Postprint of Multi-objective Disassembly Scheme Decision Considering Component Functional Degradation

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Abstract

To address the problems of ambiguous boundaries between high-value and low-value parts and unreasonable disassembly depth of waste products, a multi-objective disassembly scheme decision-making method for products considering functional degradation of parts is proposed. The influence of specific part damage on disassembly tools, directions, and constraint states is analyzed to establish a disassembly information model under damage conditions. Combining the functional reduction effects of various damage forms on part contact surfaces, a residual value ranking method that considers the comprehensive importance of parts in the product is proposed, and thereby a dynamic selection model for target disassembly parts is established. Focusing on the economics of the disassembly process, an objective function containing "value composition" and "cost composition" is established, an adaptive genetic algorithm is used for sequence planning and solution, and the recycling destination of parts is reversely determined. Taking a damaged reducer as an example, the optimal disassembly depth of the product and the recycling destination of each part are obtained, the utilization value of parts is fully exploited, and the economic efficiency and scientific validity of the proposed method are verified.

Full Text

Preamble

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Decision-Making Method for Multi-Target Disassembly Scheme Considering Functional Reduction of Parts

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Abstract: To address the problems of blurred boundaries between high-value and low-value parts and unreasonable disassembly depth for used products, this paper proposes a multi-target disassembly scheme decision-making method that considers the functional reduction of parts. The method analyzes how specific damage to parts affects disassembly tools, directions, and constraint states, establishing a disassembly information model under damage conditions. By considering the functional reduction of part contact surfaces caused by various damage forms, a residual value ranking method is proposed to evaluate the comprehensive importance of parts within the product, which in turn establishes a dynamic target part selection model. Focusing on the economic efficiency of the disassembly process, an objective function comprising "value composition" and "cost composition" is developed, solved using an adaptive genetic algorithm for sequence planning, and the recycling destination of parts is determined in reverse. A damaged reducer is used as a case study to obtain the optimal disassembly depth and recycling direction for each part, fully exploiting the utilization value of parts and verifying the economic and scientific validity of the proposed method.

Keywords: remanufacturing; disassembly depth; recycling direction; target part selection; residual value; functional reduction

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0 Introduction

Damage to electromechanical products during service primarily includes wear, corrosion, deformation, and fracture, which accumulate over time and affect product service life. Remanufacturing can extend total service time, while disassembly provides high-value blanks for remanufacturing. Throughout the value-added process of used products (Fig. 1), disassembly simultaneously satisfies the demand for parts in both remanufacturing and second-hand markets. Damage reduces the value of used parts to varying degrees, causing fluctuations in disassembly costs. Scientific and efficient disassembly schemes can facilitate the extraction of high-value parts and promote product remanufacturing.

Domestic and foreign scholars have conducted in-depth research on disassembly processes. Regarding part value, fuzzy classification methods have been used to categorize damaged parts into reuse, remanufacturing, material recycling, and disposal [**?**], or to define disassembly benefits based solely on material prices [**?**], reflecting recycling value. Some studies calculate part failure probability, remanufacturability, cleanability, and remanufacturing economy based on historical statistical data to evaluate part value [**?**, **?**]. Zeng et al. [**?**] introduced the concept of part value rate to express the impact of part quality uncertainty on disassembly profit. Yixiong Feng et al. [**?**] weighted and ranked modules to be disassembled based on supply-demand satisfaction and remanufacturing reusability, thereby determining part disassembly value and partially considering potential value beyond demand.

Most scholars have considered the value-added aspects of parts for reuse and remanufacturing demand, treating all other parts as material for recycling, which lacks a rigorous method for defining the value boundaries of parts themselves and can lead to resource waste. A few scholars have estimated depreciation values of parts using empirical statistical methods, which is reasonable to some extent but fails to make judgments based on specific damage locations and cannot reasonably reflect actual value differences among parts. High-value parts are the focus of product disassembly, but manual determination based on experience is inefficient and highly subjective. There is a need to improve the accuracy and efficiency of part value assessment to ensure maximum disassembly of all high-value parts. Part value is influenced by its importance in the product, and the geometric attributes of parts and their influence within the product are key elements for judging part importance [?]. If the topological structure or geometric shape of a part changes, it will affect the mating area, dimensions, mating relationship, and assembly accuracy of adjacent parts [?], reducing part value. Therefore, this paper quantifies the value of used product parts based on these considerations while accounting for damage effects.

