

Article

A Decision Tree-Based Method for Evaluating the Remanufacturability of Used Parts

Shuhua Chen ^{1,2,*}, Jian Hao ^{1,*}, Yanxiang Chen ^{2,3} and Zhongyuan Yang ²¹ Department of Chemistry, Shanghai University, Shanghai 200444, China² School of Mechanical and Electrical Engineering, Wuhan City Polytechnic, Wuhan 430064, China; chenyanx516@163.com (Y.C.); rocky_young@163.com (Z.Y.)³ Academy of Green Manufacturing Engineering, Wuhan University of Science and Technology, Wuhan 430081, China

* Correspondence: whcpcsh@163.com (S.C.); jhao@shu.edu.cn (J.H.)

Abstract: Assessing the remanufacturability of used parts is a crucial basis for determining their value and optimal utilization methods. Due to the uncertain quality of used parts and the varying processing capacity of enterprises, coupled with the continuous expansion of the scale of the remanufacturing industry, the traditional weighted-analysis model, which considers all indicators at the same level, is inefficient for decision-making. In order to evaluate the remanufacturability of used parts more efficiently, a decision tree-based method is proposed, which hierarchically processes the evaluation criteria to enhance decision-making efficiency and adaptability. First, using a data platform, the remaining value of used parts reflected in the failure degree is analyzed and predicted, with the aid of artificial neural networks and the Weibull model, providing an initial remanufacturability assessment. Then, remanufacturability is assessed sequentially from the technical, economic, and environmental feasibility aspects, based on the enterprise's processing capabilities. Finally, the effectiveness of the proposed method is validated through a case study on the remanufacturing of used blades.

Keywords: remanufacturing; remanufacturability evaluation; processing capability; factor analysis



Citation: Chen, S.; Hao, J.; Chen, Y.; Yang, Z. A Decision Tree-Based Method for Evaluating the Remanufacturability of Used Parts. *Processes* **2024**, *12*, 1220. <https://doi.org/10.3390/pr12061220>

Academic Editors: Sara Liparoti and Diane Mynors

Received: 4 May 2024

Revised: 30 May 2024

Accepted: 10 June 2024

Published: 14 June 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In the past few decades, environmental problems, including the escalating issue of global warming, have gained considerable prominence. Consequently, there has been a growing emphasis on achieving sustainable industrial development worldwide. The exponential growth and constant upgrading of industrial products have accelerated the early retirement of industrial parts. Thus, dealing with these used parts sustainably has become a major concern for the sustainable development of the industry [1,2]. Remanufacturing, an environmentally friendly approach to managing end-of-life products, has been employed in the processing of used products such as machine tool spindles, engine blades, crankshafts, and other parts known for their high cost, intricate technology, and extended processing cycles [3,4]. Upon completing their service cycle, these parts retain substantial residual value [5]. However, directly scrapping them wastes these residual values and causes severe environmental pollution during the scrapping processes, contradicting sustainable industrial development principles. In contrast, remanufacturing these used parts enables full utilization of their residual values, leading to a remarkable 50% reduction in production costs, a 60% decrease in energy consumption, and an 80% reduction in pollution emissions compared to manufacturing new parts [6]. Therefore, remanufacturing used machinery parts is a crucial strategy for achieving efficient resource utilization and sustainable economic development [7]. However, it is important to note that not all used parts are suitable for remanufacturing. In cases where the parts have sustained severe damage or possess low technical content, the materials and energy consumed in the remanufacturing process may not be significantly lower than those required for manufacturing new parts.

Hence, accurately evaluating whether a used part is suitable for remanufacturing is a vital prerequisite for obtaining satisfactory economic and environmental benefits from the remanufacturing process.

Evaluating the remanufacturability of used parts determines their suitability for remanufacturing. As remanufacturing production scales up, both the number of parts and the size of databases increase rapidly. Given this background, the efficiency requirements for evaluating the remanufacturability of used parts are increasing. However, due to uncertainties in the quality of used parts and the remanufacturing capabilities of different enterprises, efficiently and accurately evaluating remanufacturability in targeted parts has become crucial.

Various studies have been conducted for assessing the remanufacturability of used parts. These studies can be categorized into two types, based on their research scope. The first type of research primarily focuses on specific used parts, with the evaluation indicators determined based on the characteristics of their remanufacturing processes. This approach takes into account the unique requirements and considerations associated with remanufacturing a particular type of used part.

For instance, Goodall et al. [8] conducted an analysis of various tools and technologies used in remanufacturing and found that the remanufacturing cost was the most critical factor affecting the process, followed by environmental factors. San [9] utilized the DEMATEL method to investigate the factors influencing the remanufacturability of used mobile phones and identified the critical factors among them. The study revealed that innovation rate and retirement time were the predominant factors affecting remanufacturability.

Another type of research involves identifying general evaluation indicators by summarizing the similar remanufacturing characteristics of various used parts. Du et al. [10] presented a method for evaluating the remanufacturability of used machine tools, which considered the technological feasibility, economic feasibility, and environmental benefits of remanufacturing machine tools. Ding et al. [11] proposed a remanufacturability evaluation method that integrated CD-TOPSIS and improved the analytical hierarchy process (AHP), to determine whether machine tool guideways were suitable for remanufacturing. The aforementioned studies have identified key indicators for evaluating the remanufacturability of general used parts, but they have overlooked the impact of uncertainties in enterprise processing capabilities on the evaluation results.

To quantify the remanufacturability evaluation indicators of used parts, existing research typically selects an appropriate quantification method based on the attribute of the chosen evaluation indicator. For example, Fang et al. [12] proposed a remanufacturability evaluation model based on the CAD model of products, where evaluation indices such as disassembly and recoverability were expressed using quantitative numbers obtained from the CAD model. Karaulova and Bashkite [13] utilized the life-cycle assessment (LCA) method to evaluate the remanufacturability of used industrial products from three perspectives: technology, economy, and environment. They integrated these aspects with the TRIZ method to determine the re-use method of used industrial products. Omwando et al. [14] presented a two-layer fuzzy computing system to analyze the qualitative and quantitative remanufacturability-evaluation indicators, which included technical, economic, resource-utilization, and environmental factors. Similarly, Zhang et al. [15] synthesized fuzzy evaluation and extended AHP to assess the qualitative and quantitative indicators affecting the remanufacturability of used machinery parts, considering technical, economic, and environmental feasibility. The above studies have conducted productive research on the quantification of indicators for evaluating the remanufacturability of used parts, but they have not considered the efficiency of the evaluation when integrating multiple indicators.

As the demand for remanufacturability assessment of used parts grows, more researchers are developing systematic models that combine comprehensive evaluation indicators with specific quantification methods. For instance, Shi et al. [16] introduced a three-dimensional remanufacturability evaluation model for used engines, considering technological, economic, and environmental factors. The final remanufacturability eval-

uation result was obtained by assigning index weights using the AHP method. Lahrouer and Brissaud [17] analyzed the characteristics of additive remanufacturing in used parts and proposed a framework to evaluate the remanufacturability of used parts, employing additive manufacturing technology. Ling and He [18] established a remanufacturability evaluation model for decommissioned grinders, where the final evaluation result was obtained by weighted summation and the weight of each indicator was determined by the AHP method.

At present, technical feasibility, economic feasibility, and environmental benefits are widely recognized as the primary indicators for evaluating the remanufacturability of used parts [19–21]. However, when integrating these indicators, weighted models are typically used for decision-making. With the expansion of the remanufacturing industry and the increasing size of databases, the efficiency limitations of weighted models have become apparent. One of the important reasons for this problem is the lack of the sorting out of the logical relationship between indicators, necessitating a comprehensive database search and match for each individual used-part decision. Based on this, a remanufacturability evaluation method for used parts based on a decision tree has been proposed. By prioritizing evaluation criteria, this method reduces the number of data matched in a single instance, ultimately improving decision-making efficiency and applicability.

