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Multiobjective Ecological Strategy Optimization for Two-Stage Disassembly Line Balancing With Constrained-Resource

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ABSTRACT Effective disassembly of obsolete products is critical for remanufacturing, recycling and recycling. However, existing disassembly studies have few or no resource constraints, such as limited numbers of disassembly operators and tools. Two-stage disassembly model is used to improve the flexibility to adapt to remanufacturing market demand. Based on existing references, this paper establishes a multi-objective two-stage disassembly model based on two-stage data envelopment analysis (two-stage DEA). The resource-constructed two-stage DEA model in this paper fully considers the dynamic configuration information of the output factors in each stage. To avoid the problem where the overall efficiency is optimal, the research constructs a resource constrained efficiency two-stage disassembly model. First, with the goal of minimum disassembly time, economy, energy consumption and environment, this study proposes eNSGA-II. By using mixed mutation and ecological evolution strategies, a well-distributed noninferior solution set is obtained. Second, the group of 16 disassembly schemes is used as decision-making units (DMUs) of the two-stage DEA. A comparison with Chen's model rankings shows that the model in this paper performs better. DMU₆ has the highest efficiency ranking, which is the best disassembly solution. Finally, the effectiveness of the proposed algorithm is verified by examples. Compared with NSGA-II and SPEA-II, eNSGA-II shows better performance and effectiveness.


INDEX TERMS Disassembly, eNSGA-II, remanufacturing, resource constrained, two-stage DEA.

I. INTRODUCTION

Remanufacturing can reduce resource use and environmental impact throughout a product lifecycle. Disassembly is an essential part of remanufacturing and can promote the reuse of resources and reduce the environmental impact of products [1]–[4]. With the increase in obsolete agricultural machinery in agricultural production, the dismantling of obsolete products has become an urgent problem to be solved. Disassembly is the process of extracting valuable parts from a used system. Disassembly plays an important role in a green manufacturing system and full statement cycle evaluation. McGovern and Gupta proposed that the disassembly line balancing problem is an NP-complete problem [5]. Kalayci *et al.* [6] proposed

a hybrid discrete artificial bee colony algorithm to solve the DLBP of fuzzy processing time.

Remanufacturing is critical to sustainable development due to resource shortages and environmental pollution [7], [8]. Disassembly as one of the key technologies for remanufacturing has attracted scholarly attention. Domestic and foreign scholars have presented various studies about disassembly, mainly using time and economic performance as evaluation indicators. Marconi *et al.* [9] applied the data mining technique for calculating the effective disassembly sequence and time for industrial products. Parsa and Saadat [10] redefined the optimization parameters of the disassembly time based on detachability and component requirements. Tian *et al.* [4] used piece wise linearization and compact hyper rectangular methods to evaluate disassembly scheduling and pricing issues. Kucukkoc *et al.* [11] introduced the Type-E multi-person disassembly line balancing problem with effective

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linear and nonlinear models. Guo *et al.* [12] considered a multiobjective resource-constrained disassembly optimization problem with disassembly precedence constraints. Tian *et al.* [3] used an AND/OR diagram to solve the disassembly sequence planning problem in an uncertain disassembly environment. Wang *et al.* [13] considered the modelling and optimization of the multiobjective partial disassembly line balance problem of risk and benefit.

The algorithm and decision-making method have been widely used as the main optimization method for disassembly sequence optimization. Rickli and Camelio. [14] proposed an improved genetic algorithm to optimize partial disassembly sequences with economic and environmental factors. Avikal *et al.* [15] integrated priority constraint relationships and fuzzy analytic hierarchy processes to selectively disassemble tasks on workstations. Ren *et al.* [16] used a multitarget artificial bee colony algorithm to solve the problem of collaborative disassembly. Tang and Zhou [17] present a systematic approach to the disassembly line design in meeting the requirement of variant orders for multiple used parts with different due dates. Harivardhini *et al.* [18] presented a decision-making framework for solving the early design stage of product dismantling. Kalayci *et al.* [19] designed a hybrid genetic algorithm to solve the sequence-priority disassembly line balancing problem. Kazancoglu and Ozturkoglu [20] integrated MCDM and fuzzy AHP methods to consider green and commercial disassembly lines.

With emphasis on the environment and green remanufacturing, the use of green disassembly throughout the product life cycle has become important [21], [22]. Considering balancing and sequencing for a continuously moving conveyor, Defersha and Mohebalizadehgashti [23] proposed a mixed linear programming model. Lv *et al.* [24] developed a new sensitivity analysis method for processing mixed model production lines. Süleyman *et al.* [25] presented a mathematical model for the first balancing problem of disassembly, with the goal of minimizing the number of resources and workstations in a defined cycle time. To minimize the manufacturing cycle and total workload, Yazdani *et al.* [26] proposed a production scheduling model with multiobjective resource constraints. Deepak *et al.* [27] used a method for generating high-performance disassembly sequences with environmental and economic options. In contrast to complete disassembly, Smith *et al.* [28] developed a new partial disassembly line balancing that can reduce environmental costs and increase economics.

Disassembly is an inevitable part of product recycling. Due to the many uncertainties in the disassembly process, the disassembly process cannot be simply considered linear [29], [30]. Özcan *et al.* [31] applied a genetic algorithm to solve the task of random mixed model balancing and sequence problems. Guo *et al.* [32] presented a dual-objective optimization model for selective disassembly sequences by considering resource constraints. Fang *et al.* [33] proposed a hybrid model with automated disassembly of multiple robotic operations.

Due to the different conditions and degrees of failure, there are significant uncertainties in the disassembly process. The disassembly line balancing problem involves the processing of multiple pieces of equipment, multiple stages, and multiple workstations, which is an NP-hard problem. Based on the mixed integer programming model, Paksoy *et al.* [34] used a weighting method to solve the linear multiobjective optimization problem of mixed flow disassembly.

The traditional approach is to translate multiple goals into a single goal, but the outcome of decision optimization is influenced by personal preferences [35]. A multiobjective algorithm can compute in parallel and obtain a set of Pareto optimal solutions [36], [37]. The method of optimizing the decision first is more effective than the traditional multi-objective optimization method [38]. Therefore, this paper establishes a multiobjective two-stage disassembly line balancing model with minimum time, economy, energy consumption and environmental factors. The first stage is used to evaluate disassembly efficiency, and their evaluation system consists of equipment running time, disassembly idle time, employee working hours, employee salary, and recycling product cost as input measures and product disassembly rate as an output measure. The second stage is used to evaluate processing and remanufacturing efficiency which evaluation system consists of electricity consumption, oil consumption, chemical consumption, and waste production as input measures and comprehensive disassembly efficiency as an output measure. Based on Pareto dominance, an improved NSGA-II and two-stage DEA are proposed to provide decision makers with more choices. Existing studies have focused on disassembly sequence optimization while ignoring the impact of resource constraints on disassembly efficiency. For the first time, this paper establishes a multiobjective optimization for a two-stage disassembly model with resource constraints. The model considers multi-objective and resource constraints to determine optimal disassembly sequences. Compared with the existing research, this paper has the following contributions.

- 1) To reflect prioritization in a disassembly system, this work considers multiple resource constraints and a two-stage disassembly line balancing problem to extend the disassembly line evaluation model.
- 2) The improved algorithm incorporates ecological evolution strategies, mixed variation and Pareto solutions to better solve multi-objective disassembly line optimization problems.
- 3) Different from the traditional two-stage DEA model, this study fully considers the dynamic allocation information of input and output factors in each stage. The combination of efficiency at each stage does not require subjective setting.