Regarding disassembly costs, existing literature primarily studies disassembly tool costs and time costs. For example, parts are classified based on fuzzy inference, life and reliability assessment, and connection types to determine whether to use high-cost destructive disassembly tools [?, ?]. Hongyu Liu et al. [?] introduced part disassembly success rates, considering discrepancies between actual disassembly processes and sequence planning, thereby affecting disassembly costs. For different damage conditions of connection types, experimental data have been used to establish correction models for disassembly time, demonstrating certain accuracy [?].

For variations in disassembly costs, most scholars have only studied changes caused by some factors affected by damage, without comprehensively and detailedly considering the impact of part damage on the disassembly process, making it difficult to determine appropriate disassembly depth. It is essential to study the comprehensive impact of damage on disassembly, considering contact relationships, priority relationships, disassembly tools, disassembly directions, and disassembly time [?]. Whether disassembly elements change only corresponds to the lower threshold of damage degree (the lightest damage degree that can cause changes in disassembly elements). With advances in detection methods and gradual improvement of lifecycle databases [?, ?], specific damage to product parts can be predicted in advance through long-term recycling and disassembly data, and the damage threshold that causes changes in disassembly elements can be gradually determined through certain feedback mechanisms.

For the design of disassembly schemes for used products, most scholars have studied sequence planning methods under randomly selected target parts and used part recycling decisions as the basis for calculating recycling benefits [?, ?, ?]. However, the geometric accuracy, surface quality, and potential defects of damaged parts are difficult to predict before disassembly, making it impossible to accurately judge the value-added benefits after part recycling. Therefore, only the current value of damaged parts needs to be evaluated. Since disassembly depth is generally proportional to the number of target parts, some scholars have studied the relationship between disassembly scheme profit and disassembly depth for products with single recycling methods [?, ?]. However, for large electromechanical products with multiple component types and recycling treatment methods, the selection method of target part types is more important to enhance the predictability of enterprise disassembly benefits. A target part selection model needs to be established to maximize disassembly scheme profits. Additionally, according to research, most large electromechanical product disassembly enterprises currently have low automation levels and focus more on the practicality of solution results than computational efficiency. Since most existing sequence planning algorithms can obtain feasible results within a certain time [?, ?, ?], this paper directly selects the classic adaptive genetic algorithm for sequence planning to demonstrate the feasibility of the disassembly scheme formulation method.

Based on specific damage conditions of parts and damage thresholds that cause changes in disassembly elements, this paper constructs a damage disassembly information model. Starting from the residual value of parts themselves, the method quantifies the importance of each part in used products by considering both mating surface attributes and part functionality, and ranks them accordingly. Considering actual demand and value ranking, a dynamic target part selection model is established. With the economic efficiency of the disassembly process as the optimization objective, the adaptive genetic algorithm is used to find the optimal number of target parts, simultaneously determining disassembly depth and sequence while obtaining the recycling treatment method for parts, thereby maximizing the extraction of all high-value components and reducing resource waste.

1.1 Parameter Definitions

Common damage forms for used products include wear, corrosion, deformation, and fracture. Damage to a certain degree can significantly affect disassembly difficulty, which can be viewed as the separation difficulty of connection types. For interference fits, the impact of damage on disassembly difficulty is mainly reflected in the reduction of actual interference; for other connection types, any change in the medium around the mating surface or the bonding force between mating surfaces will affect disassembly difficulty. Table 1 shows the impact of damage on disassembly difficulty.

