Association Rule Mining-Based Generalized Growth Mode Selection: Maximizing the Value of Retired Mechanical Parts

Yuyao Guo 1, Lei Wang 1,2,*, Zelin Zhang 2,*, Jianhua Cao 1 and Xuhui Xia 1,2

1 Key Laboratory of Metallurgical Equipment and Control Technology, Wuhan University of Science and Technology, Ministry of Education, Wuhan 430081, China; guoyuyao@wust.edu.cn (Y.G.); caojianhua39@wust.edu.cn (J.C.); xiaxuhui@wust.edu.cn (X.X.)
2 Hubei Key Laboratory of Mechanical Transmission and Manufacturing Engineering, Wuhan University of Science and Technology, Wuhan 430081, China
* Correspondence: candywang@wust.edu.cn (L.W.); zhangzelin@wust.edu.cn (Z.Z.)

Abstract: Due to the inability to restore the original performance, a significant portion of retired mechanical products is often replaced with new ones and discarded or recycled as low-value materials. This practice leads to energy waste and a decline in their residual value. The generalized growth remanufacturing model (GGRM) presents opportunities to enhance the residual value of retired products and parts. It achieves this by incorporating a broader range of growth modes compared to traditional restorative remanufacturing approaches. The selection of the growth mode is a crucial step to achieve GGRM. However, there is a limited number of growth mode selection methods that are specifically suitable for GGRM. The capacity and efficiency of the method are also significant factors to consider. Therefore, we propose a growth mode selection method based on association rule mining. This method consists of three main steps: Firstly, the ReliefF method is used to select the core failure characteristics of retired parts. Secondly, a genetic algorithm (GA) is employed to identify the association between core failure characteristics, repair technology, and maximum recoverability. Finally, based on the maximum recoverability, the appropriate growth mode is selected for each retired part. We conduct a case study on retired automobile universal transmission, and the results demonstrate the feasibility, efficiency, and accuracy of the proposed method.

Keywords: remanufacturing; generalized growth remanufacturing model (GGRM); residual value; association rule mining

1. Introduction

During the peak of scrapping of retired mechanical products, there is a tendency towards industrialized and large-scale remanufacturing. Unfortunately, a significant number of parts from these retired mechanical products are often replaced by new ones due to the lack of remanufacturing value, as the original performance cannot be fully restored. This results in the wastage of energy and residual value of these parts. However, if these abundant scrapped parts can be utilized as blanks and remanufactured in batches, effectively harnessing their energy and residual value, it can lead to substantial economic and environmental benefits.

The generalized growth remanufacturing model (GGRM) provides more growth modes for retired products and their parts. As a result, the residual value of retired products and their parts can be effectively reused, thereby enriching the connotation of remanufacturing [1]. As shown in Figure 1, comparing with the existing restorative remanufacturing approach, the GGRM offers a broader range of growth modes for retired parts. Their growth modes include reuse, restorative remanufacturing, upgrading remanufacturing (UR), downgrading remanufacturing (DR), and material recycling. Restorative remanufacturing focuses on restoring the original structure and performance as much as...
possible via a set of remanufacturing processes. Upgrading remanufacturing is to upgrade the original product through performance improvement or functional module embedding. Downgrading remanufacturing is to highly utilize the existing structure and value through redesign and modification processing. UR or DR parts could be used as parts of other products (NP) instead of the original product (RP). Obviously, choosing an appropriate growth mode for retired parts is crucial for effectively reusing their residual value. However, the current evaluation and selection methods for remanufacturing primarily focus on restorative remanufacturing, leaving a limited number of growth mode selection methods that aim to maximize the residual value of retired parts. Meanwhile, the capacity and efficiency of the method are important factors that limit the scale of parts remanufacturing.

![Figure 1. Comparison of growth mode between the generalized growth model and current remanufacturing model.](image)

Existing research primarily focuses on evaluating the remanufacturability (quality, economy and environment, etc.) of retired parts to determine the appropriate reuse modes, such as reuse, remanufacturing, or scrapping [2]. However, these studies do not consider the generalized growth modes of retired parts; therefore, the residual value of parts that cannot be fully recovered is wasted when they are scrapped [3]. The evaluation methods proposed by most studies struggle to directly assess the residual value of used mechanical products and parts at the performance level. Moreover, these evaluation methods may change as benefit entities changes, and they are susceptible to other influencing factors, such as cost. Therefore, it is necessary to find a growth mode selection method that aims at maximizing the residual value of retired parts. Indeed, the maximum performance threshold after remanufacturing of retired parts is determined by the combination of failure states and existing repair techniques. This threshold could be used as a reference for selecting the appropriate generalized growth mode of retired parts.

In addition, remanufacturing companies can derive greater benefit from mass remanufacturing compared to single-product remanufacturing [4]. As shown in Figure 2, compared to complex single product, the process of selecting growth mode for parts is relatively simpler. In mass remanufacturing of parts, the different service environments before retirement parts have various failure status and residual value; therefore, the selection of growth mode has large number of options and multiple flow directions, as shown in Figure 3a. Clearly, the capacity and speed of the existing single-product remanufacturing evaluation and selection process are inadequate, thereby constraining the scalability of remanufacturing. Moreover, in the case of multiple products, the process becomes even more difficult, as depicted in Figure 3b. Hence, it is essential to consider the efficiency of growth mode selection for a large volume of retired parts. Intelligent algorithms and big data may be viable solutions to address this challenge. To efficiently select the growth
mode that maximizes the residual value of each retired part, we propose an association rule mining-based approach for generalized growth selection.