The structure of this paper is organized as follows. Section II is the problem definition where the formulation and notations are described, and a two-stage disassembly model is presented. The proposed algorithm introduced in Section III. Computational analysis and discussion are in section IV.

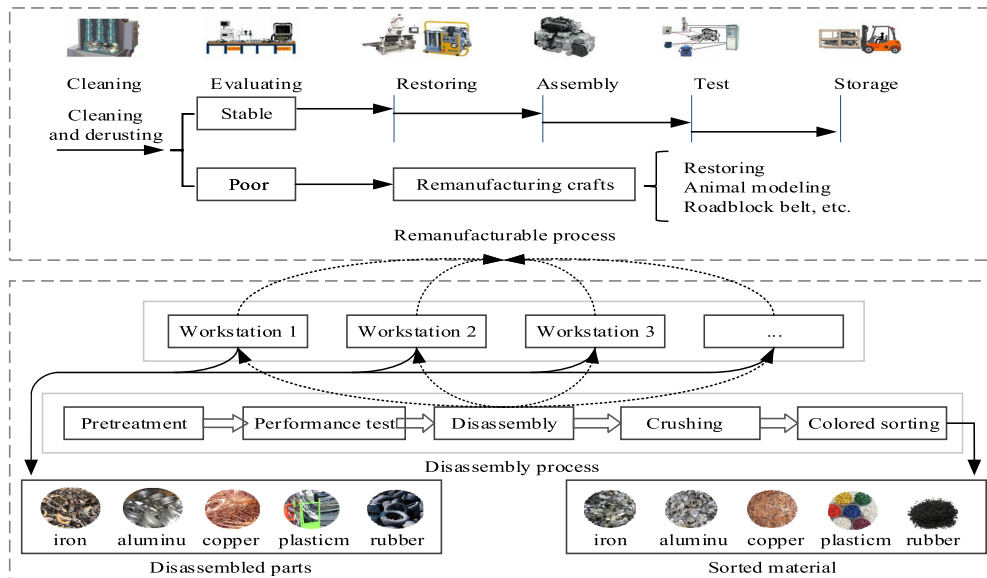


FIGURE 1. The operation flow chart of two-stage disassembly.

Finally, the main content is summarized, and future research is discussed.

II. ESTABLISHING A TWO-STAGE DISASSEMBLY MODEL

A. PROBLEM STATEMENT

This paper aims to solve the multi-objective two-stage disassembly line balancing problem with time, economic, energy consumption and environmental considerations. Obviously, there exist multiple factors that affect the disassembly process. However, energy consumption and environmental factors can be regarded as the two most difficult issues in disassembly workshops. To solve the above problem, this study establishes a multiobjective two-stage disassembly model with resource constraints.

Disassembly as a new production activity provides raw materials for the smooth implementation of manufacturing and remanufacturing production plans. Through the above literature analysis, there is little mention of research on disassembly remanufacturing workshops. The existing literature mainly studies disassembly issues from economic and environmental perspectives. The lack of an effective disassembly scheduling system leads to blindness and arbitrariness in a disassembly remanufacturing system. This paper proposed to establish a hybrid multi-objective optimization for a two-stage disassembly problem. The first stage is disassembly, and the second stage is processing and remanufacturing the disassembled parts. In this paper, the two-stage disassembly model includes disassembly process and remanufacturing process. The model diagram of the two-stage disassembly model is shown in Fig. 1. In the first stage, the collecting centre carries out pretreatment and performance test such

as degreasing, descaling, etc. The disassembly centre is dismantled according to the disassembly process standard. Most disassembled parts are sent to a crushing centre. The crushed piles are sorted by colour and sorted according to materials such as iron, aluminium, copper, plastic, rubber, etc. The sorted materials can be sold to raw material suppliers. In the second stage, The remanufactured parts enter the cleaning workshop for cleaning, descaling and evaluating. The stable parts are remanufactured by remanufacturing techniques such as laser coating, cold spraying, etc. Hard-to-repair parts can be made into works of art such as animals, flower baskets, and roadblocks, etc. The remanufactured parts are sold to the warehouse for storage. Finally, the residue is sent to a waste treatment centre for treatment according to environmental indicators and waste standards.

According to the above operation flow chart, the two-stage disassembly line balancing problem can be defined as follows: the disassembly workshop is equipped with m disassembly workstations and n workpieces to be disassembled. Under the conditions of mechanical constraints, process constraints and energy constraints, the model is built with minimum disassembly time, energy consumption, economy and environment. The model satisfies the following assumptions:

- 1) One workstation only disassembles one part at a time.
- 2) The disassembly time of each disassembled workpiece does not interfere with that of other workpieces.
- 3) Every workstation conducts zero error work.
- 4) There is a priority constraint relationship between disassembly tasks.
- 5) The main consideration is the energy consumption caused by the direction and movement time of the disassembly.

- 6) The disassembly process of the same component is fixed.
- 7) The device starts at the first task and is closed when the last task is completed.

B. MATHEMATICAL MODEL

In this study, resource constraints are considered when DLBP is solved. The objective of this study is to present a solution method for being able to solve two-stage disassembly considering resource constraints. Therefore, a mathematical model is presented. The proposed model is developed by combining the approaches of Ağpak which is resource constraint for simple assembly line balancing problem [39]. In this study, each of tasks is performed by only one resource r . For example, resource r_1 can perform {1, 5, 7, 3, 9} tasks and resource r_2 can perform {2, 6, 8, 4} tasks for 9 task disassembly planning problem. The objective of the model is to minimize number of resources that is assigned to workstations. These resources expressed in illustration may be robots, workers or specific machines in two-stage disassembly process which contains disassembly, crushing, remanufacturing, waste treatment, etc. The parameters and decision variables are defined as follows:

INDICES

- i component index set ($i = 1, 2, \dots, I$).
- j process index set ($j = 1, 2, \dots, J$).
- m machine index set ($m = 1, 2, \dots, M$).
- r resource index set ($r = 1, 2, \dots, R$).

PARAMETER

- p_{ij} unit time of the j th process of component i .
- c_{ij} unit economic of the j th process of component i .
- e_{ij} unit energy consumption of the j th process of component i .
- u_{ijm} unit environmental hazard indexes of the j th process of component i .
- ε_ϕ denoting capacity limits for the energy consumption.
- ε_γ denoting capacity limits for the environment.
- S_{jr} the set of tasks that can be fulfilled in the j th process of component i with resource r .

T cycle time.

d_{ij} the task time of normal node.

DECISION VARIABLE

y_{ijm} , ω_{ijm} , x_{ijm} and u_{ijm} indicate the binary restrictions, respectively; H_{jr} is the binary restriction with resource r , where $H_{jr} = 1$ if resource r is considered in the j th process of component i ; otherwise $H_{jr} = 0$; if workstation m opened, $F_m = 1$, otherwise, 0; if task d_{ij} is assigned to workstation m , $X_m = 1$, otherwise, $X_m = 0$; if the j th process of component i is performed, $z_{ij} = 1$, otherwise, $z_{ij} = 0$.