To address these gaps, a novel decision tree-based remanufacturability evaluation method for used parts is proposed. This method involves a comprehensive decomposition of the influencing factors from both the quality of used parts and the relevant standards of the remanufacturing enterprise. The study's novelty lies in the following three points:

1. The remanufacturability evaluation indicators are decomposed and refined based on the failure characteristics of used parts and the processing capabilities of enterprises, ensuring the comprehensiveness of the evaluation results. By considering these factors, the proposed remanufacturability evaluation method for used parts utilizes a decision tree, accounting for failure degree, technology, economy, and environment.
2. Given the high uncertainty of used parts' failure characteristics, a failure-degree evaluation model driven by service failure data of used parts is proposed to measure their residual remanufacturing value. This model quantifies the remanufacturing value of used parts by considering their failure degree.
3. To evaluate the multi-attribute indicators derived from the processing capabilities of an enterprise, a comprehensive fuzzy evaluation method is proposed. This method quantifies both qualitative and quantitative indicators while considering their relationship with the failure characteristics of the used part, ensuring the validity of the quantification process.

The remaining content of this study is structured as follows: in Section 2, a decision tree-based remanufacturability evaluation method for used parts is proposed. This method is based on the factor decomposition of failure characteristics and processing capability, and includes the sequential evaluation of the failure degree of used parts, the feasibility of implementing remanufacturing technology, the economic viability of remanufacturing, and the environmental feasibility of the remanufacturing process. The feasibility of the proposed method is verified through a case study on a used blade in Section 3. Finally, in Section 4, the conclusions are summarized and an outlook for future research is provided.

2. Methodology

The purpose of assessing the remanufacturability of used parts is to efficiently determine their suitability for remanufacturing. This assessment relies on the objective quality of the parts at the time of recovery and the subjective willingness of the enterprise. The high uncertainty regarding both the quality of the used parts and the production capabilities of enterprises further complicates the evaluation process. Based on this, a decision tree-based method is proposed to evaluate the remanufacturability of used parts, as shown in Figure 1.

In Figure 1, failure degree, technical feasibility, economic feasibility, and environmental feasibility are used as indicators to evaluate the remanufacturability of used parts. Unlike

the weighted model, where all indicators are considered simultaneously, the decision tree model reflects the sequential relationship among the indicators, improving decision-making efficiency by reducing the amount of data matching required. The explanation and selection criteria for each indicator are as follows:

1. **Failure degree:** the failure degree indicator represents the objective quality of used parts at the time of return. The residual value of these parts is reflected in different levels of failure. When the residual value is high, the enterprise can choose either direct re-use or remanufacturing in the next decision-making step. However, when the residual value is low, the used parts cannot be remanufactured.
2. **Technical feasibility:** the technical feasibility indicator represents the production capabilities of the enterprise. When evaluating the remanufacturability of used parts, the enterprise will only remanufacture those parts that align with its processing capabilities. When the enterprise's technical capabilities are insufficient, the part cannot be remanufactured.
3. **Economic expectation:** economic feasibility determines the enterprise's willingness to remanufacture. When the profit from remanufacturing is lower than expected, the enterprise will purchase new parts instead of remanufacturing. In such cases, even if the enterprise's technical capabilities meet the requirements, the used part will still not be remanufactured.
4. **Environmental feasibility:** positive environmental benefits are a key advantage of remanufacturing. When remanufacturing used parts results in high energy consumption and pollutant emissions, it is advisable to opt for material recycling. Conversely, energy consumption and pollutant emissions that meet expectations align with the goal of promoting sustainable and environmentally friendly remanufacturing practices.

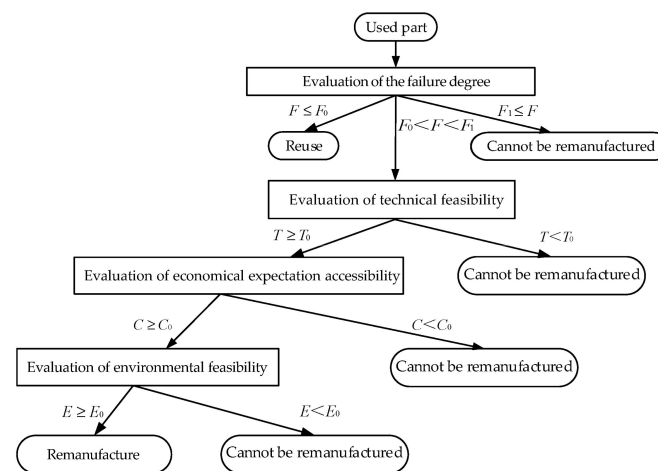


Figure 1. Flow chart of the decision tree-based remanufacturability evaluation method for used parts.

2.1. Evaluation of Failure Degree

Used parts collected from various sources often exhibit different types of failure characteristics, including wear, fracture, and corrosion [22]. Previous studies have quantified the failure degree of used parts through theoretical calculations or CAD models, focusing on a single type of failure that can be directly measured [23,24]. However, in practice, used parts may exhibit multiple types of failures simultaneously, and some failures, such as fatigue, cannot be directly measured. Furthermore, it is impractical for enterprises to directly measure multiple failures of used parts using inspection tools, as this would significantly reduce remanufacturing efficiency. Therefore, alternative methods need to be adopted to better quantify the failure degree of used parts. These methods should consider the coexistence of various failure types and address the challenges of measuring certain types of failures indirectly. By developing comprehensive evaluation criteria and utilizing advanced techniques such as machine learning algorithms or data-driven models, it may be

possible to assess the failure degree of used parts more efficiently and accurately, facilitating the decision-making process in remanufacturing operations.

For each used part operating under specific service conditions, there exists a one-to-one correspondence between its failure time and its failure degree. Therefore, the failure time corresponding to its failure degree can be utilized for evaluating the extent of failure. It is important to note that the actual operational data collected by the enterprise used to monitor the performance of the entire product, rather than a specific part. This distinction underscores the need to develop methods for extrapolating the failure degree of individual parts from the comprehensive performance data of the overall product. Such methods could involve utilizing statistical analysis, predictive modeling, or machine learning algorithms to infer the failure degree of individual parts based on the comprehensive performance data collected from the entire product. By doing so, enterprises can effectively assess the failure degree of used parts and make informed decisions regarding remanufacturing processes. The used parts discussed in this paper pertain to critical components within the product, such as the blades in an aero engine. When a core part fails, it results in the entire product failing; thus, the failure time of the core part aligns with that of the whole product. Additionally, the failure time in this context denotes the duration from when a part is put into service to the point at which the product fails, rather than the specific moment when the part itself fails.

The evaluation process of determining the failure degree of a used part involves analyzing its failure degree to calculate its residual value, thereby assessing whether it has potential for remanufacturing. However, in practical application, the residual value of a used part is a somewhat ambiguous concept, often determined subjectively by experts or experienced shop floor operators. Reliability refers to a component's ability to fulfill its design functions within specified conditions and over a designated period [25]. As a part's service progresses, its reliability diminishes. The remanufacturing processes for a used part aim to restore the reliability of used components to the same level as new parts. Therefore, if a used part still possesses a considerable remaining service life, the remanufacturing process will require less additional useful life to be imparted to the product, resulting in easier remanufacturing processes and a higher residual value. Consequently, to more objectively quantify the residual value of a used part, the remaining service life left in a used part is regarded as representative of the residual value in the evaluation process of failure degree in this paper. Consequently, the focus of the evaluation of the failure degree shifts from "assessing its residual value through the failure degree and then determining its processing method" to "assessing its reliability based on the failure time and then determining its processing method". Figure 2 illustrates the process of evaluating the failure degree.