**Figure 2.** Selection process of generalized growth mode for a single retired mechanical product.

**Figure 3.** Selection of generalized growth mode for large-scale retired mechanical parts.

The rest of this paper is structured as follows. Section 2 reviews the related studies in remanufacturing evaluation and selection, failure analysis, and association rule mining in the manufacturing industry. It also discusses the relationship between failure status and repair technology and the impact of this correlation on the transformation of the residual value in retired mechanical parts to prove the feasibility of this research. In Section 3, a hybrid approach is proposed. The core failure characteristics selected by ReliefF are used as the antecedent, and repair technologies and maximum recoverability are used as the consequent. Then, the association rules mined through GA are used to select the growth mode of each retired part. In Section 4, a case study is presented to demonstrate the selection process of the suitable generalized growth mode for each part of the automobile universal transmission. The results of the case study show the applicability and advantage of the proposed approach. Section 5 discusses the benefits and limitations of the proposed approach and concludes this article.
2. Literature Review

Remanufacturing is considered as a low-carbon and energy-efficient approach to obtain the residual value of product, achieving environmental, economic, and social benefits. Remanufacturing evaluation exists in the entire remanufacturing process. Many research studies have been conducted to study remanufacturing evaluation from multiple perspectives, such as government [5], industrial operation mode [6,7], enterprise [8,9], product [10], and process [11,12]. Remanufacturability assessment plays a crucial role in the overall process of remanufacturing evaluation. Various tools and methods have been developed to mitigate the complexity and uncertainty associated with remanufacturability assessment [13,14]. However, existing remanufacturability assessments are all dealing with traditional remanufacturing, which categorizes products into two outcomes: remanufacturable or non-remanufacturable. Meanwhile, there has been relatively less research conducted on technical feasibility assessment compared to economic and environmental assessments [15]. The decision factors, such as economic and environmental factors and the determination of their weights, are influenced by stakeholders, leading to unstable results [16]. Therefore, there is a need for a stable and technical remanufacturability assessment method specifically tailored to the generalized growth remanufacturing model of retired products.

Moreover, most research on remanufacturability assessment focuses on complete machine or specific product types. However, with the expansion of the remanufacturing industry, there is a significant profit potential in parts remanufacturing. This incentivizes the disassembly of retired products into their constituent parts, each with its own unique set of failure characteristics. The failure characteristics of a part could directly represent its own performance. Currently, most of studies on failure analysis for remanufacturing are relevant to decision making [17], remanufacturing design improvement [18], and reliability analysis [19]; only a few studies center on remanufacturability assessment. Wang et al. [20] integrated fatigue life into the existing remanufacturability evaluation system, which may directly reflect the remanufacturability of product itself. Some research evaluated the remanufacturability of parts by establishing the relationship between the failure characteristics and the remanufacturing process [21]. These studies have provided inspiration for our work. We discovered that the residual value threshold (maximum recoverability) of used parts is influenced by both their failure state and the existing remanufacturing and repair technologies associated with them. Therefore, the mining of the relationship between failure characteristics and repair technologies has become a crucial step in selecting the generalized growth mode that maximizes the residual value of retired parts. In this context, association rule mining, a type of big data mining, can be developed and utilized.

As a type of big data mining, association rule mining could be developed and applied in various aspects of intelligent manufacturing industry. It is mainly divided into quality control and reliability analysis [22], product design [23], production plan formulation [24], and process [25]. The method of mining association rules has been continuously improved and developed due to the multidimensionality and complexity of manufacturing problems. Heuristic algorithms are used by scholars because of their strong directionality, low memory ratio, and suitability for multidimensional problems [26]. These algorithms can overcome the inherent limitations of traditional algorithms. Recently, many scholars in the manufacturing industry have tried to mine multidimensional association rules by bionic algorithms, which achieve significant progress [27,28]. However, the research on mining association rules in remanufacturing is sparse [29]. The absence of common guidelines for the remanufacturing process adds complexity to the problem of remanufacturing. Moreover, mining association rules in the remanufacturing process become more complicated due to the hidden, complex, and coupled nature of most association rules. In fact, studying these association rules could improve remanufacturing efficiency and facilitate the large-scale development of remanufacturing.
The existing remanufacturability assessment methods in literature are only remanufacturing or scrapping. The evaluation indicators and their weights are susceptible to influence from various stakeholders. There is a lack of research aimed at maximizing the residual value of the part itself. This paper aims to maximize the residual value of retired parts by selecting an appropriate generalized growth mode through the mining of association rules between failure characteristics and repair technologies. The main contributions of this article are described as follows.

(1) We elucidate the differentiation between the generalized growth remanufacturing model of retired products and the traditional remanufacturing model. This novel approach offers a fresh perspective on optimizing the residual value of retired parts, thereby yielding substantial economic and environmental advantages.

(2) We propose an objective and stable method for selecting the generalized growth mode. This method aims to maximize the residual value of retired mechanical parts, which fills the gaps existed in literature.

(3) We conduct a case study to demonstrate the performance of our proposed method. The results shows that the proposed approach has superior efficiency and can better adapt to the large-scale development of remanufacturing comparing to the existing remanufacturability evaluation tools and methods.

3. Materials and Methods

In this paper, we present a novel method that utilizes association rules to guide the selection of generalized growth mode. These association rules capture the relationship among the failure characteristics of retired parts, the available repair technologies, and the maximum recoverability. We describe the details of the proposed method in the following sections.