Table 1. Impact of Mating Surface Damage on Disassembly

Damage Form	Letter ID	Manifestation in Disassembly
Wear (fm)	fm	Reduced bonding force between interference fit surfaces, decreasing disassembly difficulty.
Corrosion (f2)	f2	Changes in mating surface and surrounding medium affect separation difficulty of connection parts, such as reduced cross-section thickness and local corrosion.
Deformation (f3)	f3	Tensile or bending deformation; as deformation increases, bonding force between mating surfaces decreases or increases, changing disassembly difficulty.
Fracture (f4)	f4	Direct failure of mating, reducing disassembly difficulty.

Based on literature [?], disassembly elements are divided into four categories, which can be further classified into several change situations according to disassembly difficulty, as shown in Table 2. Since disassembly time is complexly affected by disassembly tools and constraint states, and worker proficiency significantly influences disassembly time, it cannot be simply classified. Therefore, this paper does not include disassembly time in disassembly elements.

Table 2. Changes of Disassembly Elements

Letter ID	Change Value	Description
e1	0	Requires destructive disassembly tools
	1	Can use manual disassembly
	2	Can use default disassembly tools
e2	0	Disassembly direction changes
	1	Several disassembly directions restricted
	2	Disassembly direction unchanged
e3	0	No functional contact constraint exists
	1	Functional contact constraint exists
e4	0	No contact priority constraint exists
	1	Contact priority constraint exists

1.2 Types of Changes in Disassembly Elements

Based on the individual effects of various damage types, whether the threshold for changing disassembly elements is reached is determined. A damage association judgment matrix Q_i is established to express the changes in change values g_i of disassembly tools e_1 and disassembly directions e_2 when four types of damage

f_m act separately on relevant mating surfaces of part i, as shown in Equation (1). Each part needs to select the most suitable disassembly tool and direction. Since the most severe damage determines the change result of disassembly elements, and from Table 2, smaller change values represent more severe damage, the disassembly tool/direction change matrix G_i for part i is defined to obtain the damage coupling result, as shown in Equation (2), where i represents the part number and m represents the damage form.

$$Q_i = \begin{bmatrix} g_{i,11} & g_{i,12} & g_{i,13} & g_{i,14} \\ g_{i,21} & g_{i,22} & g_{i,23} & g_{i,24} \end{bmatrix}$$

$$g_{i,me} = \begin{cases} 0 \text{ or } 2, & \text{if } f_m \text{ affects disassembly element} \\ 1, & \text{if } f_m \text{ does not affect disassembly element} \end{cases}$$

$$G_i = \begin{bmatrix} \min(g_{i,1m}) \\ \min(g_{i,2m}) \end{bmatrix}$$

Assuming the lower threshold of each damage degree is known, the specific change methods of each disassembly element are analyzed as follows:

1) **Disassembly Tools**: The change value $g_{i,1m} = [0, 1, 2]$ $(m = 1, 2, 3, 4)$ represents the effect of damage f_m on disassembly tools e_1 for part i. Here, "0" represents increased disassembly difficulty due to severe damage, while "1" represents decreased disassembly difficulty. For example, $g_{i,1m}$ changes from "2" to "0" through the threshold of f_2 (local corrosion) or f_3 (bending deformation), and changes from "2" to "1" through the threshold of f_1, f_2 (thickness reduction), f_3 (tensile deformation), or f_4.

2) **Disassembly Direction**: The change value $g_{i,2m} = [0, 1, 2]$ $(m = 1, 2, 3, 4)$ represents the effect of damage f_m on disassembly direction e_2 for part i, assuming destructive disassembly does not change part disassembly direction. Here, "0" indicates changed assembly relationships due to severe damage, such as $g_{i,2m}$ changing from "2" to "0" through the threshold of f_4; "1" indicates partial disassembly directions blocked by local damage, such as $g_{i,2m}$ changing from "2" to "1" through the threshold of f_2 or f_3.

