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An Intelligent Design Method for Product Remanufacturing Based on Remanufacturing Information Reuse

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Abstract

Design for remanufacturing (DfRem) is a green design mode that ensures good remanufacturability at the end-of-life (EOL) of the product. However, the diversity of service environments and operating modes makes it difficult to generate accurate DfRem solutions for the smooth implementation of remanufacturing. Moreover, the historical remanufacturing process contains a great deal of information conducive to DfRem. It will greatly enhance the efficiency and accuracy of remanufacturing design by feeding effective remanufacturing information back into the product design process. Unfortunately, there is a lack of direct correlation between them, which prevents remanufacturing information from effectively guiding DfRem. To improve the accuracy of DfRem solutions and the utilization rate of remanufacturing information, an intelligent design method for product remanufacturing based on remanufacturing information reuse is proposed. Firstly, rough set theory (RST) is used to identify key remanufacturability demand, and the quality function development (QFD) is used to establish a relationship between remanufacturability demand and engineering characteristics, which can accurately obtain the design objectives. Then, the correlation between remanufacturability demand, remanufacturing information, and DfRem parameters is analyzed, and the ontology technology is applied to construct the DfRem knowledge by ingratiating remanufacturing information. In addition, case-based reasoning (CBR) is applied to search for design cases from DfRem knowledge that best match the design objectives, and gray relational analysis (GRA) is used to calculate the similarity between design knowledge. Finally, the feasibility of the method is verified by taking an ordinary lathe as an example. This method has been implemented as a DfRem interface application using Visual Studio 2022 and Microsoft SQL Server 2022, and the research results indicate that this design method can accurately generate a reasonable DfRem scheme.

Keywords: remanufacturing information; intelligent design; remanufacturability; knowledge; CBR

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1. Introduction

The principle of design for remanufacturing is to consider the remanufacturability in the product development stage and make the products have good remanufacturability at the end of their life [1], which can achieve the goals of maximizing the utilization of waste resources and minimizing environmental pollution and manufacturing costs. DfRem not

only determines the product remanufacturability, but also directly affects the successful implementation of remanufacturing.

Since DfRem directly affects the effective remanufacturing process of used products, many scholars have studied DfRem [2], which mainly includes decision-making of DfRem scheme and DfRem scheme optimization and generation. DfRem is a design method to improve product remanufacturability; for example, Jiang et al. [3] applied fuzzy nonlinear regression to divide the relationship between customer demand and remanufacturing design parameters as well as the fuzzy relationship between remanufacturing design parameters. Zwolinski et al. [4] identified eight categories of design guidelines by creating a remanufacturable product outline document and encapsulating the knowledge related to remanufacturing conditions and remanufactured product characteristics. Yueksel [5] proposed the quality function deployment (QFD) methodology in the design of products for remanufacture, which can obtain the accurate importance of remanufacturing design elements. Zhang et al. [6] constructed a product failure mode recursive transfer model and used multicolor ensemble theory to mathematically express and derive the model, which provides support for the remanufacturing design process. The abovementioned works have studied the DfRem method from the aspects of customer demand, failure mode, and remanufactured product characteristics, which helps to generate DfRem solutions in a more comprehensive and reasonable way, but the above studies have not conducted DfRem from the perspective of product remanufacturability, and it is not possible to judge whether the DfRem solution can enable the product to be remanufactured smoothly at the end of its life.

Therefore, it is necessary to consider the remanufacturability of products at the design stage, allowing for the smooth implementation of remanufacturing at the end of the product's life. There are scholars who have conducted relevant studies. For example, Gong et al. [7] integrated the remanufacturing characteristics of the product into all aspects of the design and applied hesitant fuzzy sets to make decisions on design schemes. Yang et al. [8] enhanced the material selection process during the early design phase to facilitate the remanufacturing of automotive parts and implemented a multi-criteria decision-making technique to assess the performance of potential materials. Xiao et al. [9] proposed a master–slave association optimization method to achieve synergistic optimization between product architecture and eco-upgrade design, which can prolong the product's lifecycle and improve the usage efficiency. The above studies have considered the factors affecting the remanufacturability at the design stage, including material, energy, and environmental factors, which make it easier for product remanufacturing at the end of life, but these studies only considered certain characteristics of product remanufacturability, resulting in difficulties in achieving other remanufacturability characteristics. In addition, as the generated DfRem parameters have not been verified in practice, it is impossible to judge whether the DfRem solution can successfully guide product remanufacturing at the end of life, which will create uncertainty for the remanufacturing of used products.