3.1. Method Framework

Due to the uncertainty of the failure characteristics of retired parts and the dynamic nature of their repair technology, the performance of remanufactured parts exhibits anisotropic behaviors. It is therefore difficult to obtain remanufactured products with overall better performance via the “disassembly-cleaning-remanufacturing/replacement-assembly” process. Parts or module replacements in the remanufacturing may lead to a waste of the residual value of retired parts, which contradicts the fundamental concept of remanufacturing aimed at waste reduction. However, the residual value of those parts could be effectively reused through specific repair and processing techniques. To fully harness the residual value, we proposed an approach for selecting the generalized growth mode of retired mechanical parts based on association rule mining.

To address the multidimensionality and redundancy of the failure characteristics data, we employed the ReliefF algorithm as a preliminary step to select the core failure characteristic and eliminate redundant dimensions. By utilizing the ReliefF algorithm, we were able to identify the characteristics that exhibited the strongest correlation with the failure of the parts. Subsequently, we used the core failure characteristics set as the source part of association rules, while the repair technologies set and the maximum recoverability set were considered as the target part of the rules. The association rule set is mined by GA. Finally, based on the association rules set, the optimal generalized growth mode for the retired part is determined. The framework of this method is shown in Figure 4.
The method mainly involves failure characteristics, repair technologies, maximum recoverability, and parts set. We detail each object as follows.

- **Failure characteristics**

  The failure information of retired parts is multidimensional and multilayered. It is mainly divided into two categories: performance failure and geometric size failure. From the literature, it is known that several common failure modes in mechanical products can be categorized as cracks, deformation, wear, and corrosion. Based on these four dimensions, we subdivide and describe the failure characteristics according to the specific collected data. Taking wear as an example, we further categorize it into different forms, such as adhesive wear, abrasive wear, and fatigue wear. The amount of wear caused by the same wear form is varied too. Different wear characteristics have distinct impacts on the condition of parts, resulting in varying requirements for remanufacturing and repair techniques.

- **Repair technologies**

  Repair technology refers to the set of process techniques employed in the remanufacturing of retired parts with the aim of restoring them to their original performance. Due to variations in structure, failure characteristics, and materials among retired parts, the remanufacturing process can vary accordingly. In the case of the spline sleeve from an automobile universal transmission, different repair technologies are employed based on the amount of wear. If the wear is minimal, arc surfacing technology is utilized on the surface. However, if the wear is substantial, laser cladding technology is preferred. Laser cladding technology offers superior performance compared to arc surfacing. Furthermore, it is important to note that a single part may exhibit multiple failure characteristics. Therefore, relying on a single repair technique may not be sufficient, and a combination of several repair techniques may be necessary to address the various failure characteristics effectively. If the repair technologies set consists of \( n \) types of repair technologies, the number of possible repair combinations (\( K \)) can be calculated using Equation (1).

\[
K = \sum_{i=1}^{n} C_i^n + 1 \tag{1}
\]

where \( R = \{1, ..., i, ..., n\} \) is the repair technologies set, \( i \) represents the \( i \)th repair technology, \( n \) is the total number of repair technologies, and “\( C \)” is for “combination”. A combination is an unordered collection of distinct elements.
• Maximum recoverability

Maximum recoverability refers to the highest available performance level that can be restored in parts with specific failure characteristics through appropriate repairing techniques. It can directly affect the selection of the generalized growth mode of the parts. If the original performance could be restored by repair technologies, growth mode 1 or 2 should be selected. The part could be remanufactured to the level of its original performance or upgraded to other parts. If 30–90% of the original performance could be restored, growth mode 2 or 3 should be selected. The part could be remanufactured to the original one or downgraded into others. If less than 30% of the original performance could not be restored by the existing technologies, growth mode 3 or material recycling should be selected.

• Parts set

The structure and composition of retired parts also have an impact on the selection of generalized growth mode. Overall, products of the same model exhibit minimal structural variations. The main difference lies in the failure characteristics of the parts. These parts serve distinct functions and display diverse failure patterns based on their specific operating conditions.

3.2. Selection of Core Failure Characteristics Based on ReliefF

The failure characteristics of a product can be numerous and complex, influenced by factors such as its structure, materials, and working conditions. The high-dimensional and small-sample nature of failure characteristic data can pose challenges in processing, leading to dimensionality disasters and making the search for association rules particularly difficult. In practice, the failure analysis of some parts with little remanufacturing value may not be necessary, and the failure characteristics of core parts are interrelated. Therefore, accurately finding the core failure characteristics is vital for the speed and accuracy of mining association rules among failure characteristics, repair technologies, and maximum recoverability. The ReliefF approach is well-suited for selecting core failure characteristics as it can identify the most significant failure characteristic among a large number of interrelated ones and effectively reduce dimensionality.

During each iteration, the ReliefF algorithm randomly selects a sample \( R \) from the training sample set. It then identifies the \( k \) nearest neighbor samples from both the same class and different classes of the selected sample point \( R \). After obtaining the \( k \) nearest neighbor samples, a number of sample points are randomly selected to update the feature weight to obtain the feature weight ranking. Finally, effective features are selected according to the set threshold. The flowchart of ReliefF algorithm is shown in Figure 5 [30].

