)]$, then the new location is accepted, and the next step is performed; otherwise, Step 7 is executed again.

Step 10: Performance of cooling operation: $T = 0.9T$.

Step 11: Checking if the maximum number of iterations is reached: If it has been reached, then the next step is implemented; otherwise, Step 6 is performed.

Step 12: Outputting of global extremum: $P_{\rm g}$ is outputted, and SAPSO terminates.

3 Case study

Helical cylindrical gears are important parts of mechanical equipment and vehicles. Remanufacturing failed helical cylindrical gears is favorable because it improves production efficiency and reduces production costs. The following is a detailed description of the process route optimization of remanufacturing a used helical cylindrical gear in a factory.

3.1 Analysis of characteristic factors of used helical cylindrical gear

After cleaning and testing, the failure form and corresponding characteristic factors of the used helical cylindrical gear are obtained by FTA. Failure characteristics (F), material characteristics (M), surface hardness (C), and processing accuracy (P) are shown in Fig. 6.

3.2 Optional remanufacturing process routes generation of the used helical cylindrical gear

IDEF0 can be used to obtain optional process routes after the characteristic factors of the used helical cylindrical gear are acquired. The specific implementation process is shown in Fig. 7. The A-0 chart in Fig. 7 shows the remanufacturing process route design system based on IDEF0. The system includes mechanism (i.e., process route similarity degree), control (i.e., process constraint), input (i.e., process case base, characteristic factors) and output (i.e., remanufacturing process route). The A0 diagram in Fig. 7 is intended to better interpret and refine the A-0 diagram, which includes four steps: Process contrast and retrieval, local similarity degree determination, overall similarity degree calculation, optional process routes generation. The A0 diagram include mechanism (e.g., expert experience in manufacturing, AHP method), control (e.g., weight constraint, process constraint), input (e.g., process case base, characteristic factors of the used helical cylindrical gear), and output (optional process routes).

Sim Function in Fig. 7 represents the similarity function. The 10 optional process routes obtained in Fig. 7 have a total of 6 process operations. At the same time, these

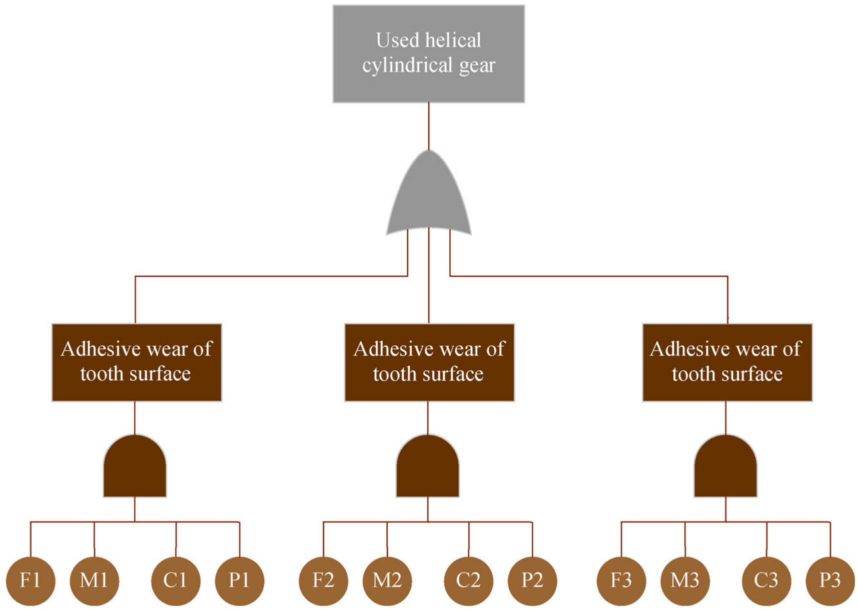

Fig. 6 Characteristic factor analysis of the used helical cylindrical gear. (F1, M1, C1, P1), (F2, M2, C2, P2), and (F3, M3, C3, P3) denote (moderate wear, cast iron, 46HRC, IT_7), (moderate crack, cast iron, 50HRC, IT_5), and (mild crack, cast iron, 46HRC, IT_7), respectively.