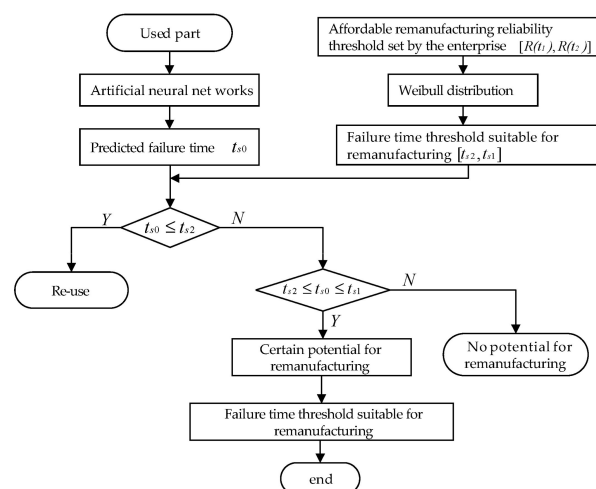


Figure 2. Evaluation flow chart of failure degree.

2.1.1. Prediction of Failure Time

The failure time represents the real service life of a part, under dynamic conditions. For parts of the same type, the actual failure time often varies due to differing service conditions. In the case of general industrial parts, their service life typically spans several years, and enterprises commonly do not record comprehensive failure time data for a part. Consequently, to ascertain the actual failure time of a specific used part, this study employs a method utilizing the self-learning characteristics of an artificial neural network (ANN) to predict the part's failure time. In this approach, the ANN utilizes the historical operating condition data of the used parts as input, with the actual failure time under these operating conditions serving as the output. This enables the prediction of the actual failure time of a particular used part under the same stable service conditions prior to failure.

2.1.2. Calculation of Failure-Time Threshold with Remanufacturing Potential

In order to determine the remanufacturing potential of a used part based on its failure time, it is not sufficient to only consider the actual failure time. It is also necessary to establish the failure-time threshold that indicates the remanufacturing potential of the used part. Since the residual value of a used part in this paper is measured by reliability, the reliability threshold specified by the enterprise for a used part suitable for remanufacturing can be converted into a failure-time threshold. By analyzing the difference between the actual failure time of the used part and the failure-time threshold, it becomes possible to determine whether the used part has the potential for remanufacturing. Once it is confirmed that there is sufficient residual value in the used part, the most appropriate method of utilizing the used part can be determined.

The use of the Weibull distribution with two parameters to convert the reliability threshold of a used part suitable for remanufacturing into the corresponding failure-time threshold is a sound approach. The Weibull distribution is commonly employed in reliability engineering to model the life expectancy and failure rates of products. By utilizing the Weibull distribution with two parameters, it becomes possible to effectively analyze and transform the reliability threshold into a failure-time threshold, providing valuable insight into the potential remanufacturing of used parts. This method enables a more comprehensive understanding of the reliability characteristics of electromechanical products and supports informed decision-making regarding remanufacturing processes.

The specific expression of the Weibull distribution with two parameters is as follows:

$$F(t) = 1 - \exp\left[-\left(\frac{t}{\eta}\right)^\beta\right] \quad (1)$$

$$R(t_s) = 1 - F(t_s) = \exp\left[-\left(\frac{t_s}{\eta}\right)^\beta\right] \quad (2)$$

where $F(t)$ represents the failure distribution function of a used part, while η and β represent the scale parameter and shape parameter in the Weibull distribution. t_s represents the failure time of the used part, and $R(t_s)$ represents the reliability of the used part at the time of t_s .

In order to apply the Weibull distribution with two parameters to determine the failure-time threshold for evaluating the remanufacturing potential of used parts, it is necessary for the remanufacturing enterprise to establish an acceptable reliability threshold based on various factors such as market strategy and target customers, shown as $(R(t_{s1}), R(t_{s2}))$. Once this reliability threshold has been determined, the corresponding failure-time threshold can be calculated using Equation (2). This provides a quantitative measure of the remanufacturing potential of the used parts, allowing for informed decision-making regarding the optimal utilization of these parts. It is worth noting that the establishment of a suitable reliability threshold for remanufacturing is a crucial step in the remanufacturing process, as it directly impacts the quality and reliability of the remanufactured products.

Therefore, careful consideration and analysis of various factors is necessary to ensure the establishment of an appropriate reliability threshold.

Least squares estimation is an effective method for estimating unknown parameters in linear functions. This work adopts least squares estimation to estimate the scale parameter η and shape parameter β in the Weibull distribution.

To accurately calculate the failure-time threshold of the used part, it is necessary to estimate the unknown parameters, scale parameter (β) and shape parameter (η), in Equation (2). Least squares estimation is indeed an effective method for estimating these parameters in linear functions. The specific process of using least squares estimation to estimate the parameter η and shape parameter β in the Weibull distribution can be outlined as follows:

1. Take the logarithm of both sides of Equation (1), and the following equation can be obtained:

$$\ln \ln[1/(1 - F(t))] = \beta [\ln t - \ln \eta] \quad (3)$$

2. Let $x = \ln t$, $y = \ln \ln[1/(1 - F(t))]$, $A = \beta$, $B = -\beta \ln \eta$, then the Equation (3) can be simplified to the following equation:

$$y = Ax + B \quad (4)$$

3. For the linear equation system (4), the least squares-estimation solution of regression coefficients A and B is

$$\begin{cases} \hat{A} = \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - n \bar{x}^2} \\ \hat{B} = \bar{y} - \hat{A} \bar{x} \end{cases} \quad (5)$$

where $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$, $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$.

To obtain the regression line with the least deviation in the least squares estimation, it is important to ensure the accuracy of the empirical distribution function. The mean rank method is indeed an effective approach to measure the accuracy of the empirical distribution function. The principle of the mean rank method can be illustrated as follows.

When dealing with incomplete lifespan data, especially when some samples have been terminated before experiencing failure, it becomes challenging to predict the failure time using conventional methods such as the average rank or approximate median-rank formula. In such cases, it is necessary to estimate all possible ranks based on the available failure and terminated samples. Subsequently, the mean rank can be obtained and used to derive the empirical distribution function by applying it to the approximate median-rank formula. The formula for calculating the average rank based on the incremental change is as follows:

$$\begin{cases} \Delta A_{t_i} = \frac{n+1-A_{t_{i-1}}}{n-k+2} \\ A_i = A_{i-1} + \Delta A_i \end{cases} \quad (6)$$

where n is the sample size; k is the sequence number of all devices which are arranged according to the size of the failure time and the deletion time; i is the sequence number of the failed device; A_i is the mean rank of the failed device; and A_{i-1} is the average rank of the previously failed device.

The empirical distribution function can be obtained as follows:

$$F_n(t_i) = \frac{A_i - 0.3}{n + 0.4} \quad (7)$$

After that, the regression line of the Weibull distribution model can be fitted by the least squares parameter-estimation method to determine the scale parameter and shape parameter of the Weibull distribution.

2.1.3. Evaluation of Failure Degree Based on Failure Time

Assuming that the failure time of a used part is predicted to be t_{s0} , based on historical operational-condition data, the reliability of the used part can be calculated $R(t_0)$ using the Weibull distribution. The Weibull distribution allows us to model the failure behavior of the part and estimate its reliability over time. To determine whether the used part has the potential for remanufacturing, we can examine the relationship between the predicted failure time and a failure-time threshold. This relationship is typically analyzed using a graphical representation, as shown in Figure 3.