The proposed hybrid multiobjective optimization for the two-stage disassembly problem can be formulated by objective functions and constraints. The multiobjective optimization mathematical model built in this paper is as follows:

$$f_1 = \sum_{i=1}^I \sum_{j=1}^J \sum_{m=1}^M p_{ij} y_{ijm} \tag{1}$$

$$f_2 = \sum_{i=1}^I \sum_{j=1}^J \sum_{m=1}^M c_{ij} \times \omega_{ijm} \tag{2}$$

$$f_3 = \sum_{i=1}^I \sum_{j=1}^J \sum_{m=1}^M e_{ij} \times x_{ijm} \tag{3}$$

$$f_4 = \sum_{i=1}^I \sum_{j=1}^J \sum_{m=1}^M h_{ij} \times u_{ijm} \tag{4}$$

$$s.t. p_{ij} \geq 0, \quad c_{ij} \geq 0, \quad e_{ij} \geq 0, \quad h_{ij} \geq 0$$

$$1 \leq i \leq I, \quad 1 \leq j \leq J, \quad 1 \leq m \leq M$$

$$y_{ijm}, \omega_{ijm}, x_{ijm}, u_{ijm}, H_{ijr} \in \{0, 1\}$$

$$\forall i \in I, \quad j \in J, \quad m \in M, \quad r \in R$$

$$\sum_{m=1}^M e_{ij} \times x_{ijm} \geq \varepsilon_\phi \quad \forall i = 1, 2, \dots, I; j = 1, 2, \dots, J$$

$$\sum_{m=1}^M h_{ij} \times u_{ijm} \geq \varepsilon_\gamma \quad \forall i = 1, 2, \dots, I; j = 1, 2, \dots, J$$

$$\sum_{i=1}^I \sum_{j=1}^J \sum_{m=1}^M (y_{ijm} + \omega_{ijm} + x_{ijm} + u_{ijm}) \leq \|H_{ijr}\| S_{ijr}$$

$$\forall r = 1, 2, \dots, R$$

$$\sum_{i=1}^I \sum_{j=1}^J X_m d_{ij} \leq TF_m \quad \forall m = 1, 2, \dots, M$$

$$\sum_{m=1}^M X_m = Z_{ij} \quad \forall i = 1, 2, \dots, I; m = 1, 2, \dots, M$$

where formulas (1)-(4) illustrate the minimum time, economy, energy consumption and environment of disassembly.

C. TWO-STAGE DEA

Data envelopment analysis (DEA) is a mathematical programming method used to evaluate the relative efficiency of DMUs with multiple inputs and outputs, first proposed by Charnes [40], [41]. DEA can deal with complex systems with multiple inputs and multiple outputs and has been rapidly developed in theory and application [42]. The traditional DEA model assumes that the internal structure of the system is a black box. The efficiency of complex systems cannot be accurately determined, so a two-stage DEA approach has emerged [43], [44]. The existing two-stage DEA is primarily used to measure the efficiency and efficiency decomposition of the entire system. When the initial investment and final output plan of the system is determined, the first stage produces fewer intermediate products to make the second stage more efficient.

A two-stage DEA disassembly model that considers resource constraints has the following description. It is

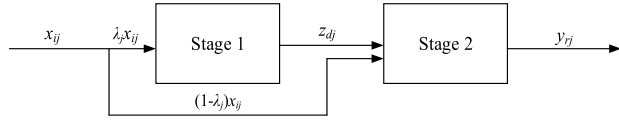


FIGURE 2. Resource constrained two-stage DEA disassembly model structure.

assumed that there are s decision units, DMUs, and each DMU $_j$ ($j = 1, 2, \dots, s$) has m initial inputs x_{ij} ($i = 1, 2, \dots, m$), q intermediate outputs Z_{dj} ($d = 1, 2, \dots, q$), and n final outputs y_{rj} ($r = 1, 2, \dots, n$). Different from the sequential two-stage production system, x_{ij} is not only consumed in the first stage but is consumed in two stages. λ_j represents the initial input of the j th DMU, $\lambda_j x_{ij}$ represents the input of the j th DMU in the first stage, and $(1-\lambda_j)x_{ij}$ represents the partial input of the second stage. The disassembly system structure of the model is shown in Fig. 2.

Different from the two-stage DEA model proposed by Chen, this paper uses the arithmetic mean and geometric mean to maximize the efficiency value of each stage and coordinate the overall efficiency of each stage. The model is as follows:

$$\theta_k = \omega_1 \frac{\sum_d \eta_d z_{dj} + u^1}{\sum_i v_i (\lambda_j x_{ij})} + \omega_2 \frac{\sum_r u_r y_{rj} + u^2}{\sum_d \eta_d z_{dj} + \sum_i v_i ((1-\lambda_j) x_{ij})} \quad (5)$$

where ω_1 and ω_2 represent the weights of the first and second phase processes, respectively, and $\omega_1 + \omega_2 = 1$; u^1 and u^2 are free; η_d , u_r , and v_i are unknown non-negative weights. These weights are not the optimal weight of a certain stage but the optimal overall solution. The global optimal solution is obtained by the following model.

$$\begin{aligned} \max \quad & \omega_1 \frac{\sum_d \eta_d z_{dj} + u^1}{\sum_i v_i (\lambda_j x_{ij})} \\ & + \omega_2 \frac{\sum_r u_r y_{rj} + u^2}{\sum_d \eta_d z_{dj} + \sum_i v_i ((1-\lambda_j) x_{ij})} \\ \text{s.t.} \quad & \frac{\eta_d z_{dj}}{v_i (\lambda_j x_{ij})} \leq 1, \quad j = 1, 2, \dots, s \\ & \frac{u_r y_{rj}}{v_i ((1-\lambda_j) x_{ij}) + \eta_d z_{dj}} \leq 1, \quad j = 1, 2, \dots, s \\ & \eta_d, u_r, v_i > 0; u^1, u^2 \text{ free.} \end{aligned} \quad (6)$$

Appendix provides detailed information on how to turn the two-stage model into a nonlinear programming model by the Charnes-Cooper transformation. The calculation of the weights ω_1 and ω_2 and the two-stage efficiency calculation are shown in Appendix.

III. ALGORITHM DESIGN

Intelligent algorithms are often used to solve multi-objective optimization problems. NSGA-II (nondominant sorting genetic algorithm-II) has excellent performance and proved to be a suitable choice for DLBP [45]–[47]. The traditional NSGA-II achieves better search performance with fast non-dominant dominance, congestion distance and elite retention strategies. Fast non-dominated sorting can reduce complexity and speed up operations [48]. Congestion can increase the diversity of the population. Elite retention strategies can improve the accuracy of the Pareto solution. However, the disadvantage of NSGA-II is that the global wide-area search and local search depth are poor. Based on NSGA-II, this paper introduces an ecological strategy and mixed variation to improve the local search algorithm and proposes an ecological strategy non-dominant sorting genetic algorithm (eNSGA-II). The advantages of eNSGA-II can reduce the impact of environmental factors on disassembly line balancing, speed up convergence and avoid local optimization.

A. CODING AND INITIALIZATION

Traditional binary coding solves the disassembly problem in a more complicated way, and the operation speed is slower, especially in the search space. This paper uses a random number of 0~1 for encoding. Each chromosome randomly generates a random number between 0 and 1. The elements in the set S correspond to the random numbers of the chromosomes. Through the traversing of the disassembly sequence, insignificant tasks are placed in the set S and compared. Parameters that need to be set include the population number pop , the maximum evolution period gen , and the control parameter.

B. CALCULATE THE DEGREE OF CONGESTION

The density around a given individual in a population is defined as the degree of congestion. To better combine the mixed flow disassembly model with the eNSGA-II, the spatial Euclidean distance is used to calculate the degree of congestion [49]. The calculation formula is shown in formula (7), as shown at the bottom of this page. where f_1, f_2, f_3 and f_4 are the objective functions.