![Figure 5. The flowchart of ReliefF approach.](image)

The selection of the number of sample points (\( m \)) and the number of neighbors (\( k \)) is determined by the actual dataset. The calculation of weight (\( W \)) is shown in Equation (2), where \( H_j \) is the \( k \) nearest neighbor samples of the same kind of the sample, and \( M_j \) is the \( k \) nearest neighbor samples of the different kind of the sample. \( \text{class}(R_j) \) represents the label type of sample point, \( \text{diff}(A, R_1, R_2) \) represents the distance between sample \( R_1 \)
and $R_2$ on feature $A$, and $P(C)$ represents the probability of sample $C$. The failure features are divided into performance failure and geometric size failure in the selection of failure feature, and the failure characteristics with the greatest correlation are discovered, respectively.

$$W[A] = W[A] - \sum_{i=1}^{k} \frac{\text{diff}(A, R_i, H_j)}{(m \cdot k)} + \sum_{c=\text{class}(R_i)} \frac{P(C)}{1 - P(C)} \sum_{j=1}^{m \cdot k} \text{diff}(A, R_i, M_j(C))$$

(2)

### 3.3. GA-Based Association Rule Mining between Failure Characteristics and Repair Technologies

The maximum performance threshold of retired mechanical parts is determined by the failure state and the existing repair technologies. Therefore, mining the relationship among the failure characteristics, repair technologies, and maximum recoverability of retired parts becomes the key to finding the generalized growth mode that maximizes parts with residual value. The core failure characteristics obtained through ReliefF is used as the input of association rule, which can improve the mining efficiency and quality. Due to its unique genetic code, GA can process multiple multidimensional rules simultaneously and significantly reduce computational time. The flowchart of GA mining association rules is shown in Figure 6, and the specific algorithm description and definition are shown as follows [31].

![Flowchart of genetic algorithm for mining association rules](image)

**Figure 6.** The flowchart of genetic algorithm for mining association rules.

#### 3.3.1. Code Designing

The failure characteristic is the antecedent of the rule, and each dimension characteristic (such as deformation) has $n$ classifications. Given the multidimensional characteristics of the data, we chose the real number array encoding due to its simplicity and ease of implementation. The number of elements in the real number array corresponds to the number of categories of the failure feature, while the value of each element represents the attribute value of the specific dimension feature. Likewise, the repair technology combination and maximum recoverability is the consequent, and the encoding method is the same as antecedent. The maximum recoverability is divided into four levels: level 1 denotes that more than 90% of original performance could retain, level 2 represents 60–90%; level 3 represents 30–60%, and level 4 represents less than 30%.
Then, each chromosome is an array of real numbers, including multiple failure characteristic attributes and two repair characteristic attributes. A gene corresponds to an attribute, and the attribute value is the gene value. For example, 1-2-5-4-0-29-1 represents a chromosome, which is also a rule. It means that parts with five failure characteristics and attributes of 1-2-5-4-0 can recover more than 90% of the original performance by using the 29th repair technology combination. Therefore, operations, such as crossover and mutation after encoding with real number arrays, actually become operations on arrays.

3.3.2. Fitness Function

Fitness function is used to evaluate an individual’s capability to adapt to the environment, which is the basis of natural selection. The expected rules could be evaluated by various indexes such as support, confidence, and coverage. In order to extract frequent terms during the mining process, we designed a fitness function represented by Equation (3):

\[
\text{fitness}(r) = \frac{S'}{S}
\]

(3)

\[
S(r) = \frac{R_C \cup R_D}{N}
\]

(4)

where \(S'\) is the support of a new rule formed by genetic operations, and \(S\) is the threshold of support given by the user. When a rule, represented by \(r\), meets the specified requirements, its fitness function value should be higher than \(l\). Otherwise, the fitness function value will be less than \(l\), and this rule will be eliminated in the next generation. In Equation (4), \(r\) represents the rule, \(N\) is the number of records in the entire dataset, \(C\) is the field related to the failure characteristic attribute in the rule, and \(D\) is the fields related to “repair technology combination” and “maximum recoverability”. Then, the frequency of occurrence of \(C\) in \(N\) is denoted by \(R_c\), the frequency of \(D\) in \(N\) is denoted by \(R_d\). Additionally, the frequency of \(C\) and \(D\) appearing in the dataset simultaneously is represented as \(R_C \cup R_D\).

3.3.3. Definition of the Genetic Operator

(1) To maximize the preservation of rules that meet the specified conditions, we chose to inherit all rules with a fitness value greater than 1.

(2) To preserve the originality of the rules, we decided to employ a relatively straightforward single-point crossover. Two individuals were randomly selected from the pairing library according to the crossover probability \(P_c\), and their parts were exchanged at the intersection. In order to obtain the optimal parameter value, we used the adaptive strategy proposed by Li [32], as shown in Equation (5).