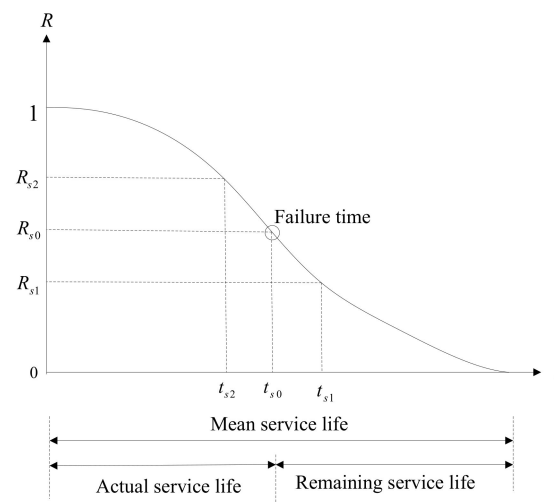


Figure 3. The relationship between failure time and reliability of used part.

1. If $t_{s0} \geq t_{s1}$, then $R(t_{s0}) \leq R(t_{s1})$; it is considered that the failure time of this used part has exceeded the threshold, which does not meet the requirements of the remanufacturing enterprise for its residual value, and it has no potential for remanufacturing.
2. If $t_{s2} \leq t_{s0} \leq t_{s1}$, then $R(t_{s1}) \leq R(t_{s0}) \leq R(t_{s2})$; it is considered that the failure time of this used part is within the required threshold, and its residual value meets the requirements of the remanufacturing enterprise. Therefore, this used part has the potential for remanufacturing.
3. If $t_{s0} \leq t_{s2}$, then $R(t_{s0}) \geq R(t_{s2})$; it is considered that the failure time of this used part is below the threshold, and its residual value exceeds the requirements of the remanufacturing enterprise. Therefore, the used part does not need to be remanufactured and can be re-used directly or with minor treatment.

Assuming that the quantified value of the failure characteristic of the used part is f , it can be quantified by $[t_{s2}, t_{s1}]$, as follows:

$$f = \frac{t_{s0} - t_{s2}}{t_{s1} - t_{s2}} \quad (8)$$

2.2. Evaluation of Technical Capability

After evaluating the failure degree of used parts and determining whether there is enough residual value left, it is crucial to assess the technical capability of remanufacturing enterprises. This evaluation ensures that the enterprise possesses the necessary expertise and resources to successfully undertake the remanufacturing processes. The technological feasibility of remanufacturing used parts primarily involves analyzing whether the functional capability of the used parts can be restored using advanced remanufacturing technology. This assessment evaluates the implementation feasibility of remanufacturing technology from three key aspects: ease of cleaning, ease of inspection, and ease of processing, as depicted in Figure 4. Since these three indicators are qualitative, this paper uses the

fuzzy evaluation method to quantify them by establishing membership functions between the qualitative indicators and the failure degree f of the used parts.

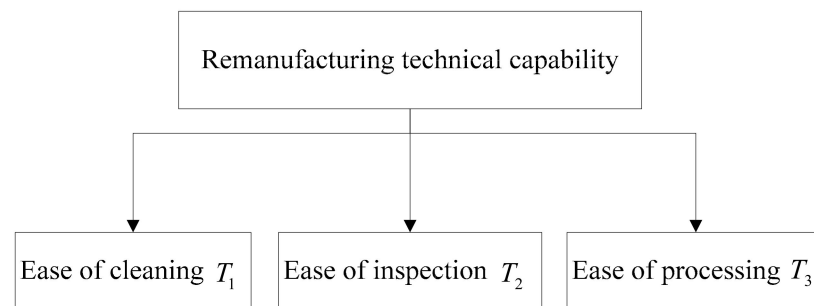


Figure 4. Indicator classification of technological feasibility.

2.2.1. Ease of Cleaning

The indicator of the ease of cleaning of remanufacturing technology has no relationship with the failure degree of the used part. It is mainly related to the amount of difficult-to-clean substances such as oil stains or rust on the surface. As it is difficult to measure the specific volume of these substances, the indicator of easy cleaning is evaluated by expert experience in this paper. According to the difficulty of cleaning, the indicator of the ease of cleaning is divided into 4 levels, expressed as $\Delta C \rightarrow$ [cannot be cleaned, difficult to clean, can be cleaned, easy to clean], and the corresponding evaluation values are $[\Delta C_1, \Delta C_2, \Delta C_3, \Delta C_4]$. The indicator of easy cleaning is judged by experts, and the result is $C = [C_1, C_2, C_3, C_4]$. Among them, $C_i = \frac{n_i}{N}$, $i = 1, 2, 3, 4$, n_i represents the number of experts who provide the i -th evaluation result, and N represents the total number of experts. After integrating the judgment result ΔC with the grade value of the ease of cleaning by experts, the quantitative evaluation value of the ease of cleaning of a used part can be obtained as follows:

$$T_1 = \begin{cases} \Delta C \times C^T & T_1 \geq \Delta T_1 \\ 0 & T_1 < \Delta T_1 \end{cases} \quad (9)$$

where T_1 is the quantitative value of the ease of cleaning and ΔT_1 is the threshold of ease of cleaning specified by the remanufacturing enterprise. The larger the value of T_1 , the easier it is to clean the used part. When the quantitative value of easy cleaning is less than the threshold set by the enterprise, it is indicated that the used part could not be cleaned, based on the enterprise's capability, so the quantitative value of easy cleaning is set to 0.

2.2.2. Ease of Inspection

The indicator of ease of inspection is mainly reflected in the length of the inspection time or the difficulty of collecting the detection data. When the used parts have excessive failure degree, such as severe corrosion, it is difficult for the inspection tool to effectively detect data like surface roughness. According to the inspection difficulty of the remanufacturing technology, the indicator of ease of inspection can be expressed by the fuzzy set $\Delta I \rightarrow$ [undetectable, difficult to detect, detectable, easy to detect], and its corresponding evaluation values are $[\Delta I_1, \Delta I_2, \Delta I_3, \Delta I_4]$. Then, the membership function between ease of inspection and failure degree can be established, as shown in Figure 5.

As shown in Figure 5, the x-axis represents the failure degree of the used part, while the y-axis represents the membership between failure degree and ease of inspection. $\{f_1, f_2, f_3, f_4\}$ are the failure degrees responding to $[\Delta I_4, \Delta I_3, \Delta I_2, \Delta I_1]$, which means a greater value of f and a lower value of ΔI_i . According to the previous quantified failure degree f and the scope of the failure degree $\{f_1, f_2, f_3, f_4\}$, the membership of failure degree f belonging to the evaluation value $[\Delta I_i, \Delta I_j]$ can be determined as $[\Delta I(f_i), \Delta I(f_j)]$ (i and j are adjacent integers), so the quantified value of the indicator of ease of inspection can be calculated as follows:

$$T_2 = \Delta I_i \times \Delta I(f_i) + \Delta I_j \times \Delta I(f_j) \quad (10)$$

This is assuming that the threshold of the indicator of ease of inspection set by the remanufacturing enterprise is ΔT_2 . When $T_2 \leq \Delta T_2$, it is demonstrated that the inspection capability of the enterprise is inadequate for collecting quality data from the used part. As a result, the remanufacturing processes of the used parts would be difficult due to a lack of support from the inspection; thus, these used parts are not suitable for remanufacturing.

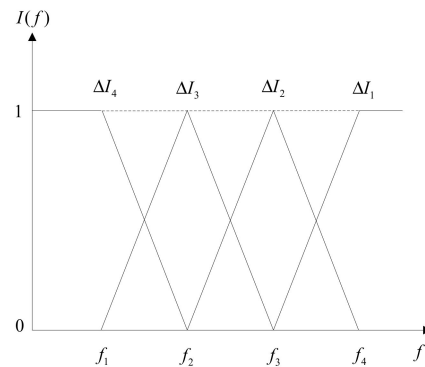


Figure 5. Membership function between inspection capability and failure degree of used part.