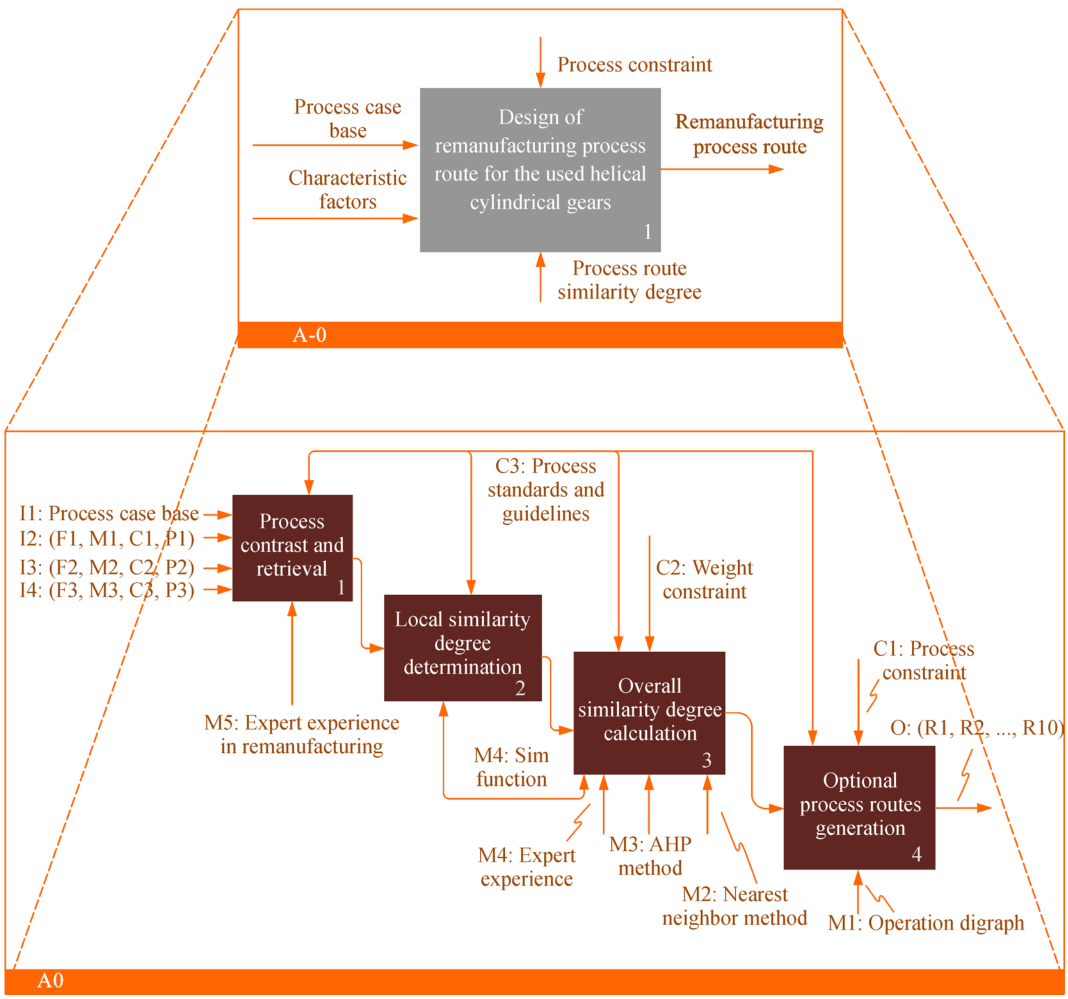

Fig. 7 IDEF0 for remanufacturing process route design of the used helical cylindrical gear.

process operations are numbered to adapt to the operation of the algorithm: Turning: 01; soldering: 02; rough grinding: 03; accurate grinding: 04; surfacing: 05; cold-welding: 06. The details of the 10 process routes in Fig. 7 can be seen in Table 1.