C. ECOLOGICAL EVOLUTION STRATEGY

The ecological strategy is an evolutionary strategy formed by natural creatures according to environmental changes. There are uncertain environmental changes in a dismantling and remanufacturing workshop, so the introduction of ecological evolution strategies can reduce the impact of environmental factors on disassembly line balancing. The environmental

$$d_i = \sqrt{(f_1^{i+1} - f_1^{i-1})^2 + (f_2^{i+1} - f_2^{i-1})^2 + (f_3^{i+1} - f_3^{i-1})^2 + (f_4^{i+1} - f_4^{i-1})^2} \quad (7)$$

TABLE 1. Indicator pareto non-inferior solution of disassembly scheme.

No.	f_1	f_2	f_3	f_4	No.	f_1	f_2	f_3	f_4
1	398.25	832.46	56900	32	9	402.35	842.46	41500	65
2	425.25	852.35	42200	57	10	493.62	863.36	44200	43
3	439.53	923.15	45600	40	11	483.25	924.16	53400	33
4	492.14	942.14	43200	49	12	512.56	794.36	42700	53
5	502.42	867.24	48100	36	13	505.46	912.47	47000	38
6	534.63	835.25	55700	32	14	483.53	862.38	43600	46
7	473.26	902.45	41300	68	15	493.36	897.35	41800	61
8	482.34	869.25	51300	34	16	465.36	882.14	49500	35

change monitoring operator is calculated with formula (8).

$$s(t, k) = \frac{\sum_i^{m_0} \|f(x_i, t) - f(x_i, k)\|}{m_0 \max_{x_i \in M} \{\|f(x_i, t) - f(x_i, k)\|\}} \quad (8)$$

where $\|f(x_i, t) - f(x_i, k)\|$ represents the Euclidean distance of environmental location $f(x_i, t)$ and $f(x_i, k)$; if $s(t, k) \geq 0.5$, there is a change between environments, that is, environments t and k are non-similar environments, m_0 represents the primal environment, and M represents the environmental set.

D. MIXED VARIATION

Mixed variation is the combination of Gaussian mutation and the Cauchy mutation variant factor. Cauchy mutation can speed up convergence, while Gaussian mutation can avoid local optimization. The variation factor is selected based on the relevance of each variation and weights of the optimization goal. The Gaussian mutation of function y_k is expressed as follows:

$$y'_k = y_k + s_g \cdot \delta \quad (9)$$

$$s_g = random(+, -) \sqrt{2 \ln(\omega_g \sqrt{2\pi})} \quad (10)$$

where s_g represents the length of the variation; ω_g is a non-negative random number; and δ represents a normal distribution with a mean of 0 and variance of 1.

The Cauchy density of function $f_{cau}(y)$ is calculated by formulas (11)-(13).

$$f_{cau}(y) = \frac{1}{\pi(1+y^2)} \quad (11)$$

$$s_c = random(+, -) 1/\sqrt{\omega_c \pi} \quad (12)$$

$$s_c = random(+, -) 1/\sqrt{\omega_c \pi} \quad (13)$$

where ε_k represents the random Cauchy variable; s_c represents the asynchronous Cauchy variable; and ω_c is a random number in $(0, f_{cau}(0))$.

E. MIXED PARETO SOLUTION DOMINATES

Pareto dominance is used to optimally order objective functions. When no solution is better than x , a set of all Pareto optimal solutions is the Pareto optimal set. The image of the Pareto optimal set in the target space is called the Pareto front. It is possible to determine the relative sizes of two interval

numbers, as defined below. The probability $P(f_z(x_1, u) \leq f_z(x_2, u)) \geq \varrho$, where $\varrho \in [0.5, 1]$, meaning the probability is less than or equal to $f_z(x_1, u)$ in an interval ϱ . If all $f_i(x_1, u)$ are less than or equal to $f_i(x_2, u)$ in the interval sense of 0.5, and there is an $f_i(x_1, u)$ less than or equal to $f_i(x_2, u)$ in an interval of ϱ , then weigh x_1 with Pareto to dominate x_2 , recorded as $x_1 > p x_2$, namely, $\forall i \in (1, 2, \dots, z), P(f_z(x_1, u) \leq f_z(x_2, u)) \geq 0.5, i \in (1, 2, \dots, z), P(f_z(x_1, u) \leq f_z(x_2, u)) > \varrho, \varrho \in [0.5, 1]$. If x_1 does not dominate x_2 and x_2 does not dominate x_1 , then x_1 and x_2 are said to be non-exclusive, recorded as $x_1 || p x_2$.

IV. ALGORITHM EXPERIMENTAL RESULTS AND ANALYSIS

A. DESCRIPTIVE STATISTICS

To evaluate the eNSGA-II performance, a series of benchmark instances need to be generated. A series of benchmark instances for the disassembly problem is available from the literature [50], [51]. To illustrate the performance of the proposed algorithm in this study, the data of the dismantling enterprise are selected to run in MATLAB 2016. The system running settings were Windows 10 with an Intel Core i5, 2.8 GHz CPU, and 8 GB RAM. According to NSGA-II parameter setting in [45], [50]–[52]. We select best parameters for two stage disassembly as follows: the maximum number of iterations 200; number of sizepop 100; crossover probability 0.7; mutation probability 0.5; crossover index 2; mutation index 15. All the experiments are run independently 30 times. The success rate may get reduced if the number of trial runs is increased.

B. DESCRIPTIVE STATISTICS

This study selects time, economy, energy consumption and environment as the performance evaluation targets. The two-stage DEA in this study is multivariate input and single output. Since the actual disassembly is affected by many factors, the main factor is selected as the variable. The selection of 9 variables is based on an assessment of 100 people associated with disassembly, including engineers, experts, technicians, dismantling employees and academics. The data used in this study come from the comprehensive assessment of the nine dismantling enterprises in China in 2019.

eNSGA-II is used to optimize the Pareto solution of the disassembly sequence. The two-stage DEA model is used

TABLE 2. Input-output variables used in two-stage DEA models.

Type	Stage 1 variables	Units	Stage 2 variables	Units
Input	Equipment running time (ERT)	minute	Electricity consumption (EC)	Chinese yuan
	Disassembly idle time (DIT)	minute	Oil consumption (OC)	Chinese yuan
	Employee working hours (EWH)	minute	Chemical consumption (CC)	Chinese yuan
	Employee salary (ES)	Chinese yuan	Waste production (WP)	Kilogram
	Recycling product cost (RPC)	Chinese yuan		
Output	Product disassembly rate (PDR)		Comprehensive disassembly efficiency	

TABLE 3. The initial data of two-stage DEA model input and output variables.

DMU	Resource-constrained two-stage DEA model input and output variables										
	ERT	DIT	EWH	ES	RPC	PDR (z)	EC	OC	CC	WP	CDE(y)
1	142	23	193	70	1484	0.87	10.4	21.5	8.0	23	0.79
2	109	19	237	63	1174	0.92	12.7	16.6	7.4	18	0.95
3	117	24	192	68	1250	0.94	9.3	17.3	6.9	19	1.33
4	128	26	225	72	1363	0.85	8.6	20.6	8.2	22	0.84
5	136	33	237	76	1179	0.91	11.4	16.8	7.4	26	1.06
6	133	15	208	81	1165	0.89	10.5	19.9	7.6	17	0.84
7	128	17	189	83	1143	0.95	9.5	15.4	8.1	28	0.76
8	114	22	240	85	1208	0.79	8.4	17.2	6.5	15	0.79
9	132	20	228	73	1213	0.82	7.2	19.4	9.2	17	1.24
10	135	19	213	74	1258	0.93	8.6	20.1	6.4	14	0.68
11	152	17	208	69	1319	0.95	9.2	18.5	7.8	20	0.47
12	148	22	214	82	1326	0.91	10.1	17.3	8.3	16	0.82
13	142	25	217	85	1107	0.88	8.3	19.2	7.1	14	1.21
14	110	29	226	83	1223	0.85	9.1	19.6	9.4	19	0.84
15	115	31	231	76	1241	0.92	7.7	18.3	8.5	17	0.66
16	122	26	225	77	1328	0.94	9.2	20.2	8.8	21	0.98

for the first time to optimize the dismantling sequence of obsolete agricultural machinery. The Pareto solution of the multi-objective disassembly sequence obtained by eNSGA-II is shown in Table 1.