2.2.3. Ease of Processing

The indicator of ease of remanufacturing processing is closely related to the failure degree of the used part. Only when the failure degree is lower than a certain threshold can the functional ability of the used part be recovered by the processing capability of the enterprise. The indicator of ease of processing can be expressed by the fuzzy comment set of experts as $\Delta R \rightarrow [\text{unable to process, difficult to process, possible to process, easy to process}]$, and its corresponding evaluation values are $[\Delta R_1, \Delta R_2, \Delta R_3, \Delta R_4]$. The membership function of the indicator of easy processing and failure degree can be established, as shown in Figure 6 [26].

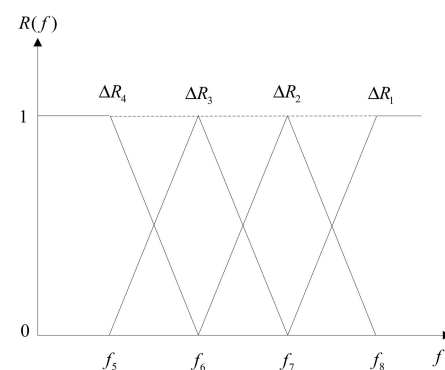


Figure 6. Membership function between processing capability and failure degree of used part.

Similarly, the x-axis represents the failure degree of the used part, while the y-axis represents the membership between failure degree and ease of processing. $\{f_5, f_6, f_7, f_8\}$ are the failure degrees responding to $[\Delta R_4, \Delta R_3, \Delta R_2, \Delta R_1]$, which means a greater value of f and a lower value of ΔR_i . According to the previous quantified failure degree f and the scope of the failure degree $\{f_5, f_6, f_7, f_8\}$, the membership of failure degree f belonging to the evaluation value $[\Delta R_i, \Delta R_j]$ can be determined as $[\Delta R(f_i), \Delta R(f_j)]$ (i and j are adjacent integers), so the quantified value of the indicator of ease of processing can be calculated as follows:

$$T_3 = \Delta R_i \times \Delta R(f_i) + \Delta R_j \times \Delta R(f_j) \quad (11)$$

This is assuming that the processing capability for the used part within the remanufacturing enterprise is set to ΔT_3 . When $T_3 \leq \Delta T_3$, it indicates that the enterprise's processing capabilities cannot recover the function of the used part, making it unsuitable for remanufacturing.

2.3. Evaluation of Economic Feasibility

After the evaluation of technological feasibility, if it is confirmed that it is viable to remanufacture the part with the existing technical capability of the enterprise, it is necessary to consider whether the economic benefits of the remanufacturing meet the expectations of the enterprise. When the economic benefits are lower than the enterprise's expectations, even if the enterprise has the technological capability for the remanufacturing, the enterprise does not desire to remanufacture. Therefore, sufficient economic benefit is an internal driving force for the enterprise to remanufacture used parts. Remanufacturing cost is the most direct indicator for measuring the economic benefits of the remanufacturing of a used part [27]. The economic benefits of remanufacturing are measured by comparing the cost of remanufacturing a used part with the cost of manufacturing a new one, in this paper. So, this work takes the comparison result of remanufacturing cost and manufacturing cost as the quantitative value of remanufacturing economic benefits, as follows.

$$EC = \begin{cases} 1 - \frac{C_r}{C_m} & \frac{C_r}{C_m} < 0.5 \\ 2 \times \frac{C_r}{C_m} - 1 & 0.5 \leq \frac{C_r}{C_m} \leq 1 \\ 0 & \frac{C_r}{C_m} > 1 \end{cases} \quad (12)$$

where EC represents the quantitative value of the economic benefits from the remanufacturing of a used part. C_r represents the total cost of the remanufacturing process of a used part, which includes remanufacturing labor costs, equipment depreciation costs, auxiliary material costs, transportation costs, and energy costs. C_m represents the total cost of manufacturing an identical new part. It is worth noting that for an independent third-party remanufacturer, the value of C_m is often not known. Therefore, 60% of the sale price for a new part represents the total cost of manufacturing, in this paper.

As shown in Equation (12), when the ratio of the cost of the remanufacturing to the cost of manufacturing is less than the 0.5 which is determined by the remanufacturing enterprise, it indicates that the cost of the remanufacturing process of the used part is low, and the economic benefits from remanufacturing meet the expectations of the remanufacturing enterprise; when the ratio is greater than 0.5, the economic benefits generated by the remanufacturing process decrease gradually. When the ratio increases to greater than 1, it means that the cost of the remanufacturing processes is even higher than the cost of manufacturing a new part, and the remanufacturing enterprise could not benefit from the remanufacturing. At this time, the quantitative value of remanufacturing economic benefits is set to 0.

2.4. Evaluation of Environmental Feasibility

The environmental feasibility of remanufacturing processes of the used part refers to the assessment of environmental impacts of pollutants developed during the entire remanufacturing process. Concerned about global pollution, governments have implemented strict requirements regarding the number of pollutants released in industrial production. Remanufacturing, as an industrial treatment method at the end of the product life cycle, will also be subject to the corresponding environmental protection requirements. Therefore, after ensuring that the remanufacturing technology of the enterprise is implementable and the remanufacturing economic benefit is satisfied, it is necessary to ensure the compliance of remanufacturing activities with governmental legislation and standards, during remanufacturing.

Though remanufacturing is far more environmentally friendly compared to manufacturing new parts, the remanufacturing process of used parts would inevitably release

various pollutants, such as waste oil, wastewater, and exhaust gas. As these polluted substances are difficult to accurately measure, and different industrial sectors may be subjected to different legislation and regulations, this work relies on the experts at the enterprise who have local knowledge about the legislations or regulations about the specific products, and a fuzzy judgment method is employed to quantitatively assess the environmental impact of the remanufacturing process. According to the pollutants generated in the remanufacturing processes, the environmental feasibility of the remanufacturing process can be divided into 4 levels: $\Delta E \rightarrow$ [poor environmental friendliness (the amount of pollutant just meets the regulation requirements), certain environmental friendliness (less than the amount for regulation requirements), good for environment (far less than the amount for regulation requirements), and benefit for environment (few pollutants)], and its corresponding evaluation values are $[\Delta E_1, \Delta E_2, \Delta E_3, \Delta E_4]$. The membership degree between the environmental feasibility of the remanufacturing process and the comment set is determined by expert judgment as $E_i = [E_1, E_2, E_3, E_4]$. Where $E_i = \frac{n_i}{N}$, $i = 1, 2, 3, 4$, n_i represents the number of experts who select the i -th evaluation result, and N represents the total number of experts participating in the evaluation.

The quantified value of the environmental feasibility of the remanufacturing process can be obtained by integrating the results of expert judgments with the evaluation value of the environmental level of the remanufacturing process, as follows:

$$EN = \begin{cases} \Delta E \times E_i^T & EN \geq \Delta EN \\ 0 & EN < \Delta EN \end{cases} \quad (13)$$

where EN represents the quantified value of the environmental feasibility of the remanufacturing process and ΔEN is the threshold value specified by the experts. It can be concluded from Equation (13) that when EN is greater than the threshold, it means that the pollutants released in the remanufacturing process meet the national requirements and the used part can be remanufactured; otherwise, it is considered that the pollutants released in the remanufacturing process of the used part exceed the national requirements. The enterprise needs to reconsider alternatives to reduce the pollutants developed during the remanufacturing process; otherwise, the used part is not suitable for remanufacturing in this enterprise.

3. Case Study

An engine blade (JT8D-217) is used as a case study to validate the effectiveness of the proposed model. The selection of the used blade for this case study is based on several criteria. Firstly, engines are widely used mechanical equipment, and the blade is a critical component in engines, whose failure can lead to significant performance degradation or complete engine failure. Secondly, the high manufacturing cost and complex technology involved in blade production make remanufacturing a cost-effective alternative. Thirdly, the availability of extensive operational data for these blades allows for a robust application of the proposed evaluation method. Finally, the failure characteristics of engine blades, including wear, cracks, and deformation, are representative of common issues encountered in other high-value, precision-engineered parts.