Table 1 Optional process route information of the used helical cylindrical gear

Code	Process route
R1	01 → 02 → 03 → 04 → 05 → 06
R2	06 → 02 → 03 → 04 → 05 → 01
R3	01 → 06 → 03 → 04 → 05 → 02
R4	05 → 02 → 03 → 04 → 01 → 06
R5	01 → 05 → 03 → 04 → 02 → 06
R6	01 → 03 → 04 → 02 → 05 → 06
R7	06 → 03 → 04 → 02 → 05 → 01
R8	01 → 06 → 05 → 03 → 04 → 02
R9	05 → 02 → 01 → 06 → 03 → 04
R10	01 → 05 → 02 → 06 → 03 → 04

3.3 Optimized process route of SAPSO

After the optional process routes are generated (Table 1), SAPSO can be used to identify the process route with the maximum eco-efficiency via MATLAB 2016b programming.

The parameters in Eq. (4) are provided by the remanufacturer, in which $C_1 = 38$ CNY/h, $S = 25$ CNY, and $R = 3$ CNY. The operating parameters of SAPSO are set as particle dimension = 2, population = 50, and iterations = 100. Tables A1 and A2 present remanufactured mechanical equipment information and tool information, respectively, which are provided by the remanufacturing factory. The eco-efficiency of helical cylindrical gear remanufacturing can be obtained from the information shown in Tables A1 and A2 after the SAPSO algorithm is optimized. In addition, machines E-001, E-002, E-003, and E-006 contain tools T-001, T-002, T-003, and T-004, respectively, and perform cutting operations. Machines E-004 and E-005 do not contain tools and perform mending operations. The equipment that performs the process operation is determined by the function of the equipment, and several of the machines have various functions. For example, E-001 can complete process operations 03 and 06 simultaneously. The specific information is listed: E-001: 03 and 06; E-002: 04; E-004: 05; E-005: 02; E-007: 01.

The optimal process route and its details are obtained by running the SAPSO program in accordance with the initialization information and constraints and with the operation parameters set by the SAPSO algorithm. A comparison of the used helical cylindrical gear before and after remanufacturing is shown in Fig. 8.

3.4 Comparison of optimization results

To highlight the advantages of SAPSO, the remanufacturing of the used helical cylindrical gear is still regarded as an example, and PSO and SA are set as the comparison algorithms. PSO has fast convergence and high calculation accuracy. SA can effectively escape local optima by simulating the principle of metal annealing. PSO and SA have been widely used in various optimization problems because of these advantages. The running results of the three algorithms are given in Table 2. The goal of the experiments is to optimize eco-efficiency. PSO and SA are executed with MATLAB 2016b programming on the same PC, and the parameters of PSO and SA are the same as those in the previous section. Figure 9 shows the iterative convergence curves optimized with SA, PSO, and SAPSO, respectively.

Figures 9(a) and 9(b) show that the optimal solutions obtained by SA and PSO are 12.868 and 11.105, respectively. PSO easily falls into the local optimum with

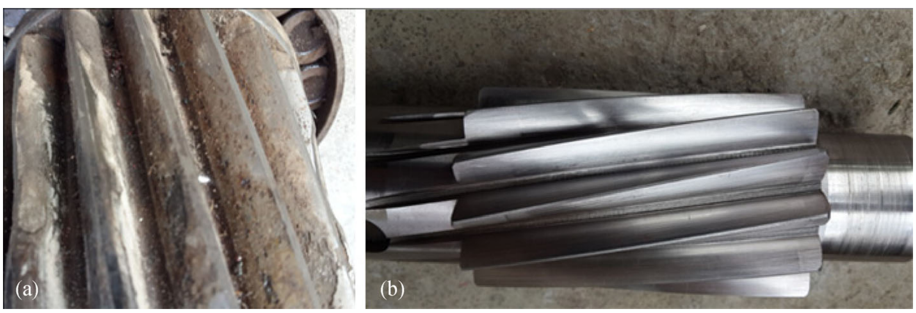

Fig. 8 Used cylindrical helical gear (a) before and (b) after remanufacturing.