(3) Mutation is used to ensure the diversity of the population. The mutation operation we used is simple mutation. This mutation method randomly changes the value of a certain gene in the chromosome (array of real numbers) with a given mutation probability. The probability of mutation, denoted as \(P_m\), is not constant and is generally a very small value. Likewise, an adaptive strategy is adopted, as shown in Equation (6).

\[
P_c = \begin{cases} 
(P_c_1 - P_c_2) + \frac{1 - e^{-f'}}{f'_{avg}} & f' \geq f_{avg} \\
P_c_1 & f' < f_{avg}
\end{cases}
\]

(5)

\[
P_m = \begin{cases} 
(P_m_1 - P_m_2) + \frac{1 - e^{-f'}}{f'_{avg}} & f \geq f_{avg} \\
P_m_1 & f < f_{avg}
\end{cases}
\]

(6)
\[ G = \frac{t_{\text{max}} - t}{t_{\text{max}}} \]  

where \( t_{\text{max}} \) is the maximum number of iterations, \( t \) is the current number of iterations, \( f_{\text{avg}} \) is the average fitness of each generation population, \( f' \) is the larger fitness value among the two individuals to be crossed, and \( f \) is the fitness value of the individual to be mutated; \( P_{c1} \) and \( P_{c2} \) are the cross probability at \( P_{c1} = 0.9 \) and \( P_{c2} = 0.5 \), and \( P_{m1} \) and \( P_{m2} \) are the mutation probability at \( P_{m1} = 0.1 \) and \( P_{m2} = 0.01 \).

### 3.3.4. Extraction of Rules

Some of the association rules obtained above do not meet the requirements of credibility and independence. Therefore, the rules must be extracted to find out the association rules that meet the requirements. The extraction criterion is used to generate rules that satisfy the user-defined criteria of credibility and coverage. Rules that do not meet these requirements are discarded.

**Step 1** Select a candidate rule from the candidate collection;
**Step 2** Calculate the confidence \( C(r) \) and coverage \( D(r) \) of the rule;
**Step 3** if \( C(r) > C_r \) then
   - calculating the coverage of the rule
   - if \( D(r) > D_o \) then
     - output the rule; Go to step 4
   - else
     - Go to step 4
else
   - Go to step 4
**Step 4** If the candidate collection is empty, the extraction process ends. Otherwise, go to step 1.

where,

\[ C(r) = \frac{R_c \cup R_d}{R_c} \]  

\[ D(r) = \frac{R_c \cup R_d}{R_d} \]

### 4. Case Study

#### 4.1. Data Collection

In recent years, the auto parts remanufacturing industry system, an integral part of green manufacturing, has undergone consistent enhancements. Furthermore, the remanufacturing technology for auto parts has also seen significant advancements. Universal transmission devices, being a vital element of the automobile transmission system, are prone to eventual damage. In automobile remanufacturing, the majority of these damaged devices are typically replaced with new ones. However, the retired universal transmission devices have great residual value, and choosing suitable generalized growth model for their parts can significantly reduce waste. The universal transmission device is positioned between any pair of intersecting axes, and its relative position undergoes frequent changes. It is responsible for transferring power between two shafts, such as the transmission and the driving axle. An example universal transmission device from a car is shown in Figure 7.
After conducting consultations and data collection within a company, we obtained a dataset comprising 6580 samples of failure characteristics pertaining to a particular automobile universal transmission device. The dataset encompasses a total of 18 specific failure characteristics. The collected data exhibit noise and require normalization. Each failure characteristic is categorized into levels ranging from 1 to 10, with higher values indicating more severe failures. For instance, in the case of wear, the value of the failure characteristic is related to the form and extent of wear. A higher value corresponds to a greater amount of wear. The more irreversible the wear form, the greater the value. After filtering out the core failure characteristics, the attribute values associated with these failure characteristics for different parts were specifically categorized based on the results and expert consultation.

Automobile universal transmission device are composed of many parts, and the failure states of these individual parts are diverse. As a result, it is not feasible to describe the attribute values of failure characteristics with using unified specific values. To capture the failure state of different parts, we defined the attribute value of each failure characteristic based on the degree of failure. The failure degree increases as the attribute value grows larger. The division of failure degree is based on specific parts. To facilitate mining association rules, the attribute values are uniformly divided into five scales. Taking the drive shaft as an example, its specific attribute division is shown in Table 1.

**Table 1. Division of failure attribute for universal transmission shaft.**

<table>
<thead>
<tr>
<th>failure modes</th>
<th>attribute value</th>
<th>Crack</th>
</tr>
</thead>
<tbody>
<tr>
<td>The degree of failure</td>
<td>Nothing</td>
<td>Slight</td>
</tr>
<tr>
<td>failure modes</td>
<td>attribute value</td>
<td>Bending (amount of bending)</td>
</tr>
<tr>
<td>The degree of failure</td>
<td>0–1 mm</td>
<td>1–3 mm</td>
</tr>
<tr>
<td>failure modes</td>
<td>attribute value</td>
<td>Wear (gauge clearance)</td>
</tr>
<tr>
<td>The degree of failure</td>
<td>0–0.05 mm</td>
<td>0.05–0.1 mm</td>
</tr>
<tr>
<td>failure modes</td>
<td>attribute value</td>
<td>Deformation (sag)</td>
</tr>
<tr>
<td>The degree of failure</td>
<td>Nothing</td>
<td>One</td>
</tr>
</tbody>
</table>

It should be noted that Table 1 only lists the specific standards for the division of the transmission shaft, it may not represent the failure characteristics of the entire automobile universal transmission device. For example, the bearing would also be corroded, but the division standards are inconsistent with the transmission shaft.

At present, remanufacturing repair technologies for automobile universal transmission device typically include five main approaches: surfacing welding, surface strengthening, laser cladding, machining, and fitter technology (i.e., \( n = 5 \)). According to the Equation (1), there exist 32 possible combinations of repair technologies.
To sum up, the failure characteristics of various parts of the universal transmission device are taken as the antecedent of the rule, and the repair technology combinations and maximum recoverability are taken as the consequent. The association rules between them are mined to provide guidance for selecting generalized growth mode and facilitating the large-scale remanufacturing process.