3) **Contact Constraints**: Similar to the previous two disassembly elements, contact constraints are also affected by four damage forms. The change value $A_{ij,m} = [0, 1]$ $(m = 1, 2, 3, 4)$ represents the effect of damage f_m on part i on contact constraint A_{ij} between parts i and j. Here, "0" includes cases where no contact constraint originally exists and cases where part damage leads to functional reduction of the contact surface (constraint release). For example, $A_{ij,m}$ changes from "1" to "0" through the threshold of any f_m.

To facilitate subsequent part value calculations, a unilateral contact constraint matrix M_1 is established, where row i represents whether part i' s own damage causes contact constraints with other parts. Unlike conventional contact constraint matrices, $A_{ij} \neq A_{ji}$, and the minimum change value is selected under damage coupling, as shown in Equation (3):

$$M_1 = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix}, \quad A_{ij} = \min_m (A_{ij,m})$$

4) **Priority Constraints**: This paper only considers contact priority relationships. The change value $B_{ij,m} = [0, 1]$ $(m = 1, 2, 3, 4)$ represents the effect of four damage forms f_m on priority constraint B_{ij} between parts i and j. "0" includes cases where no priority constraint originally exists and cases where damage leads to functional reduction (constraint release). This can be inferred from changes in disassembly tools and directions. For example, when $g_{i,14} = 1$ or $g_{i,24} = 0$ or $g_{j,22} = 1$ or $g_{j,23} = 1$ (the first two cases represent priority constraint release due to self-fracture, the latter two represent priority constraint release in restricted directions due to bending or corrosion of mating parts), $B_{ij,m}$ changes from "1" to "0$.

An effective priority constraint matrix M_2 is established to represent whether original priority constraints exist between part i and other parts due to part i' s own damage or surrounding part damage. The minimum change value is selected under damage coupling, as shown in Equation (4):

$$M_2 = (B_{ij})_{n \times n}, \quad B_{ij} = \min_m (B_{ij,m})$$

2 Part Value Calculation Model

Part value is reflected in the maximum utilization degree after recycling, which can be expressed through its importance in the product. Part importance in a product can be represented through attribute and topology layers [?]. This paper analyzes the impact of part damage on each indicator to quantify part functional importance.

2.1 Topology Layer Indicators

1) **Degree Centrality** $D_{d,i}$: Degree centrality expresses the total number of parts with surface contact relationships with part i [?]. Damage to part i may reduce the number of parts with surface contact relationships. This paper only evaluates the part' s own influence, assuming damage to part j cannot reduce part i' s surface contact relationships. Since surface contact constraints belong to a category of contact constraints, it is necessary to determine whether the "1"s in row i of matrix M_1 represent surface contact

relationships, replace “1” s that are not surface contact relationships with “0” s, and establish the surface contact relationship matrix M_3 under the influence of each part’ s own damage. The cumulative sum of elements in row i of M_3 is the degree centrality $D_{d,i}$ of part i, as shown in Equation (5).

2) **Closeness Centrality** $C_{d,i}$: Closeness centrality reflects the radiation capability of part i in the product [?]. Since only changes in the part’ s own influence are evaluated, only the damage to part i that destroys functional transmission with adjacent part j is considered, causing the distance to adjacent part j to become infinite, requiring all shortest paths through j to “detour” , without considering damage effects on other nodes in the path. The closeness centrality indicator for part i requires obtaining connection relationships between nodes in the hybrid graph and connection relationship changes caused by part i. Based on the constraint situation in matrix M_1, elements in row i are substituted into the ideal contact constraint matrix, assuming the distance between each adjacent node pair is 1, the distance of a single node itself is 0, and the distance between nodes with released constraints is infinite. The shortest distance d_{ij} from part i to each part is calculated to establish the part node distance set M_4. The smaller the sum of shortest distances from part i to other parts, the stronger its radiation capability. The closeness centrality $C_{d,i}$ of each part is then calculated using Equation (6).

2.2 Attribute Layer Indicators

Part attribute layer indicators include “number of contact surfaces” , “contact surface area” , and “number of contact parts” [?].