Table 2 Optimization results of algorithms

Algorithm	Process route	Maximum iterations	Optimal eco-efficiency value
SAPSO	05 → 02 → 03 → 04 → 01 → 06	32	13.379
PSO	01 → 02 → 03 → 04 → 05 → 06	54	11.105
SA	01 → 05 → 02 → 06 → 03 → 04	77	12.868

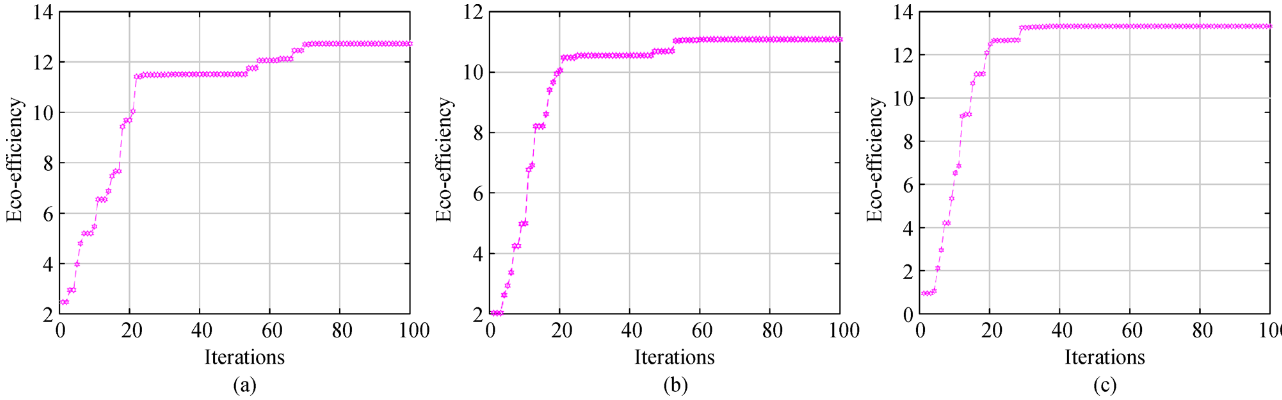

Fig. 9 Convergence curve of (a) SA, (b) PSO, and (c) SAPSO.

respect to SA during optimization. The maximum numbers of iterations for PSO and SA are 54 and 77, respectively. Therefore, the convergence speed of PSO is higher than that of SA on the whole. Figure 9(c) reveals that the optimal solution obtained by SAPSO is 13.379, and the number of iterations required to obtain the optimal solution is 32. Therefore, SAPSO has a better convergence rate than the two compared algorithms and is closer to the optimal solution. The trend of the curve in Fig. 9 show that after the SA mechanism is introduced to PSO, the local optimum can be escaped from in the early stage of convergence, and the overall convergence speed of the convergence curve is improved.

Overall, the results of algorithm optimization verify that SAPSO is more suitable for remanufacturing process route optimization than SA and PSO.

4 Conclusions and prospects

An optimization model for remanufacturing process routes oriented toward eco-efficiency is proposed to study remanufacturing process route optimization from the perspective of eco-efficiency. The model includes extraction of characteristic factors, construction of the objective function, generation of feasible process routes, and optimization of process routes. First, FTA is used to extract the characteristic factors. Second, the eco-efficiency function is established by defining remanufacturing eco-efficiency. Third, IDEF0 is applied to design the optional process routes. Finally, SAPSO is utilized to identify the optimal process route, and the remanufacturing of a used helical cylindrical gear is regarded as an example to verify the feasibility of the proposed model.

Generally, remanufacturing process route optimization for optimal eco-efficiency is more comprehensive and objective than other optimization goals. If the eco-efficiency function is not the objective function, then the selected optimal process route cannot fully exploit the remaining added value of the used components. SAPSO can be adopted to quickly generate the process route with the maximum eco-efficiency after establishing the objective function of eco-efficiency. However, certain factors, such as changes in reconditioning process operation and machine processing capacity, are excluded in the optimization process. This exclusion may lead to several limitations. How to consider these factors during optimization will be the focus of future research.