The Pareto solutions serve as DMUs for the two-stage DEA model. Table 2 shows the input and output variable descriptions of the two-stage DEA. The disassembly process is divided into two stages. Time, economy and energy consumption in the dismantling phase account for the majority. The impact on the environment is mainly in the remanufacturing stage, and the number of parts that can be remanufactured is also very small. Therefore, there are five inputs to stage one, which is characterized by disassembly time and economic generation. The second stage has four inputs and one output, which are characterized by the disassembly of energy consumption and the environment. The first stage inputs are the equipment running time, disassembly idle time, employee working hours, employee salary and recycling product cost. The second stage inputs are electricity consumption, oil consumption, waste production, and chemical consumption, and the output is the comprehensive disassembly efficiency. There is also an intermediate metric between these two phases, namely, the product disassembly rate. The data are provided in Table 3.

C. MIXED VARIATION COMPUTATIONAL COMPLEXITY ANALYSIS

The disassembly efficiency results from the resource constrained two-stage DEA model are reported in Table 4. The fifth column shows the overall disassembly efficiency of the obtained models. Columns 2 and 4 are the rankings of the overall disassembly efficiency. To illustrate the effectiveness of the two-stage DEA for resource constraints, the model is compared with Chen’s model. Chen’s model efficiency is in the first three columns. The DMU weights are reflected under columns 6 and 7. The last two columns of Table 4 report the efficiency scores in stage one and stage two, respectively. The remaining columns represent the efficiency score for each phase. w_1 and w_2 reflect the decision maker’s preference. Regarding Chen’s CCR efficiency, N_{14} has the lowest efficiency score of 0.6319, while N_4 has the highest score of 0.7869. Our model’s CCR efficiency, N_{10} , has the lowest efficiency score of 0.7216, and N_3 has the highest score of 0.9325. The weight coefficient w_1 ranges from 0.3472 to 0.5214, and w_2 ranges from 0.4786 to 0.6528.

The overall efficiency definition proposed in this paper is different from Chen’s model, and it is not possible to directly compare the overall efficiency scores of the two methods. Except for the 6 DMUs (4, 6, 8, 9, 10 and 16),

TABLE 4. Ranking of efficiency score.

DMU	Chen's CCR results		Our model results					
	Ranking	θ_k	Ranking	θ_k	w_1	w_2	θ_k^{1*}	θ_k^{2*}
N ₁	12	0.6543	11	0.7934	0.4251	0.5749	0.7832	0.8729
N ₂	8	0.7281	10	0.8251	0.5214	0.4786	0.8474	0.9214
N ₃	3	0.7624	1	0.9325	0.3977	0.6023	1.0000	0.8329
N ₄	1	0.7869	9	0.8272	0.4281	0.5719	0.8417	0.8242
N ₅	13	0.6332	15	0.7391	0.3562	0.6438	0.7482	0.8629
N ₆	15	0.5983	4	0.8427	0.4325	0.5675	0.7385	0.8791
N ₇	9	0.7114	7	0.8392	0.3982	0.6018	0.8324	0.8538
N ₈	5	0.7429	12	0.7919	0.3472	0.6528	1.0000	0.9132
N ₉	2	0.7652	8	0.8274	0.3329	0.6671	0.9163	0.8521
N ₁₀	10	0.6935	16	0.7216	0.4742	0.5258	0.8741	0.9537
N ₁₁	16	0.5831	14	0.7425	0.4261	0.5739	0.8353	0.7858
N ₁₂	7	0.7328	2	0.8942	0.4236	0.5764	1.0000	0.9371
N ₁₃	4	0.7441	3	0.8492	0.5135	0.4865	1.0000	0.9274
N ₁₄	14	0.6319	13	0.7472	0.3968	0.6032	0.7483	0.9528
N ₁₅	6	0.7362	5	0.8421	0.4869	0.5131	0.7428	0.8985
N ₁₆	11	0.6832	6	0.8417	0.3811	0.6189	0.8427	0.9284

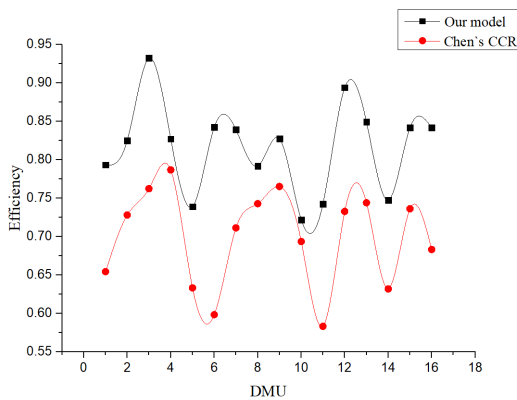


FIGURE 3. ResEfficiency comparison of two DEA models.

the efficiency scores of the two models are similar. The ranking difference of DMU₆ is approximately 11. The difference between DMU₄ and DMU₈ is close to 8. The ranking difference between DMU₉ and DMU₁₀ is equal to 6. The efficiency score of the first stage of DMUs (3, 8, 12 and 13) is the same, that is, 1. The reason for this may be that the disassembly quality of this batch of disassembled products is very poor. The Spearman rank correlation coefficient ranked in Table 4 is 0.964, which is significant at the level of 0.01. It is shown that the rankings based on two different models are approximately equal. The Pearson correlation coefficient of the two efficiency models is 98%. Therefore, the model is better than Chen's. DMU₆ is the best disassembly solution. As seen from Fig. 3, the efficiency of our model is significantly higher than the efficiency value of Chen's CCR, and the trends of both are roughly the same. Fig. 4 is an

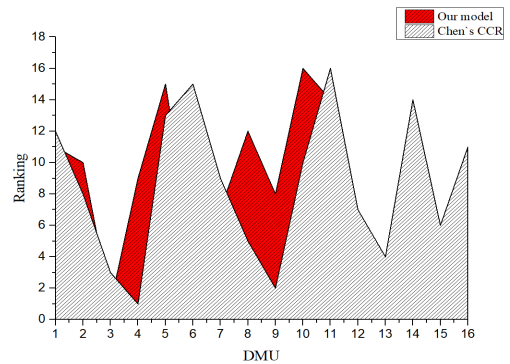


FIGURE 4. Area chart of the ranking comparison of two DEA models.

area chart of the efficiency ranking. The higher the ranking is, the more prominent the area. As seen from Fig. 6, the efficiency ranking of N₃ to N₁₀ in our model is higher than the efficiency ranking of Chen's CCR, but the ranking of other DMUs is lower.

D. BENCHMARK RESULTS AND DISCUSSIONS

The proposed eNSGA-II is compared with SPEA-II (Strength Pareto evolution algorithm-II) and NSGA-II. The framework of SPEA-II and NSGA-II is very similar to that of eNSGA-II. Second, SPEA-II and NSGA-II are benchmark algorithms for evaluating multiobjective optimization problems. The CPU time of all the algorithms is set to the same size, namely, 200 seconds in this study.