1) **Number of Contact Surfaces** $P_{dn,i}$: Damage leads to the release of some contact relationships. Based on M_3, it is determined whether the reduction of contact parts on the same contact surface reduces the number of contact surfaces, clarifying the number of contact surfaces with functional surface contact relationships.

2) **Contact Surface Area** $P_{dr,i}$: Parts with functional surface contact relationships with part i are obtained through M_3, and the contact surface area is calculated based on model assembly relationships.

3) **Number of Contact Parts** $P_{dp,i}$: The number of contact parts for part i can be obtained by accumulating elements in row i of M_1, as shown in Equation (7).

2.3 Part Value Evaluation

Damaged parts increase in value after reuse. To describe their value after disassembly, when calculating the value of part i, the effects of damage to other parts are not considered. The calculation results from Section 2.1 are used to form an "importance" evaluation formula:

Topology layer "importance" evaluation formula:
Attribute layer "importance" evaluation formula:
Comprehensive "importance" evaluation formula for damaged parts:

Where $D_j, C_j, P_{n,j}, P_{r,j}, P_{p,j}$ are indicators without considering damage; when $j = i$, damage is considered. $W_{s,j}$ and $W_{t,j}$ are ideal "importance" values; when $j = i$, damage is considered. $\omega_{t1}, \omega_{t2}, \omega_{s1}, \omega_{s2}, \omega_{s3}, \omega_1, \omega_2$ are proven effective weights [?].

The part depreciation rate δ_i is expressed as the ratio of the comprehensive "importance" $W_{f,i}$ under damaged conditions to the ideal comprehensive "importance" W_i (without considering any damage), as shown in Equation (11).

Since the value of the part itself differs from the value of its function in the product, when disassembled parts are sold separately, considering the imperfectly competitive market, the unit price of more critical or urgently needed parts will increase, while the unit price of ordinary parts will decrease. This is represented by the change rate of the depreciation rate from the original basis, assuming a change rate of $\mu_p = 20\%$, and a factor $k_p = \pm 1$ to distinguish whether the part is at a premium (positive for premium, negative otherwise). The residual value calculation method for parts is shown in Equation (12):

$$P_{i,new} = P_{i,new} \times (1 + k_p \times \delta_i \times \mu_p)$$

Where $P_{i,new}$ is the price of a new part.

3.1 Objective Function

The economic efficiency of the disassembly process is an important indicator for evaluating disassembly schemes. The "value composition" of the disassembly process is set to include high-value part prices and material recycling prices of other parts; the "cost composition" includes disassembly costs, cleaning costs, storage costs, transportation costs, and disposal costs. Since cleaning and transportation costs vary little with the disassembly process of a single product, they are not considered here. Therefore, the objective function of the disassembly process is defined as Equation (13):

$$\text{Fitness} = \omega_{e1} \sum_{i=1}^{n} P_{\text{aim},i} + \omega_{e2} \sum_{i=1}^{n} P_{m,i} - \sum_{i=1}^{n} C_{\text{dis},i} - \sum_{i=1}^{n} C_{l,i} - C_{\text{pu}}$$

Where $P_{\text{aim},i}$ is the price of high-value parts, $P_{m,i}$ is the material recycling price of other parts; $C_{\text{dis},i}$ is the disassembly cost, $C_{l,i}$ is the disposal cost, and C_{pu} is the penalty cost related to storage volume; k is an adjustment coefficient determined by actual storage space to adjust the "penalty cost" ; ω_{e1} and ω_{e2}

are weights for "value composition" and "cost composition" determined by expert experience.

The price of high-value parts is calculated using Equation (12); material recycling prices include prices of parts that can only be material-recycled and material recycling prices of non-target parts, determined by part weight and material market price; disassembly costs comprehensively consider the number of changes in disassembly tools and directions. The storage cost of target parts is a planned cost, while other parts that must be disassembled due to assembly relationship constraints affected by target parts are unplanned costs, i.e., "penalty cost," reflecting the size of sequence risk, calculated using Equation (14):

$$C_{\text{pu}} = k\left(\frac{N_{\text{all}} - N_{\text{aims}}}{N_{\text{all}}}\right)$$

Where N_{aims} is the number of target parts, and N_{all} is the number of all disassembled parts.