4.2. Experiments

To verify the feasibility and effectiveness of GA in mining association rules, we conduct assessments using the mushroom dataset in UCI. Subsequently, we meticulously analyzed and compared the resulting experimental outcomes. The mushroom data share similarities to the problem studied in this article, as both datasets are characterized by multiple dimensions and attributes. By changing the threshold of support and the number of tasks, we observe variations in the algorithm’s execution time and the number of extracted rules. The comparative algorithms used in this study include classic Apriori, FP-growth, and particle swarm optimization (PSO). PSO, a bionic algorithm, is commonly used for rule mining purposes.

1. Comparison of execution time

The first experiment is to evaluate the execution efficiency of the algorithm by comparing the running time. The experimental results are shown in Figures 8 and 9. Figure 8 shows the running time of each algorithm under various numbers of tasks. It is evident that as the number of tasks increases, the running execution time for all four algorithms also exhibit a corresponding increase. However, the running time of GA and PSO algorithm is consistently smaller than that of Apriori and FP-growth. Moreover, when the number of tasks is small, the PSO algorithm shows a slightly better time efficiency compared to the GA algorithm. However, as the number of tasks increases, the efficiency of GA gradually surpasses that of PSO. This indicates that GA is relatively efficient in association rule mining in large-scale datasets. Figure 9 shows the running time of each algorithm across various minimum support values. Experimental results show that GA is more efficient than other three algorithms. When the minimum support value reaches 0.4, the running time of the four algorithms remains relatively unchanged. This phenomenon may occur due to the algorithm encountering difficulties in mining association rule, or it may indicate that no association rules are being discovered.

![Comparison of Algorithm Runtimes with Different Number of tasks](image-url)
The second experiment aims to evaluate the performance of the algorithm by comparing the number of mined rules. The experimental results are shown in Figures 10 and 11. Figure 10 illustrates the number of rules mined by the four algorithms across various minimum support values. Figure 11 displays the number of rules mined by the four algorithms at varying numbers of tasks.
The above experiments clearly demonstrate that GA exhibits superior performance in terms of both speed and the number of association rules extracted, especially in multi-dimensional and multi-attribute datasets. Additionally, both GA and PSO outperform the classic Apriori and FP-growth algorithms in terms of mining performance. Particularly, when dealing with a large amount of data, the GA and PSO algorithms exhibit a clear advantage in terms of efficiency. However, as the number of tasks increases, the mining efficiency of GA outperforms than that of PSO, indicating that GA is better suited for mining large-scale multidimensional and multi-attribute datasets. Moreover, GA consistently demonstrates the capability to discover a greater number of association rules. Therefore, GA is deemed more suitable for addressing our research problem.

4.3. Generalized Growth Mode Selection Based on Association Rule Mining

4.3.1. Core Failure Characteristics Selection

To select the core failure characteristics, the failure of the automobile universal transmission device is divided into two types: performance failure and geometric size failure. After conducting multiple tests on the same dataset, we found that the results are clearer and more stable when using the following parameter settings: $M$ (sampling times) = 25, $K$ (nearest neighbor) = 8, and $N$ (running times) = 20. The output results corresponding to these settings are shown in Figure 12.
Table 2 shows the results of a particular operation, specifically showcasing the average weights assigned to each characteristic after 20 rounds of selection. The weights of characteristics 2, 4, 6, 7, and 16 are relatively large. Therefore, the corresponding crack, bend, deformation, wear, and ablation are the core failure characteristics.

Table 2. The average weight value of each failure characteristic calculated at a certain operation.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0973</td>
<td>0.1846</td>
<td>0.0685</td>
<td>0.1557</td>
<td>0.0966</td>
<td>0.1710</td>
<td>0.2191</td>
<td>0.1195</td>
<td>0.0595</td>
<td></td>
</tr>
<tr>
<td>0.0600</td>
<td>0.0367</td>
<td>0.0417</td>
<td>0.0310</td>
<td>0.0609</td>
<td>0.0409</td>
<td>0.1242</td>
<td>0.0300</td>
<td>0.0507</td>
<td></td>
</tr>
</tbody>
</table>

4.3.2. Mining Association Rules Based on Genetic Algorithm

* Data preprocessing and coding

We merged the core failure characteristics database with the repair process database. According to the above results, a database table was established for mining association rules between the core failure characteristics set and the repair technologies set. The attributes of this database table are shown in Table 3, where each row of the table is a chromosome.

Table 3. Attributes of the new database table.

<table>
<thead>
<tr>
<th>Name</th>
<th>C</th>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
<th>F5</th>
<th>X1</th>
<th>X2</th>
</tr>
</thead>
<tbody>
<tr>
<td>data type</td>
<td>Char</td>
<td>Char</td>
<td>Char</td>
<td>Char</td>
<td>Char</td>
<td>Char</td>
<td>Repair technologies combination</td>
<td>maximum recoverability</td>
</tr>
<tr>
<td>meaning</td>
<td>Parts</td>
<td>Crack</td>
<td>Bending</td>
<td>Wear</td>
<td>Deformation</td>
<td>Ablation</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

We adopted a real number array encoding scheme for our approach. A rule is a real number encoding string. It was divided into two parts. The antecedent of the rule is a variety of failure characteristics, and the consequent is the repair technology combination and maximum recoverability. As described in Section 4.1, each failure characteristic attribute (F1–F5) is mapped to a numeric value ranging from 1 to 5 based on the degree of
failure. In addition, we identified 32 combinations of repair technology (X1), which are encoded as values from ranging from 1 to 32. The maximum recoverability (X2) is encoded using values 1 to 4, while the 15 parts (C) are encoded with values from 1 to 15.