Using the proposed decision tree method, a remanufacturability analysis of the used blade is conducted based on the hierarchical quantification sequence of indicators: “failure degree $\rightarrow$ technical feasibility $\rightarrow$ economic feasibility $\rightarrow$ environmental feasibility”. The thresholds for each indicator are set by the enterprise, based on its processing capabilities and relevant standards. The specific process for each indicator is as follows. It is noteworthy that in actual production, if any indicator falls below the enterprise’s threshold, the remanufacturability evaluation process for the used part is immediately halted, to ensure evaluation efficiency.

3.1. Failure-Degree Evaluation of the Used Blade

3.1.1. Failure-Time Prediction of the Used Blade

The enterprise database for the JT8D-217 contains 20 sets of four-dimensional time series data, recording engine operating time and four engine parameters: high-pressure rotor speed, low-pressure rotor speed, exhaust temperature, and pressure ratio. The first 15 sets were used for training and the last 5 for testing. The inputs to the artificial neural network are the four engine parameters, and the output is the blade's failure time. Table 1 shows the corresponding input notations for the neural network. The neural network model uses a $4 \times 10 \times 1$ structure, with a learning rate of 0.01 and an error limit of 0.00001.

Table 1. Interpretation of Neural network input data.

Input Notation	Explanation
Operation condition data1	Speed of high-pressure rotor
Operation condition data2	Speed of low-pressure rotor
Operation condition data3	Exhaust temperature
Operation condition data4	Pressure ratio

The comparison between the predicted value and the actual value of the verification data is shown in Figure 7, and the difference between them (error) is shown in Table 2, which shows the relative predictive error of the network model is small, proving that this neural network model can effectively predict the failure time of used blades. This paper takes the 16# testing date as an example. According to the prediction by the neural network, the failure time of this used blade is 9751 h.

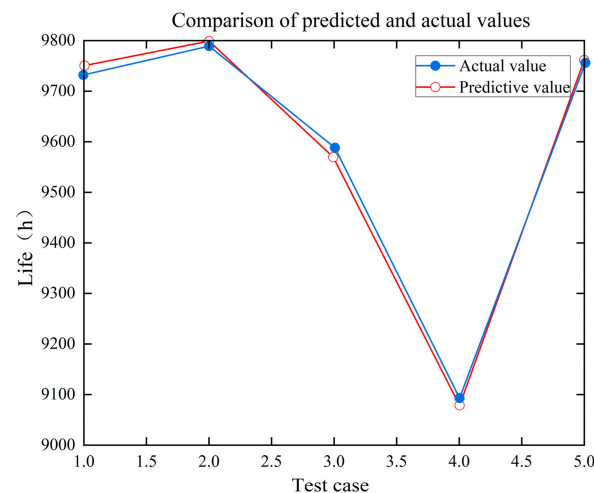


Figure 7. Comparison of predicted and actual values.

Table 2. Relative error of predicted value and actual value.

No.	Actual Value/(h)	Predictive Value/(h)	Relative Error/(%)
16	9734	9751	0.175%
17	9790	9797	0.072%
18	9589	9571	0.188%
19	9091	9082	0.099%
20	9758	9762	0.040%

3.1.2. Failure-Time Threshold of the Used Blade

To adopt Weibull distribution to measure the relationship between the failure time and the reliability of the used blades, it is necessary to estimate the parameters accurately.

The data used to estimate the Weibull parameters in this paper are shown in Table 3, where F means failure and S means no failure.

Table 3. Experimental data for used blades.

Serial Number	Running Time (h)	Status	Serial Number	Running Time (h)	Status	Serial Number	Running Time (h)	Status
1	7221	F	23	9199	F	45	11,454	S
2	7356	S	24	9239	S	46	11,563	F
3	7433	F	25	9358	S	47	11,661	S
4	7561	S	26	9413	F	48	11,736	S
5	7589	S	27	9592	S	49	11,910	F
6	7680	S	28	9601	S	50	12,024	F
7	7766	F	29	9662	F	51	12,109	S
8	7951	S	30	9754	S	52	12,203	F
9	7865	F	31	9801	F	53	12,331	S
10	8025	S	32	9814	F	54	12,441	F
11	8207	S	33	9874	S	55	12,519	S
12	8234	F	34	9937	S	56	12,763	S
13	8366	F	35	10,023	S	57	12,866	F
14	8471	S	35	10,237	F	58	12,975	S
15	8688	F	37	10,563	S	59	13,077	S
16	8713	S	38	10,758	F	60	13,286	F
17	8751	S	39	10,885	F	61	13,436	F
18	8809	S	40	10,920	F	62	13,568	F
19	8815	F	41	11,097	S	63	13,689	S
20	8820	F	42	11,188	F	64	13,710	F
21	9052	F	43	11,259	S	65	14,105	S
22	9125	S	44	11,351	F			

To estimate the parameters of Weibull distribution accurately, it is necessary to remove the censored data in Table 3 and substitute the effective failure data into Equations (3)–(7) to obtain the corresponding fitted line plot. As shown in Figure 8, the obtained parameters are $A = 6.2348$ and $B = -58.8083$, and the fitted line is $y = 6.2348x - 58.8083$; then, the scale parameter and shape parameter in the Weibull distribution are $\eta = 12484.2004$ and $\beta = 6.2348$. After substituting the above two parameters into Equation (2), the reliability distribution function of the used blades can be obtained as follows:

$$R(t_s) = \exp \left[- \left(\frac{t_s}{12484.2004} \right)^{6.2348} \right] \quad (14)$$

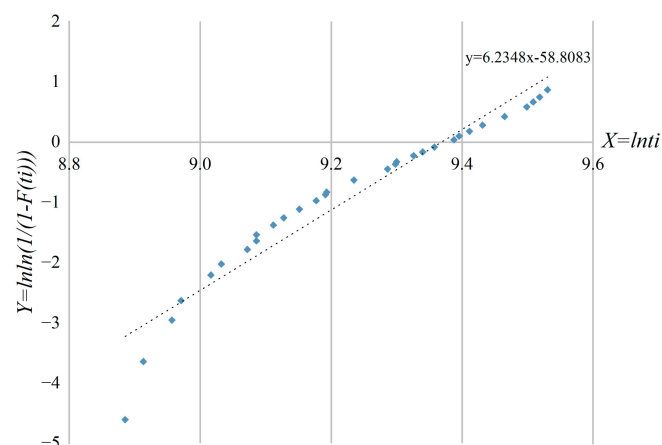


Figure 8. The simulation diagram of the least-squares method gained by the mean rank method.

Due to the limitation of remanufacturing capability, the acceptable reliability range of the remanufacturing enterprise is set to (0.52, 0.96). The failure-time range satisfying the reliability range can be obtained as (7474 h, 11,662 h) by substituting the reliability constraint range into the reliability distribution function.

3.1.3. Evaluation Result of Failure Degree

After the actual failure time and the failure-time threshold are obtained, the failure degree of the used blade can be evaluated by its numerical size relationship. When the failure time of a used blade is within $[t_{s2}, t_{s1}] = [7474h, 11662h]$, it is considered that its reliability meets the requirements of the enterprise and it has the potential for remanufacturing. When the failure time of a used blade is less than 7474 h, its reliability is more than 0.96, and it can be re-used after minor treatment. When the failure time of a used blade is more than 11,662 h, its reliability is lower than the acceptable range of the remanufacturing capability of the enterprise, so it is not suitable for remanufacturing, and it will be recycled. As the predicted failure time of the cited used blade is $t_{s0} = 9368h$, which is within the constrained failure-time range, it has the potential for remanufacturing.