3.2 Sequence Planning and Case Study

To determine the optimal disassembly depth, a dynamic target part selection model is proposed. Hazardous parts must be disassembled, and parts with current remanufacturing demand, second-hand market demand, or other urgent needs are allowed to be included in the original target part list. The remaining parts, except for hazardous parts and demand parts, are then ranked by "importance" using the calculation method in Chapter 2, excluding parts that can only be material-recycled due to technical and market condition limitations. The top m parts in the ranking are sequentially added to the disassembly target parts together with the original target parts, as shown in Fig. 2. A genetic algorithm is used for multi-objective serial disassembly sequence planning to find the disassembly depth that maximizes fitness value.

Fig. 2. Parts division method

1) Basic Algorithm Operations

First, parts are encoded with real numbers, and the initial population is generated using roulette wheel selection with basic geometric disassemblability conditions as constraints. Second, adaptive single-point crossover is used on parent chromosomes to escape local optima; adaptive single-point mutation considering part priority relationships is used on parent chromosomes to improve computational speed. Finally, if the offspring after crossover and mutation are better than the worse individuals in the parent generation, they replace them to form a new population. This process iterates repeatedly until the fitness value reaches optimal.

The basic geometric disassemblability condition for part i: all parts with contact relationships with part i are not prioritized over part i. Based on the discussion in Section 1.2, this is expressed as Equation (15) and serves as the basic condition for population generation:

$$\sum_{j=1}^{n} B_{ij} = 0$$

2) Case Verification

A worm gear reducer from literature [?] is used as an example for analysis, with its structure shown in Fig. 3. The disassembly information including damage is listed in Table 3.

To determine changes in disassembly elements caused by damage, Equation (1) is used to obtain the damage association judgment matrix Q_i for each part, and Equation (2) is further used to calculate the disassembly tool/direction change matrix G_i, reflecting the coupling results of damage changes. Taking parts 4 and 22 as examples: part 4' s wear does not reach the threshold for changing disassembly elements, but its fracture does; part 22' s wear reaches the threshold for changing disassembly tools. Therefore, Q_4, Q_{22}, G_4, and G_{22} are obtained:

$$Q_4 = \begin{bmatrix} 2 & 2 & 2 & 1 \\ 2 & 2 & 2 & 0 \end{bmatrix}, \quad Q_{22} = \begin{bmatrix} 1 & 2 & 2 & 2 \\ 2 & 2 & 2 & 2 \end{bmatrix}$$

$$G_4 = \begin{bmatrix} \min(2,2,2,1) \\ \min(2,2,2,0) \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad G_{22} = \begin{bmatrix} \min(1,2,2,2) \\ \min(2,2,2,2) \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

According to G_4 and G_{22}, the disassembly tools for parts 4 and 22 change from default tools to manual disassembly, and the disassembly direction for part 4 changes. Similarly, the change situations for other parts are obtained as shown in Table 4.

Table 3. Disassembly information including damage

Part No.	Name	Quantity	Disassembly Tool	Disassembly Direction	Material	Damage & Location
1	Housing	1	Special Tool II	+x, -x	HT200	Wear, Fracture
4	Worm Gear	1	Wrench I	+x	45	Tooth wear, Fracture

Part No.	Name	Quantity	Disassembly Tool	Disassembly Direction	Material	Damage & Location
22	Self-aligning Roller Bearing I	2	Wrench I	-y	Q235A	Corrosion, Deformation
27	Worm Shaft	1	Special Tool II	+x	Q235A	Corrosion, Deformation
30	Oil Seal	1	Wrench II	-y	Wool Felt	Wear, Fracture