Appendix

Table A1 Mechanical equipment information for the remanufacturing process

Equipment code	Equipment name	Equipment type	Manufacturer	Power/kW	Cost/(CNY·h^{-1})
E-001 (T-001)	Microelectronic component automated spot welder	WL-C-1K	Guangdong Huashi Technology Co., Ltd.	1.52	1.73
E-002 (T-002)	Pulse fast cold and spot welding equipment	SDHB-2	Shanghai Shanda Electronic Technology Co., Ltd.	1.50	1.82
E-003 (T-003)	Digital automatic surface grinder	M820AHS	Yancheng Dafeng District Ruihua Machinery Manufacturing Co., Ltd.	14.50	11.00
E-004	Hydraulic internal and external cylindrical grinding machine	M1420H/F×500	Shanghai Zhouying Machine Tool Manufacturing Co., Ltd.	9.00	6.30
E-005	Circling turning blade CNC grinding equipment	EMGE-SKMDJ	Suzhou Yimai Trading Co., Ltd.	3.40	4.10
E-006 (T-004)	Horizontal lathe	CA6180C	Tengzhou Luzhong Machine Tool Co., Ltd.	1.80	2.10

Table A2 Tool information for the remanufacturing process

Tool number	Tool type	Tool specification	Cost/(CNY·h^{-1})
T-001	Offset tool	$\alpha = 90°$	3.2
T-002	Grooving tool	$d = 12$ mm	4.5
T-003	Cornish bit	$d = 110$ mm	4.2
T-004	Screw cutting tool	$\alpha = 45°$	5.5

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References

1. Xu B S. Innovation and development of remanufacturing with Chinese characteristics for a new era. China Surface Engineering, 2018, 31(1): 1–6 (in Chinese)
2. Xu B S, Li E Z, Zheng H D, et al. The remanufacturing industry and its development strategy in China. Engineering and Science, 2017, 19(3): 61–65 (in Chinese)
3. Liao H, Shi Y, Liu X, et al. A non-probabilistic model of carbon footprints in remanufacture under multiple uncertainties. Journal of Cleaner Production, 2019, 211: 1127–1140
4. Shen N, Liao H, Deng R, et al. Different types of environmental regulations and the heterogeneous influence on the environmental total factor productivity: Empirical analysis of China’s industry. Journal of Cleaner Production, 2019, 211: 171–184
5. Liao H, Deng Q. A carbon-constrained EOQ model with uncertain demand for remanufactured products. Journal of Cleaner Production, 2018, 199, 334–347
6. Behret H, Korugan A. Performance analysis of a hybrid system under quality impact of returns. Computers & Industrial Engineering, 2009, 56(2): 507–520
7. Quariguasi-Frota-Neto J, Bloemhof J. An analysis of the eco-efficiency of remanufactured personal computers and mobile phones. Production and Operations Management, 2012, 21(1): 101–114
8. Li C B, Feng Y, Du Y B, et al. Decision-making method for used components remanufacturing process plan based on modified FNN. Computer Integrated Manufacturing Systems, 2016, 22(3): 729–737 (in Chinese)
9. Golinska-Dawson P, Kosacka M, Mierzwiak R, et al. The mixed method for sustainability assessment of remanufacturing process using grey decision making. In: Golinska-Dawson P, Kübler F, eds. Sustainability in Remanufacturing Operations. EcoProduction (Environmental Issues in Logistics and Manufacturing). Cham: Springer, 2018, 125–139
10. Subramoniam R, Huisingh D, Chinnam R B, et al. Remanufacturing decision-making framework (RDMF): Research validation using the analytical hierarchical process. Journal of Cleaner Production, 2013, 40: 212–220
11. Wang H, Jiang Z G, Zhang X G, et al. A fault feature characterization based method for remanufacturing process planning optimization. Journal of Cleaner Production, 2017, 161: 708–719
12. Jiang Z G, Jiang Y, Wang Y, et al. A hybrid approach of rough set and case-based reasoning to remanufacturing process planning. Journal of Intelligent Manufacturing, 2019, 30(1): 19–32
13. Yazdi M, Nikfar F, Nasrabadi M. Failure probability analysis by employing fuzzy fault tree analysis. International Journal of System Assurance Engineering and Management, 2017, 8(Suppl 2): 1177–1193
14. Ang C L, Luo M, Khoo L P, et al. A knowledge-based approach to the generation of IDEF0 models. International Journal of Production Research, 1997, 35(5): 1385–1412
15. Jiang Z, Zhou T, Zhang H Y, et al. Reliability and cost optimization for remanufacturing process planning. Journal of Cleaner Production, 2016, 135(4): 1602–1610
16. Zhang X G, Zhang H, Jiang Z G, et al. An integrated model for remanufacturing process route decision. International Journal of Computer Integrated Manufacturing, 2015, 28(5): 451–459
17. Schaltegger U, Krähenbühl U. Heavy rare-earth element enrichment in granites of the Aar Massif (Central Alps, Switzerland). Chemical Geology, 1990, 89(1–2): 49–63
18. Schmidheiny S. Changing Course: A Global Business Perspective on Development and the Environment. Cambridge: MIT Press, 1992
19. Huisman J, Stevels A L N, Stobbe I. Eco-efficiency considerations on the end-of-life of consumer electronic products. IEEE International Symposium on Electronics and the Environment, 2009, 27(1): 9–25
20. Kicherer A, Schaltegger S, Tschochohei H, et al. Eco-efficiency. The International Journal of Life Cycle Assessment, 2007, 12(7): 537–543
21. Derwall J, Guenster N, Bauer R, et al. The eco-efficiency premium puzzle. Financial Analysts Journal, 2005, 61(2): 51–63
22. Kerr W, Ryan C. Eco-efficiency gains from remanufacturing: A case study of photocopier remanufacturing at Fuji Xerox Australia. Journal of Cleaner Production, 2001, 9(1): 75–81
23. Bonyadi M R, Michalewicz Z. Particle swarm optimization for single objective continuous space problems: A review. Evolutionary Computation, 2017, 25(1): 1–54
24. Gong Y J, Li J J, Zhou Y, et al. Genetic learning particle swarm optimization. IEEE Transactions on Cybernetics, 2016, 46(10): 2277–2290
25. Li L, Cheng F X, Cheng X Q, et al. Enterprise remanufacturing logistics network optimization based on modified multi-objective particle swarm optimization algorithm. Computer Integrated Manufacturing Systems, 2018, 24(8): 240–250 (in Chinese)
26. Chen Y J, Liu D B. An uncertain programming model for