To verify the effectiveness of eNSGA-II, this paper introduces 12 typical benchmark functions for testing, including single-mode functions, multimodal functions, and

TABLE 5. Description of different mode benchmark functions.

Function	Dim	Range	f_{min}
$f_1(x) = \sum_{i=1}^n x_i^2$	20	[-50,50]	0
$f_2(x) = \sum_{i=1}^n (\sum_{j=1}^i x_j)^2$	20	[-50,50]	0
$f_3(x) = \sum_{i=1}^n [100(x_{i-1} - x_i)^2 + (x_i - 1)^2]$	20	[-50,50]	0
$f_4(x) = \sum_{i=1}^n ix_i^4 + random [0,1]$	20	[-100,100]	0
$f_5(x) = \sum_{i=1}^n [x_i^2 - 10 \cos(2\pi x_i) + 10]$	30	[-5,5]	0
$f_6(x) = \frac{1}{4000} \sum_{i=1}^n x_i^2 - \prod_{i=1}^n \cos(\frac{x_i}{\sqrt{i}}) + 1$	30	[-500,500]	0
$f_7(x) = \sum_{i=1}^n -x_i \sin(\sqrt{ x_i })$	30	[-500,500]	0
$f_8(x) = \sum_{i=1}^n [a_i - \frac{a_i^2(x_i - 0.5)}{1.5 + x_i - 0.5 }]^2$	5	[-5,5]	0
$f_9(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{5}x_1^6 + x_1x_2 - 4x_2^2$	4	[-5,5]	0
$f_{10}(x) = -\sum_{i=1}^n c_i \exp(-\sum_{j=1}^i a_j(x_j - p_j)^2)$	6	[1,3]	-1.7534
$f_{11}(x) = -\sum_{i=1}^n [(X - a_i)(X - a_i)^2 + c_i]^2$	5	[1,5]	-8.3235
$f_{12}(x) = -\sum_{i=1}^n [(X - a_i)(X - a_i)^2]^2$	5	[1,5]	-9.3235

TABLE 6. Three algorithms computational times and results.

Instance	NSGA-II			SPEA-II			eNSGA-II		
	t_1	t_2	T	t_1	t_2	T	t_1	t_2	T
Case 1	7.9	179.3	183.7	5.7	213.6	214.4	3.9	158.3	159.2
Case 2	5.6	196.7	201.2	6.2	164.8	165.9	5.3	163.6	165.5
Case 3	4.2	184.5	188.7	4.9	205.2	206.6	4.6	192.4	193.9
Case 4	6.7	212.7	215.1	4.6	214.5	216.1	5.8	185.2	186.7
Case 5	8.3	225.6	227.9	7.5	235.3	237.8	6.2	204.9	206.1
Case 6	4.8	166.4	170.8	6.3	172.4	175.2	5.3	148.5	149.4
Case 7	5.5	178.2	184.5	8.4	169.5	172.9	4.7	165.4	166.7
Case 8	6.1	192.5	202.8	5.3	225.9	226.3	5.1	202.7	203.8
Case 9	7.4	173.1	181.6	6.7	186.6	188.5	5.7	152.3	154.4
Case 10	5.2	164.6	169.4	5.5	196.2	197.7	4.1	144.8	148.3
Case 11	8.6	208.7	213.1	4.9	204.6	207.4	6.4	176.2	177.2
Case 12	6.5	214.6	214.8	7.1	225.7	227.2	5.7	186.5	188.5
Average	6.4	191.4	196.1	6.09	201.2	205.5	5.2	173.4	175.0

fixed-dimensional multimodal functions. Table 5 lists the corresponding formulas and descriptions of these functions. Dim is the dimension of the task, f_{min} is the optimal solution, and $Range$ is the function boundary of the search space. Table 6 shows the average calculation time of the three algorithms for the 12 instances in the first stage (t_1), the second stage (t_2), and the total calculation (T). The total calculation times of the three algorithms in Table 6 are 196.1, 201.2, 175.0, which are SPEA-II, NEGA-II, and eNSGA-II in order of size. A dotted line graph of the total calculation time for different examples is shown in Fig. 5. The smaller the value is, the better the performance of the algorithm. From the above analysis, we can see that the two-stage calculation time and total calculation time of NSGA-II are significantly better than those of the other two algorithms.

To verify the effectiveness of the improved algorithm, this paper introduces the Friedman test. The Friedman test is a nonparametric test for pipeline judgement that can be used to evaluate the performance of different algorithms. In addition, the lower the ranking is, the better the performance of the algorithm. As shown in Table 7, eNSGA-II has the highest

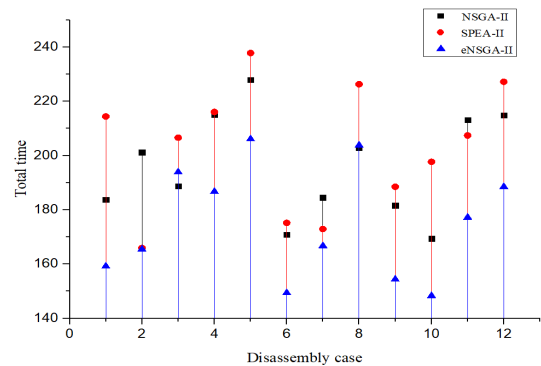


FIGURE 5. Comparison of algorithm total computational times.

TABLE 7. Average ranking values of the Friedman test.

Algorithm	eNSGA-II	SPEA-II	NSGA-II
Ranking	2.7832	2.9786	3.1632

average ranking, followed by SPEA-II and NSGA-II. This shows that eNSGA-II has a clear advantage over other comparison algorithms.

TABLE 8. Comparison results of algorithms for several instances.

Instance	100			200			500			
	eNSGA-II	SPEA-II	NSGA-II	eNSGA-II	SPEA-II	NSGA-II	eNSGA-II	SPEA-II	NSGA-II	
P1	avg	3.42E-09	5.34E-08	6.21E-09	2.96E-09	1.82E-07	5.35E-09	2.76E-09	1.93E-07	3.52E-09
	stdv	5.35E-09	7.55E-09	3.72E-09	2.85E-09	1.57E-08	4.35E-08	3.44E-09	1.74E-08	3.62E-08
P2	avg	3.94E-06	8.26E-04	5.26E-04	5.25E-06	6.83E-05	9.35E-04	4.24E-06	6.48E-06	7.25E-04
	stdv	4.66E-06	6.24E-05	3.77E-05	4.72E-06	6.35E-05	5.74E-05	4.83E-06	6.29E-05	4.75E-05
P3	avg	6.12E-04	9.22E-03	5.99E-03	7.42E-04	2.35E-03	6.51E-03	7.25E-04	1.96E-03	6.42E-03
	stdv	3.18E-04	6.36E-04	4.28E-05	3.25E-04	5.35E-04	5.51E-05	4.74E-04	5.78E-04	5.73E-05
P4	avg	2.54E-06	4.37E-05	7.14E-06	2.62E-06	4.88E-05	2.27E-05	2.74E-06	6.36E-05	2.57E-05
	stdv	5.82E-05	1.24E-07	4.43E-07	5.11E-05	1.39E-07	4.74E-07	5.47E-05	1.57E-07	4.23E-06
P5	avg	2.55E-04	9.74E-03	2.34E-03	2.49E-04	4.67E-03	2.46E-03	2.85E-04	4.51E-03	2.38E-03
	stdv	6.37E-03	9.42E-03	3.45E-04	5.72E-03	8.42E-03	3.88E-04	5.39E-03	8.22E-03	3.96E-04
P6	avg	8.63E-05	1.83E-04	7.41E-04	6.23E-05	9.61E-03	6.25E-04	6.17E-05	8.42E-04	7.41E-04
	stdv	1.77E-04	5.46E-04	3.25E-03	3.52E-04	4.26E-04	2.52E-03	3.76E-04	4.14E-04	3.62E-04
P7	avg	3.44E-04	6.22E-04	1.98E-03	3.92E-05	4.58E-04	2.52E-04	4.39E-05	3.75E-05	2.34E-04
	stdv	8.53E-05	1.75E-04	7.14E-05	7.36E-05	6.16E-04	6.72E-05	7.57E-05	6.29E-04	6.52E-05
P8	avg	2.85E-07	8.24E-06	1.43E-06	3.66E-07	6.89E-06	2.39E-06	3.74E-07	6.27E-06	3.62E-06
	stdv	3.42E-06	5.32E-06	6.45E-07	5.73E-06	5.83E-06	4.52E-07	5.82E-06	5.39E-06	4.35E-07
P9	avg	7.31E-05	1.66E-04	3.85E-05	4.27E-06	1.79E-04	3.13E-06	4.61E-06	1.63E-04	3.53E-06
	stdv	2.35E-04	2.74E-05	2.16E-04	3.76E-04	2.43E-06	5.74E-05	3.88E-04	2.54E-06	5.25E-05