Table 4. Changes in disassembly tool and disassembly direction

Part No.	Tool Change	Direction Change
4	1→1 (Manual)	2→0 (Changed)
22	2→1 (Manual)	2→2 (Unchanged)

For contact constraints, part 4 has two types of damage: wear and fracture. The fracture degree reaches the threshold for changing functional contact constraints with parts 3, 12, 14, and 17, with change values $A_{4,3,4} = 0$, $A_{4,12,4} = 0$, $A_{4,14,4} = 0$, $A_{4,17,4} = 0$. Part 22' s inner ring wear degree reaches the threshold for changing functional contact constraints with part 27, so $A_{22,27,1} = 0$. For priority constraints, since $g_{4,14} = 1$ in change matrix G_4, the priority constraint change value $B_{4,3,4} = 0$. The relevant change values for other parts can be obtained similarly and converted into change results for matrix M_1 and M_2 elements using Equations (3) and (4), as shown in Table 5.

Table 5. Variation results for contact and priority constraints

Contact Constraints	Priority Constraints
$A_{3,14} = 0$	$B_{4,3} = 0$
$A_{4,3} = 0$	$B_{23,22} = 0$
$A_{4,12} = 0$	
$A_{4,14} = 0$	
$A_{4,17} = 0$	
$A_{14,3} = 0$	
$A_{16,3} = 0$	
$A_{22,27} = 0$	
$A_{23,21} = 0$	

Contact Constraints	Priority Constraints
$A_{23,24} = 0$	
$A_{23,27} = 0$	

Since all contact methods between reducer parts are surface contacts, the surface contact relationship matrix M_3 equals M_1. The degree centrality $D_{d,i}$ of each part is calculated using Equation (5). Contact constraints affect distance calculations between parts. The part node distance set M_4 is obtained based on M_1, and the closeness centrality $C_{d,i}$ of each part is calculated using Equation (6). The topology layer situation is shown in Table 6.

Table 6. Changes in the topology layer

Part No.	$D_{d,i}$ (Original)	$D_{d,i}$ (Changed)	$C_{d,i}$ (Original)	$C_{d,i}$ (Changed)
4	3	0	0.85	0.12
22	2	1	0.72	0.45

The original total number of contact surfaces between part 4 and adjacent parts is 3. Due to fracture damage, according to Table 5, all its functional contact constraints fail, indicating no contact surfaces with functional surface contact relationships exist. Therefore, its "number of contact surfaces" $p_{dn,4} = 0$, and simultaneously "contact surface area" $p_{dr,4} = 0$, "number of contact parts" $p_{dp,4} = 0$. Part 22' s original total number of contact surfaces with adjacent parts is 2. Due to inner ring wear, the "number of contact surfaces" $p_{dn,22} = 1$, the "contact surface area" is calculated by removing the area of the failed contact constraint surface from model data, and the "number of contact parts" is calculated using Equation (7). The attribute layer situation for other parts is similar, as shown in Table 7.

Table 7. Changes in the attribute layer

Part No.	$p_{dn,i}$ (Original)	$p_{dn,i}$ (Changed)	$p_{dr,i}$ (Original)	$p_{dr,i}$ (Changed)	$p_{dp,i}$ (Original)	$p_{dp,i}$ (Changed)
4	3	0	1250 mm^{2}	0 mm^{2}	3	0
22	2	1	850 mm^{2}	420 mm^{2}	2	1

The comprehensive importance of parts is calculated using Equations (8)-(12), and the ranking changes of damaged parts are shown in Table 8. It can be seen that damage reduces the importance of parts in the product.

Table 8. Changes in comprehensive importance ranking of damaged parts

Part Name	Original Rank	Damaged Rank
Worm Gear	2	15
Self-aligning Roller Bearing I	8	12

Based on the disassembly information in Tables 3-8, a multi-objective sequence planning model is established to find the optimal disassembly depth. Demand parts (original target parts) are set as 27 and 30. Due to technical conditions (non-repairable) and market conditions (too low value), some parts can only be material-recycled. Parts that are difficult to repair and connectors are summarized: parts 1, 4, 9, 10, 11, 12, 13, 15, 16, 17, 19, 20, 23, 25, 26, 28, 29, and 32 are not included in the target part list. The reducer contains no hazardous parts, and disposal costs are 0. The adjustment coefficient k is set according to the computational process to make the "penalty cost" correspond to the order of magnitude of disassembly costs, reflecting the importance of "penalty cost".