The failure degree f of the used blade is shown as follows:

$$f = \frac{t_{s0} - t_{s2}}{t_{s1} - t_{s2}} = 0.452$$

3.2. Evaluation Result of Technical Feasibility

The technical feasibility indicators include ease of cleaning, ease of disassembly, and ease of processing. The quantification of these three indicators for the used blade is as follows:

- a. The ease-of-cleaning indicator is quantified using the expert judgment method. The difficulty level for cleaning is $\Delta C = [0.1, 0.4, 0.7, 1.0]$, the result judged by experts is $C = [0.0, 0.1, 0.8, 0.1]$, and the threshold of enterprise is $\Delta T_1 = 0.65$. According to Equation (9):

$$\begin{aligned} T_1 &= \Delta C \times C^T \\ &= [0.1, 0.4, 0.7, 1.0] \times [0.0, 0.1, 0.8, 0.1]^T \\ &= 0.7 > 0.65 \end{aligned}$$

- b. The ease-of-inspection indicator and ease-of-processing indicator are quantified using a fuzzy evaluation model. Taking the ease-of-inspection indicator as an example, the failure grade interval is $f = [0.45, 0.60, 0.75, 0.90]$, corresponding to the inspection response interval $\Delta I = [0.9, 0.7, 0.5, 0.3]$, and the threshold of enterprise is $\Delta T_2 = 0.600$. According to Equation (10),

$$\begin{aligned} T_2 &= \Delta I_i \times \Delta I(f_i) + \Delta I_j \times \Delta I(f_j) \\ &= 0.9 \times \frac{0.6-0.452}{0.6-0.45} + 0.7 \times \frac{0.452-0.45}{0.6-0.45} = 0.8973 > 0.600 \end{aligned}$$

The evaluation result of technical feasibility is shown in Table 4.

Table 4. Evaluation result of technological feasibility.

Indicator	Evaluation Process	Evaluation Result
Ease of cleaning	$\Delta C = [0.1, 0.4, 0.7, 1]$ $C = [0, 0.1, 0.8, 0.1]$ $T_1 = 0.7$ $\Delta T_1 = 0.65$	The used blade is easy to clean and the debris on it can be removed.
Ease of inspection	$\Delta I_4 \sim \Delta I_1 = [0.9, 0.7, 0.5, 0.3]$ $f_1 \sim f_4 = [0.45, 0.6, 0.75, 0.9]$ $T_2 = 0.9 \times 0.987 + 0.7 \times 0.013 = 0.893$ $\Delta T_2 = 0.600$	The used blade is easy to process by the remanufacturing technologies of the enterprise.
Ease of processing	$\Delta R_4 \sim \Delta R_1 = [0.9, 0.7, 0.5, 0.3]$ $f_5 \sim f_8 = [0.4, 0.6, 0.8, 1]$ $T_3 = 0.9 \times 0.74 + 0.7 \times 0.26 = 0.848$ $\Delta T_3 = 0.545$	Various data about the condition of the used blade are easy to collect because of the detection capability of the remanufacturing enterprise.

3.3. Evaluation Result of Economic Feasibility

As the original manufacturing data of the used blade involve commercial secrets, it is difficult to obtain its manufacturing cost data. The sale price of the same new blade can be searched as being USD 409,170; therefore, 60% of the sale price, which is $C_m = 245,500$ USD, represents the cost of manufacturing the new blade. The remanufacturing cost of the used blade is predicted to be $C_r = 73,100$ USD, and the threshold of enterprise is $\Delta EC = 0.5$. According to Equation (12),

$$\begin{aligned}\frac{C_r}{C_m} &= 0.298 < 0.5 \\ EC &= 1 - 0.298 = 0.702\end{aligned}$$

The economic benefits developed by remanufacturing the used blade can meet the expectation of the enterprise, and it is worth remanufacturing.

3.4. Evaluation Result of Environmental Feasibility

Blades are precision products, and remanufacturing processes are relative environmental friends, with significantly fewer pollutants released compared to those in the manufacturing of new products. In this paper, the quantitative value of the expert evaluation set of environment feasibility of the remanufacturing process is $\Delta E = [0, 0.3, 0.6, 0.9]$, the membership degree of expert judgment is $E = [0, 0.1, 0.15, 0.75]$, and the threshold $\Delta EN = 0.700$. According to Equation (13),

$$\begin{aligned}T_1 &= \Delta E \times E^T \\ &= [0, 0.3, 0.6, 0.9] \times [0, 0.1, 0.15, 0.75]^T \\ &= 0.795 > 0.700\end{aligned}$$

The quantitative value indicates that the pollutant emissions developed in the remanufacturing process of the used blade are under the amount set by regulation, and the remanufacturing process is environmentally friendly.

3.5. Remanufacturability Evaluation Result

The evaluation result of the remanufacturability of the used blade calculated by the method proposed in this paper is shown in Table 5. The evaluation result shows that the failure characteristic of the used blade is within the requirements of the remanufacturing enterprise, and it has potential for remanufacturing. From the perspective of the remanufacturing capability of the enterprise, the used blade can be cleaned, processed, and detected by the remanufacturing technology of the enterprise, and the economic benefits developed by the remanufacturing process of the used blade meet the expectations of the enterprise. Moreover, the pollutant emissions from the remanufacturing process of the used blade meet the specified standards, which makes it clear that the used blade is suitable for remanufacturing. After the comparative analysis with the actual situation of remanufacturing enterprises, the evaluation result is consistent with the actual situation, which verifies the effectiveness of the evaluation results.

Table 5. Remanufacturability evaluation result of the used blade.

Indicator	Notation	Evaluation Value	Threshold
Failure degree	f	0.452	[0.38, 0.55]
Technical feasibility	T_1	0.70	0.65
	T_2	0.894	0.600
	T_3	0.848	0.545
Economic feasibility	EC	0.702	0.5
Environmental feasibility	EN	0.795	0.700

As shown in Table 5, the remanufacturability evaluation based on the decision tree model, which follows a preset sequence of indicators, shows that the quantification values for failure grade, technical feasibility, economic feasibility, and environmental feasibility of the used blade meet the corresponding enterprise thresholds. Therefore, this used blade can be remanufactured by the enterprise. It should be noted that if any intermediate indicator fails to meet the enterprise's threshold during the decision-making process, the process is immediately halted, indicating that the used part cannot be remanufactured by the enterprise. This interruption mechanism gives the decision tree model an efficiency advantage over traditional weighted methods in remanufacturability evaluation.

4. Conclusions and Future Work

This study proposes a remanufacturability evaluation method for used parts, based on decision tree analysis. By implementing hierarchical decision-making and quantification of evaluation targets, this method improves decision-making efficiency and adaptability, compared to traditional evaluation models. For indicator quantification, the method addresses the uncertainty in the quality of used parts at the time of recovery by using artificial neural networks and the Weibull distribution model to predict the remaining value of used parts, thereby quantifying the failure degree. To account for the uncertainty in enterprise processing capabilities, the method uses a sequence of indicators—technical feasibility, economic feasibility, and environmental feasibility—quantified through expert judgment and fuzzy analysis. The practicality of the proposed method is validated through a case study on the remanufacturing of used blades.

In general, the remanufacturability evaluation method for used parts based on decision tree analysis offers significant advantages in efficiency and practicality compared to traditional weighted-analysis methods, where all indicators are considered on the same level. In future research, technologies such as big data and the Internet of Things (IoT) can be integrated. By utilizing dynamic data on enterprise equipment, personnel, and logistics, real-time adjustments to enterprise standards (such as indicator thresholds) can be made, aiding in remanufacturing production scheduling. Additionally, by linking multiple remanufacturing enterprise databases, real-time adjustments to remanufacturability evaluation results can be made. This enables the creation of a remanufacturability evaluation system across multiple enterprises, evolving the decision-making process from “can the current enterprise remanufacture this part?” to “which enterprises can remanufacture this part?” and ultimately to “which enterprise is best suited to remanufacture this part?” This approach maximizes the residual value of used parts and enhances resource utilization efficiency. However, it is worth noting that the diverse data formats introduced by big data and IoT from various enterprises and equipment pose challenges with regard to the efficiency and accuracy of using the decision tree model for remanufacturability evaluation of used parts. Future research will need to focus on how to quickly filter, match, and standardize data formats during the evaluation and decision-making process.