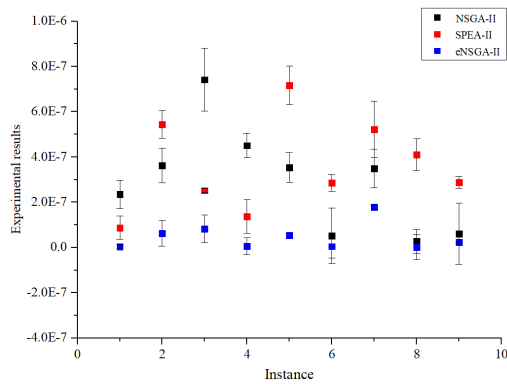


FIGURE 6. Error graph for small-scale calculation instance.

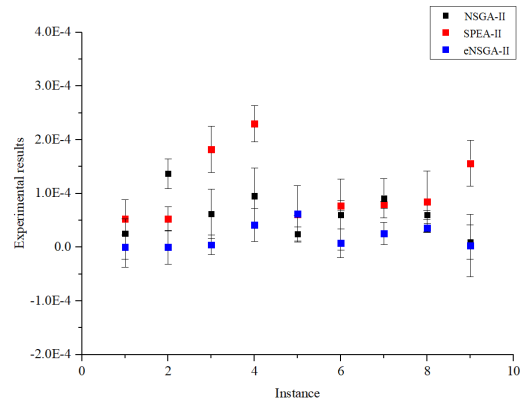
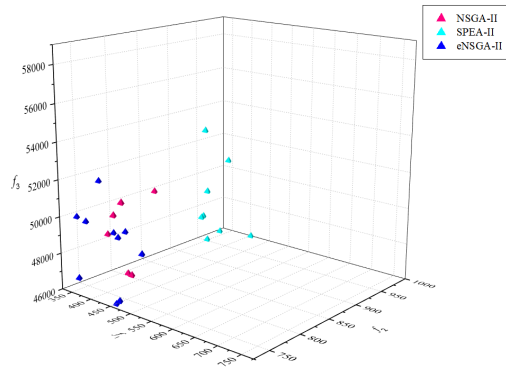


FIGURE 7. Error graph for large-scale calculation instance.

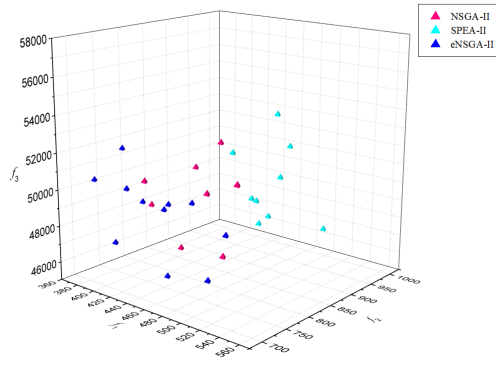
E. PERFORMANCE COMPARISON OF ALGORITHMS

This paper conducted scalability tests to verify the algorithm’s ability to handle different size optimization tasks and tested the algorithm on 100, 200, and 500. All experiments were performed under the same conditions, and the average (avg) and standard deviation (stdv) of all test results in each group of parameter settings are reported in Table 8. The bold type in Table 8 is the best result, indicating that the average error is small. In all test functions, eNSGA-II’s average index and standard deviation are better than those of SPEA-II and NSGA-II for low, medium and high sizes. The statistical results in Table 8 show that the average solution of eNSGA-II is better than those of SPEA-II and NSGA-II. The results and errors of the medium-scale and small-scale tests are very close. Therefore, to make the comparison effect more obvious, this article chooses small-scale and large-scale for testing. Figs. 6 and 7 are the test error graphs for small-scale and large-scale examples, respectively. Fig. 6 shows that the

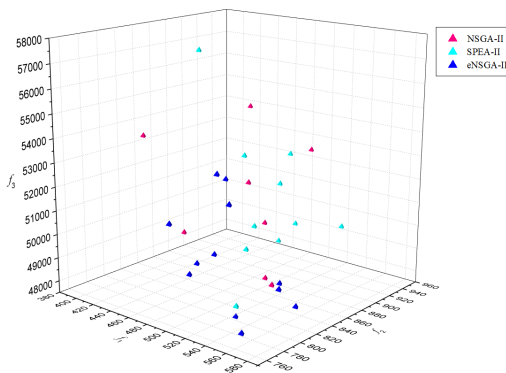
errors and experimental results of eNSGA-II are better than those of NSGA-II and SPEA-II. It can be seen from Fig. 7 that the experimental results of NSGA-II are very close to those of eNSGA-II, and individual examples even exceed the improved algorithm. However, the test results of eNSGA-II are generally better than those of NSGA-II and SPEA-II. The above results show that eNSGA-II has better stability and efficiency. To better show the spatial distribution of the Pareto solution, Fig. 8 is a three-dimensional spatial layout diagram of the Pareto solution obtained by NSGA-II, SPEA-II and eNSGA-II. Fig. 8(a)-(c) represent the spatial distribution of Pareto solutions at small, medium, and large scales, respectively. Considering that there are many uncertain factors and variables in environmental goals, we only choose three objective functions: time, economy and energy consumption. It can be seen from Fig. 8 that eNSGA-II performs better than NSGA-II and SPEA-II in both the number of Pareto solutions and the spatial distribution of the solutions. From the above



(a) Pareto solution distribution at small-scale



(b) Pareto solution distribution at medium-scale



(c) Pareto solution distribution at medium-scale

FIGURE 8. The three-dimensional scatter plots for Pareto solution by eNSGA-II, NSGA-II and SPEA-II.

analysis, it is known that by using the ecological evolution strategy and hybrid mutation operation, the convergence of eNSGA-II is accelerated.