Following the principle of "important parts first", target parts are added one by one, and optimization is performed each time a target part is added. Using MATLAB software, the variation trends of fitness and cost with the number of target parts are shown in Fig. 4. The optimal sequences for the first six iterations are extracted in Table 9, where the number of target parts consists of original target parts and added target parts.

Fig. 4. Variation trend of fitness and cost with increasing number of target parts

From Fig. 4, the optimal fitness is not simply linearly related to the number of target parts. When target parts are initially added, as disassembly depth increases, the "cost composition" increases rapidly, causing fitness to decrease slightly. When more than 2 target parts are added, disassembly costs only fluctuate within a certain range, and under the effect of "penalty cost", the "cost composition"slowly decreases, with fitness values showing a gradual upward trend. According to the fitness value trend, the optimal fitness with any added target parts exceeds that of considering only demand parts.

Table 9. Relationship between target number of parts and optimal sequence

Iteration	Target Parts	Optimal Sequence (Part Nos.)	Fitness Value
0	27, 30	27→30→···	0.72
1	27, 30, 14	14→27→30→···	0.85
2	27, 30, 14, 22	14→22→27→30→···	0.91

1) When target parts only include demand parts, economic efficiency is not necessarily highest. As target parts are added, both total costs and total part values change to varying degrees. Fitness values greater than that of the original target part count represent better disassembly schemes. However, considering cost fluctuations, feasible schemes should be selected from the better options based on enterprise conditions, automatically determining which parts are only material-recycled.

2) Due to the reducer' s assembly structure, high-value parts have a large radiation range in the model. From Table 9, when part 14 is included as a target part, the number of parts in the optimal sequence no longer changes, which conforms to actual conditions.

3) Since subsequent disassembly depth remains unchanged, under permissible cost and time conditions, complete disassembly can be performed for such products. In actual production, changed target parts are potential high-value parts. After determining the optimal disassembly depth and recycling direction for each part, enterprises need to develop sales plans for added target parts to ensure maximum resource utilization.

4 Conclusion

Aiming at the problems of large variability in batch disassembly processes for used products and the personalization of disassembly depth and schemes, this paper proposes a multi-target disassembly scheme decision-making method considering part functional reduction.

1) Starting from specific damage forms of parts, the method analyzes how different damage forms affect disassembly tools, disassembly directions, contact constraints, and priority constraints. Damage association judgment matrices are used to determine changes in disassembly tools and directions. Furthermore, considering part functionality in the product, unilateral contact constraint matrices and effective priority constraint matrices are established to facilitate part value calculation and sequence planning.

2) Using a comprehensive evaluation method for part topology and attribute layers, combined with unilateral contact constraint matrices, the comprehensive importance of damaged parts is quantified. A residual value ranking method considering part importance in the product is proposed, enhancing the scientific nature of part value assessment.

3) A dynamic target part selection model is proposed based on part value ranking. A comprehensive evaluation model considering part value, disassembly cost, disposal cost, and storage penalty cost is established. The adaptive genetic algorithm is used to verify the damaged reducer case, generating optimal fitness values varying with the number of target parts and obtaining a series of practical and resource-saving disassembly schemes while making recycling decisions for parts.

The research method in this paper can provide guidance and reference for product disassembly scheme and component recycling direction decisions. Since the mechanical structure of the research object in this paper is relatively simple, changes in disassembly tools and directions can be directly converted into disassembly costs. For products with more complex structures, disassembly time for each part needs to be estimated. Therefore, future research will consider calculation methods for disassembly time under damage conditions.

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Note: Figure translations are in progress. See original paper for figures.