Author Contributions: Software, Z.Y.; formal analysis, Y.C.; resources, J.H.; writing—original draft, S.C.; writing—review and editing, J.H. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Wuhan Education Bureau Foundation Project [Grant No. 52075396], and the Guiding Project of the Scientific Research Plan of Hubei Provincial Department of Education (B2022605). These financial contributions are gratefully acknowledged.

Data Availability Statement: All data are contained within the article.

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

References

1. Peng, H.; Jiang, Z.; Wang, H. Research on ecological efficiency for the remanufacturing process considering optimization and evaluation. *Processes* **2019**, *7*, 567. [[CrossRef](#)]

2. Gong, Q.; Li, J.; Jiang, Z.; Wang, Y. A hierarchical integration scheduling method for flexible job shop with green lot splitting. *Eng. Appl. Artif. Intell.* **2024**, *129*, 107595. [\[CrossRef\]](#)
3. Du, Y.; Zheng, Y.; Wu, G.; Tang, Y. Decision-making method of heavy-duty machine tool remanufacturing based on AHP-entropy weight and extension theory. *J. Clean. Prod.* **2020**, *252*, 119607. [\[CrossRef\]](#)
4. Fang, H.C.; Ong, S.K.; Nee, A.Y.C. An integrated approach for product remanufacturing assessment and planning. *Procedia CIRP* **2016**, *40*, 262–267. [\[CrossRef\]](#)
5. Fang, H.C.; Ong, S.K.; Nee, A.Y.C. Product remanufacturability assessment based on design information. *Procedia CIRP* **2014**, *15*, 195–200. [\[CrossRef\]](#)
6. Zhang, X.; Ao, X.; Cai, W.; Jiang, Z.; Zhang, H. A sustainability evaluation method integrating the energy, economic and environment in remanufacturing systems. *J. Clean. Prod.* **2019**, *239*, 118100. [\[CrossRef\]](#)
7. Liu, Q.; Shang, Z.; Ding, K.; Guo, L.; Zhang, L. Multi-process routes based remanufacturability assessment and associated application on production decision. *J. Clean. Prod.* **2019**, *240*, 118114. [\[CrossRef\]](#)
8. Goodall, P.; Rosamond, E.; Harding, J. A review of the state of the art in tools and techniques used to evaluate remanufacturing feasibility. *J. Clean. Prod.* **2014**, *81*, 1–15. [\[CrossRef\]](#)
9. San, G.S. Analyzing Remanufacturability of Mobile Phones using DEMATEL Approach. *J. Tek. Ind.* **2019**, *21*, 33–42.
10. Du, Y.; Cao, H.; Liu, F.; Li, C.; Chen, X. An integrated method for evaluating the remanufacturability of used machine tool. *J. Clean. Prod.* **2012**, *20*, 82–91. [\[CrossRef\]](#)
11. Ding, Z.; Jiang, Z.; Zhang, H.; Cai, W.; Liu, Y. An integrated decision-making method for selecting machine tool guideways considering remanufacturability. *Int. J. Comput. Integr. Manuf.* **2020**, *33*, 686–700. [\[CrossRef\]](#)
12. Fang, H.C.; Ong, S.K.; Nee, A.Y.C. Product remanufacturability assessment and implementation based on design features. *Procedia CIRP* **2015**, *26*, 571–576. [\[CrossRef\]](#)
13. Karaulova, T.; Bashkite, V. Decision-making framework for used industrial equipment. *Eng. Econ.* **2016**, *27*, 23–31. [\[CrossRef\]](#)
14. Omwando, T.A.; Otieno, W.A.; Farahani, S.; Ross, A.D. A bi-level fuzzy analytical decision support tool for assessing product remanufacturability. *J. Clean. Prod.* **2018**, *174*, 1534–1549. [\[CrossRef\]](#)
15. Zhang, X.; Wang, Y.; Xiang, Q.; Zhang, H.; Jiang, Z. Remanufacturability evaluation method and application for used engineering machinery parts based on fuzzy-EAHP. *J. Manuf. Syst.* **2020**, *57*, 133–147. [\[CrossRef\]](#)
16. Shi, J.; Li, T.; Liu, Z. A three-dimensional method for evaluating the remanufacturability of used engines. *Int. J. Sustain. Manuf.* **2015**, *3*, 363–388. [\[CrossRef\]](#)
17. Lahrou, Y.; Brissaud, D. A technical assessment of product/component re-manufacturability for additive remanufacturing. *Procedia CIRP* **2018**, *69*, 142–147. [\[CrossRef\]](#)
18. Ling, T.; He, Y. The remanufacturing evaluation for feasibility and comprehensive benefit of retired grinding machine. *PLoS ONE* **2020**, *15*, e0234603. [\[CrossRef\]](#)
19. Shi, J.; Wang, Y.; Cheng, J. Remanufacturability evaluation for waste mechanical product from technical point of view. In Proceedings of the 2017 Global Conference on Mechanics and Civil Engineering (GCMCE 2017), Guangzhou, China, 24–25 June 2017; Atlantis Press: Amsterdam, The Netherlands, 2017; pp. 401–404.
20. Zhang, X.; Tang, Y.; Zhang, H.; Jiang, Z.; Cai, W. Remanufacturability evaluation of end-of-life products considering technology, economy and environment: A review. *Sci. Total Environ.* **2021**, *764*, 142922. [\[CrossRef\]](#)
21. James, A.T.; Kumar, G.; Arora, A.; Padhi, S. Development of a design based remanufacturability index for automobile systems. *Proc. Inst. Mech. Eng. Part D J. Automob. Eng.* **2021**, *235*, 3138–3156. [\[CrossRef\]](#)
22. He, Y.; Hao, C.; Li, Y.; Lim, M.K.; Wang, Y. A failure feature identification method for adaptive remanufacturing. *Procedia CIRP* **2020**, *90*, 552–556. [\[CrossRef\]](#)
23. Huang, W.; Jiang, Z.; Wang, T.; Wang, Y.; Hu, X. Remanufacturing scheme design for used parts based on incomplete information reconstruction. *Chin. J. Mech. Eng.* **2020**, *33*, 1–41. [\[CrossRef\]](#)
24. Wang, H.; Jiang, Z.; Zhang, X.; Wang, Y.; Wang, Y. A fault feature characterization based method for remanufacturing process planning optimization. *J. Clean. Prod.* **2017**, *161*, 708–719. [\[CrossRef\]](#)
25. Du, Y.; Wu, G.; Tang, Y.; Cao, H.; Liu, S. Reliability allocation method for remanufactured machine tools based on fuzzy evaluation importance and failure influence. *Int. J. Precis. Eng. Manuf. Green Technol.* **2021**, *8*, 1617–1628. [\[CrossRef\]](#)
26. Otieno, W.; Chen, P.H.; Chen, K.J. Assessing the remanufacturability of office furniture: A multi-criteria decision making approach. *J. Remanuf.* **2020**, *14*, 1–16. [\[CrossRef\]](#)
27. Jiang, Z.; Ding, Z.; Liu, Y.; Wang, Y.; Hu, X.; Yang, Y. A data-driven based decomposition–integration method for remanufacturing cost prediction of end-of-life products. *Robot. Comput. Integr. Manuf.* **2020**, *61*, 101838. [\[CrossRef\]](#)

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.