- **Parameter setting**

  Subsequently, we conducted further experiments to determine optimal GA parameters, including the crossover probability \((P_c)\) and mutation probability \((P_m)\), tailored to the research problem addressed in this paper. We employed an adaptive change strategy, as described in Equations (5) and (6), to dynamically adjust the values of \(P_c\) and \(P_m\). Through analyzing the changes of \(P_c\) and \(P_m\) as the number of iterations changes, we aimed for \(t\) to determine the best parameters. We set the maximum number of iterations \((t_{\text{max}})\) to 1000 and the population size to 30 in our experiments. The experimental results are shown in Figure 13. It can be seen from Figure 13a that the value of \(P_c\) decreases as the number of iterations increases and eventually reaches a stable value of 0.4. Figure 13b shows that the value of \(P_m\) increases as the number of iterations rises, finally converging to a value of 0.09. Hence, we determined that the optimal parameter values for \(P_c\) and \(P_m\) are \(P_c = 0.4\) and \(P_m = 0.09\).

![Figure 13. The iterative process curve of \(P_c\) and \(P_m\). (a) Evolution curve of crossover probability; (b) evolution curve of mutation probability.](image)

- **Extraction rules**

  Finally, we obtained a set of 29 rules that meet the minimum support requirement. After applying screening criteria for confidence and coverage, we further identified a subset of 13 rules that successfully satisfy the conditions. For the convenience of observation and comparison, the rules that meet the conditions by using the proposed method are presented in Table 4. Their corresponding support, confidence, and coverage values are also presented in this table.

<table>
<thead>
<tr>
<th>Number</th>
<th>Rule</th>
<th>Support</th>
<th>Confidence</th>
<th>Coverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12</td>
<td>0</td>
<td>0</td>
<td>35</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>3</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>4</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>14</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 4. Results of mining association rules.
4.3.3. Selection of Generalized Growth Mode

Rule 1 indicates that when the spline shaft sleeve exhibits grade 2 wear, and it is possible to retain 60–90% of original performance by using laser cladding technology and fitter technology; rule 2 indicates that when the cross shaft experiences grade 3 crack, grade 2 wear, and grade 2 ablative, the utilization of surfacing welding, surface strengthening, and fitter repair methods can only retain 30–60% of its original performance. The mined rules could reveal the relationship between failure characteristics and maximum recoverability, thus obtaining the maximum remanufacturing value of each part ontology. According to the meaning of generalized growth, Table 5 shows the generalized growth mode of each part of the universal transmission device, in which generalized growth mode 1 is upgrading remanufacturing, growth mode 2 is restorative remanufacturing, and growth mode 3 is downgrading remanufacturing.

Table 5. The generalized growth mode of each part.

<table>
<thead>
<tr>
<th>Parts number</th>
<th>Name of the part</th>
<th>Generalized growth mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cross shaft</td>
<td>2 or 3</td>
</tr>
<tr>
<td>2</td>
<td>universal joint fork</td>
<td>2 or 3</td>
</tr>
<tr>
<td>3</td>
<td>needle roller</td>
<td>3 or scrap</td>
</tr>
<tr>
<td>4</td>
<td>bearing cover</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>bearing sleeve</td>
<td>2 or 3</td>
</tr>
<tr>
<td>6</td>
<td>gasket</td>
<td>1 or 2</td>
</tr>
<tr>
<td>7</td>
<td>oil seal</td>
<td>2 or scrap</td>
</tr>
<tr>
<td>8</td>
<td>oil nozzle</td>
<td>2 or scrap</td>
</tr>
<tr>
<td>9</td>
<td>safety valve</td>
<td>2</td>
</tr>
<tr>
<td>10</td>
<td>cover</td>
<td>2 or 3</td>
</tr>
<tr>
<td>11</td>
<td>oil seal cover</td>
<td>2 or 3</td>
</tr>
<tr>
<td>12</td>
<td>spline shaft sleeve</td>
<td>2 or 3</td>
</tr>
<tr>
<td>13</td>
<td>spline shaft</td>
<td>1 or 2</td>
</tr>
<tr>
<td>14</td>
<td>transmission shaft</td>
<td>1 or 2</td>
</tr>
<tr>
<td>15</td>
<td>balance plate</td>
<td>2</td>
</tr>
</tbody>
</table>

4.4. Discussions

1. Parameter analysis of rule extraction (setting of confidence and coverage)

During the extraction process of rules, users have the flexibility to adjust the threshold values of confidence and coverage based on their priorities and preferences for different indicators. By modifying these thresholds, users can identify rules that align with their specific expectations and requirements. In this fashion, the goal of directional mining could be achieved, and the quality of mining rules could also be improved. Figure 14 shows the number of final rules under various thresholds of confidence $C(r)$ and coverage $D(r)$ in this case.
For the performance comparison, two comparative experiments were designed to demonstrate the applicability and advantages of the proposed method in addressing the research problem. In the first experiment, we compared the mining efficiency and the number of mining rules between the original data and the data processed by the ReliefF algorithm. The result is shown in Table 6. In the second experiment, we verified the mining efficiency and accuracy of the proposed method. The results are shown in Table 7 and Figure 15. The accuracy is calculated using Equations (10)–(12).

\[
P = \frac{TP}{TP + FP} \tag{10}
\]

\[
P = \frac{TP}{TP + TN} \tag{11}
\]

\[
F1 = \frac{2P \times R}{P + R} \tag{12}
\]

where \(TP\) represents the number of frequent items mined, \(FP\) represents the number of infrequent items mined, \(TN\) represents the number of frequent items missed in the mining process, \(P\) represents the accuracy of mining results, \(R\) represents the recall rate of mining effects, and \(F1\) represents the accuracy of mining by comprehensively considering the two indexes of accuracy and recall rate.