V. CONCLUSIONS

This paper establishes a multiobjective optimization for a two-stage disassembly model with resource constraints. The goal is to maximize the overall disassembly efficiency of time, economy, energy consumption and environment. The improved NSGA-II can obtain a solution set of 16 Pareto solutions. Based on Chen’s two-stage DEA, this

paper proposes a new two-stage DEA efficiency measurement model that can effectively rank disassembly sequences sequentially. Decision makers can choose different weights according to their own preferences and make better disassembly decisions. The DMU’s overall efficiency score is defined as the weighted sum of the efficiency of each stage, not a simple product of these efficiencies. This model is used to evaluate two-stage disassembly efficiency, which may be more attractive because it gives a weight for each stage. This study does not use a simple arithmetic mean to solve the efficiency values of each stage but instead weights the two efficiencies in different ways. To evaluate the proposed algorithm, SPEA-II and NSGA-II types were compared. Experimental results show that eNSGA-II is superior to SPEA-II and NSGA-II in different evaluations.

Although the effectiveness of the proposed model and algorithm has been verified, there are still some interesting directions for further research [53]. For example, in the actual production process, it is difficult to know the exact information of the job in advance and uncertain events occur, e.g., machine failure and new orders arrival. Therefore, it is necessary to establish new models for multi-objective situations in uncertain environments [54]. Design some mathematical optimization algorithms, e.g., branch and bound method, dynamic programming method. The collaborative processing of complex information can be considered in disassembly line balancing problems, e.g., disassembly workshop scheduling incorporating digital twin technology [55]. In addition, better algorithms need to be designed to handle fuzzy and complex optimization problems.

APPENDIX

It is obvious that this model cannot be transformed into a linear model solution using the classic Charnes-Cooper transformation. Based on the idea of Chen, this model is transformed into a linear model by rationally selecting values of ω_1 and ω_2 .

For the overall efficiency of each DMU, ω_1 and ω_2 are weighted, which shows the relative importance of the first phase and the second phase, respectively. The ratio of input to total input at each stage is the weight of this stage. as in equations (A1) and (A2).

$$\omega_1 = \frac{\sum_i v_i (\lambda_j x_{ij})}{\sum_i v_i (\lambda_j x_{ij}) + \sum_d \eta_d z_{dj} + \sum_i v_i ((1 - \lambda_j) x_{ij})} \quad (A1)$$

$$\omega_2 = \frac{\sum_d \eta_d z_{dj} + \sum_i v_i ((1 - \lambda_j) x_{ij})}{\sum_i v_i (\lambda_j x_{ij}) + \sum_d \eta_d z_{dj} + \sum_i v_i ((1 - \lambda_j) x_{ij})} \quad (A2)$$

where $\sum_i v_i (\lambda_j x_{ij}) + \sum_d \eta_d z_{dj} + \sum_i v_i ((1 - \lambda_j) x_{ij})$ represents the total amount of inputs in the two-stage process and $\sum_i v_i (\lambda_j x_{ij})$ and $\sum_d \eta_d z_{dj} + \sum_i v_i ((1 - \lambda_j) x_{ij})$ represent the amount of input in the first and second stages, respectively.

These weights are the model’s optimized variable functions rather than decision variables and are related to decision variables in formula (11). The sensitivity of ω_1 and ω_2 can

be set by the decision maker's preference. The expressions of ω_1 and ω_2 are substituted into the objective function of formula (A3).

$$\theta_k^* = \max \frac{\sum_d \eta_d z_{do} + u^1 + \sum_r u_r y_{ro} + u^2}{\sum_i v_i (\lambda_j x_{ij}) + \sum_d \eta_d z_{dj} + \sum_i v_i ((1 - \lambda_j) x_{ij})}$$

$$s.t. \frac{\sum_d \eta_d z_{dj} + u^1}{\sum_i v_i (\lambda_j x_{ij})} \leq 1, \quad j = 1, 2, \dots, s$$

$$\frac{\sum_r u_r y_{rj}}{\sum_d \eta_d z_{dj} + \sum_i v_i ((1 - \lambda_j) x_{ij})} \leq 1, \quad j = 1, 2, \dots, s$$

$$v_1, \eta_1, u_1 \geq \varepsilon; u^1, u^2 \text{ free.} \quad (A3)$$

Based on the idea of Kao, this paper first calculates the optimal efficiency of the first stage under the premise of ensuring the overall efficiency. The above nonlinear programming is converted to linear programming by the Charnes Cooper transformation.

The efficiency of the second stage is calculated based on the linear relationship between the first stage and second stage. The first stage optimal efficiency is obtained under the premise of ensuring that the overall efficiency of formula (A1) is optimal.

$$\theta_k^1 = \max \frac{\sum_d \eta_d z_{do} + u^1}{\sum_i v_i (\lambda_j x_{ij})}$$

$$s.t. \frac{\sum_d \eta_d z_{dj} + u^1}{\sum_i v_i (\lambda_j x_{ij})} \leq 1, \quad j = 1, 2, \dots, s$$

$$\frac{\sum_r u_r z_{ro} + u^2}{\sum_d \eta_d z_{dj} + \sum_i v_i ((1 - \lambda_j) x_{ij})} \leq 1, \quad j = 1, 2, \dots, s$$

$$\frac{\sum_d \eta_d z_{dj} + u^1 + \sum_r u_r z_{ro} + u^2}{\sum_i v_i (\lambda_j x_{ij}) + \sum_d \eta_d z_{dj} + \sum_i v_i ((1 - \lambda_j) x_{ij})} = \theta_k^*$$

$$v_i, u_r, \eta_d \geq \varepsilon; u^1, u^2 \text{ free} \quad (A4)$$

In formula (A4), the constraints ensure that the efficiency scores of all the DMUs in both stages are no greater than one. The overall efficiency score can be equivalent to formula (A5).

$$\theta_k^{1*} = \max \sum_d \alpha_d z_{do} + u^{1*}$$

$$s.t. \sum_d \alpha_d z_{dj} + u^{1*} \leq \sum_i \varphi_i^1 x_{ij}, \quad j = 1, 2, \dots, s$$

$$\sum_r \beta_r z_{rj} + u^{2*} \leq \sum_d \alpha_d y_{dj} + \sum_i \varphi_i^2 x_{rj}, \quad j = 1, 2, \dots, s$$

$$\sum_d \alpha_d z_{dj} + \sum_r \beta_r y_{rj} + u^{1*} + u^{2*} > 0$$

$$\sum_i \varphi_i^1 x_{io} = 1$$

$$\varphi_i^1, \varphi_i^2, \alpha_d, \beta_r \geq \varepsilon, u^{1*}, u^{2*} \text{ free} \quad (A5)$$

where $\varphi_i^1, \varphi_i^2, \alpha_d, \beta_r, u^{1*}, u^{2*}$ represent optimal values of $\varphi_i^1, \varphi_i^2, \alpha_d, \beta_r, u^1, u^2$.

Similarly, the second-stage linear model efficiency score is solved as model (A6). The total efficiency score is maintained, and the efficiency of the first or second stage is not

greater than θ_0^* .

$$\theta_k^{2*} = \max \sum_d \alpha_d z_{do} + u^{2*}$$

$$s.t. \sum_d \alpha_d z_{dj} + u^{1*} \leq \sum_i \varphi_i^1 x_{ij}, \quad j = 1, 2, \dots, s$$

$$\sum_r \beta_r z_{rj} + u^{2*} \leq \sum_d \alpha_d z_{dj} + \sum_i \varphi_i^2 x_{rj}, \quad j = 1, 2, \dots, s$$

$$\sum_d \alpha_d z_{do} + \sum_i \varphi_i^2 x_{io} = 1$$

$$\varphi_i^1, \varphi_i^2, \alpha_d, \beta_r \geq \varepsilon, u^{1*}, u^{2*} \text{ free.} \quad (A6)$$

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