manufacturing/remanufacturing hybrid system in reverse logistics environment. Applied Mechanics and Materials, 2013, 288: 251–255
27. Chatterjee S, Sarkar S, Hore S, et al. Particle swarm optimization trained neural network for structural failure prediction of multistoried RC buildings. Neural Computing & Applications, 2017, 28(8): 2005–2016
28. Jiang P, Ge Y, Wang C. Research and application of a hybrid forecasting model based on simulated annealing algorithm: A case study of wind speed forecasting. Journal of Renewable and Sustainable Energy, 2016, 8: 015501
29. World Business Council for Sustainable Development. The business case for sustainable development: Making a difference towards the Earth Summit 2002 and Beyond. Corporate Environmental Strategy, 2002, 9(3): 226–235
30. Wang H, Jiang Z G, Zhang H, et al. An integrated MCDM approach considering demands-matching for reverse logistics. Journal of Cleaner Production, 2019, 208: 199–210
31. Liao H, Deng Q, Wang Y, et al. An environmental benefits and costs assessment model for remanufacturing process under quality uncertainty. Journal of Cleaner Production, 2018, 178: 45–58
32. Liao H, Deng Q, Wang Y. Optimal acquisition and production policy for end-of-life engineering machinery recovering in a joint manufacturing/remanufacturing system under uncertainties in procurement and demand. Sustainability, 2017, 9(3): 338
33. Yu S, Wei Y M, Guo H, et al. Carbon emission coefficient measurement of the coal-to-power energy chain in China. Applied Energy, 2014, 114(2): 290–300