**Table 6.** Comparison of mining efficiency between original dataset and core feature dataset.

<table>
<thead>
<tr>
<th></th>
<th>Time(s)</th>
<th>Number of Rules</th>
<th></th>
<th>Time(s)</th>
<th>Number of Rules</th>
<th>Time(s)</th>
<th>Number of Rules</th>
<th>Time(s)</th>
<th>Number of Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(S = 0.01)</td>
<td>(S = 0.02)</td>
<td>(S = 0.03)</td>
<td>(S = 0.04)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GA</td>
<td>112</td>
<td>99</td>
<td>43</td>
<td>35</td>
<td>25</td>
<td>21</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ReliefF—GA</td>
<td>16</td>
<td>90</td>
<td>12</td>
<td>30</td>
<td>7</td>
<td>12</td>
<td>4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 7.** Comparison of mining efficiency and accuracy (S = 2%).

<table>
<thead>
<tr>
<th></th>
<th>Time(s)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>43</td>
<td>81.8</td>
</tr>
<tr>
<td>ReliefF—APRIORI</td>
<td>39</td>
<td>87.5</td>
</tr>
<tr>
<td>ReliefF—FP-growth</td>
<td>27</td>
<td>88.5</td>
</tr>
<tr>
<td>IPSO (ReliefF—PSO)</td>
<td>14</td>
<td>93.3</td>
</tr>
<tr>
<td>IGA (ReliefF—GA)</td>
<td>12</td>
<td>96.7</td>
</tr>
</tbody>
</table>
Table 6 shows that after ReliefF processing, the mining time is reduced from 43 s to 12 s (S = 2%), but the number of rules mined was slightly reduced. This is because the number of attributes after processing is small (the number of attributes was reduced from 18 to 5), resulting in a certain reduction in the number of frequent items mined. Figure 15 shows the execution time and mining accuracy of the five methods under various support thresholds. Table 7 shows their running time and the rules mined by the five methods under different minimum support. It can be seen that GA improves the mining speed while maintaining mining accuracy. When the threshold of support is 2%, the accuracy can reach 96.7%. Therefore, we believe that the proposed method can be effectively and efficiently used to discover the association rules between failure characteristics and repair ability.

2. Implications

We proposed a new method (GGRM) to maximize the residual value of retired mechanical products. Using this method, the residual value of retired products and parts that cannot be recovered to their original performance could be reused appropriately.

Our research could inspire remanufacturing service providers or managers. First, GGRM has a broader perspective. It not only considers the existing restorative remanufacturing, but also innovatively proposes upgrading and downgrading remanufacturing of parts that could be used in other products. It can further reduce waste and thus achieve enormous environmental and economic benefits. Second, this method can measure the residual value threshold from the failure characteristics of retired parts and the existing repair technologies. It successfully addresses the challenge of determining the residual value of parts ontology, thereby filling a significant gap in the field of remanufacturing evaluation research. Third, this method improves the efficiency of selecting generalized growth mode for large-scale remanufacturing. In comparison to existing remanufacturability evaluation methods, this association rule mining-based method is more efficient in handling large quantities of parts. This method provides higher resource utilization rate and more efficiency for remanufacturing service providers or managers.

5. Conclusions

In this paper, we mainly focus on the selection of the generalized growth mode that can maximize the residual value of retired parts. Based on the correlation between failure characteristic and repair technology, we proposed a method for selecting the generalized growth mode of retired mechanical parts based on association rule mining. The ReliefF method was used to select the core failure characteristics for eliminating the multidimensionality and redundancy. Then, GA was employed to mine the association rules among failure characteristics, repair technology, and maximum recoverability, which guides the selection of generalized growth mode of retired parts. By using this method, we aim to maximize the residual value of retired parts that would otherwise be scrapped. The proposed method provides a novel perspective for remanufacturing industry to promote
cleaner production. This method is more objective and efficient compared to existing remanufacturability evaluation methods. In comparison to APRIORI algorithm, GA methods are much more efficient. Hence, our method is applicable for the selection of generalized growth modes for large quantities of parts and serves as a guidance for large-scale remanufacturing processes. However, it is important to note that the failure degree measurement of ReliefF may have some subjective elements, and the GA coding process needs to be customized for specific parts, which limits its universal applicability. Therefore, future work should focus on eliminating the differences in data characteristics between different parts and developing a more generalized method that can be applied to various parts. This will enhance the versatility and applicability of the proposed approach.

Author Contributions: Conceptualization, L.W. and X.X.; methodology, Y.G.; software, Y.G. and J.C.; validation, J.C. and Z.Z.; formal analysis, Y.G. and J.C.; investigation, Y.G.; resources, L.W.; data curation, Z.Z.; writing—original draft preparation, Y.G.; writing—review and editing, L.W.; visualization, Z.Z.; supervision, X.X.; project administration, X.X.; funding acquisition, L.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 52275503.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References


Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.