Moreover, the remanufacturing process contains a large amount of remanufacturing information, which can reflect the difficulty of product remanufacturing in the EOL. Since remanufacturing information has already been verified in actual processes, it can reflect whether product remanufacturability is good. Therefore, it is necessary to reuse historical remanufacturing information for DfRem and feed the valid remanufacturing information back into the DfRem process to solve the DfRem solution. Currently, there have been studies on remanufacturing information feedback to support DfRem. For example, Yao et al. [10] presented some concepts related to remanufacturing and remanufactured product design based on the complete remanufacturing process and proposed the inclusion of remanufacturability research in the product design stage and qualitative design principles. Haziri et al. [11] proposed a framework for the implementation of remanufacturing infor-

mation feedback to product design and described a framework for the practical application of the process. The abovementioned scholars have studied the acquisition of effective information from the remanufacturing process and its feedback to the DfRem process, which is conducive to accurately obtaining design parameters that can satisfy remanufacturability as well as contributing to the accurate implementation of EOL remanufacturing.

However, these studies are still in the conceptual design stage and have not established a mapping relationship between remanufacturing information and DfRem parameters. Remanufacturing information includes disassembly information, cleaning information, reprocessing information, and upgrading information, which are all related to product design information. For example, disassembly information is related to information on the connection structure of the product, cleaning information is related to information on the surface structure and appearance structure, reprocessing information is related to information on the material properties, and upgrading information is related to information on the module structure of the product, etc. The remanufacturing information is complex and heterogeneous, which makes it difficult to represent, organize, and reuse remanufacturing knowledge in a complete way with an effective method. Therefore, it is a critical step in accurately implementing DfRem to effectively map and integrate remanufacturing information and there are many methods to achieve this, such as the matter-element method [12,13], Petri nets [14,15], ontology technology [16–18], etc. These methods can integrate information and characterize the relationships between different pieces of information. However, the matter-element method is suitable for modeling contradictory problems and uncertain phenomena, while Petri nets are suitable for modeling dynamic processes. Neither are suitable for modeling domain knowledge or describing semantic relationships between internal information, and neither can perform accurate knowledge inference. The ontology technology is a standardized and formalized description of domain knowledge. By clearly defining “concepts”, “relationships”, “attributes”, and “axioms”, it enables the sharing and reuse of domain knowledge. Therefore, the ontology technology is capable of modeling remanufacturing information to obtain effective DfRem knowledge.

Nevertheless, the DfRem is a complex process that includes conceptual design, structural design, process design, and other stages. Traditional design methods are time-consuming and inefficient. Therefore, intelligent technology needs to be used to generate design solutions. There have been many studies related to intelligent design; for example, Liu et al. [19] introduced an intelligent generative design framework for industrial products. This method facilitates the swift creation of nearly optimal design solutions, which can then be refined further. Bai et al. [20] introduced an intelligent conceptual design method for railway bridges using graph neural networks, enhancing design efficiency. Zhang et al. [21] applied the non-parametric machine learning and intelligent recognition algorithms to generate the product appearance design scheme, which can improve the accuracy of the design scheme. Although these intelligent design methods improve design efficiency and accuracy, they do not fully utilize design knowledge to generate design solutions and cannot accurately explain the intrinsic relationship between design requirements and design solutions. Furthermore, the robustness of design solutions still has shortcomings. CBR is an intelligent method for solving new problems based on solutions to similar problems in the past. This method mirrors human thought processes, swiftly identifying the most relevant past examples while also assessing and refining them. In addition, new cases are added to the case database, enhancing the success rate of retrieval. Case-based reasoning (CBR) technology has found extensive application in the field of intelligent manufacturing, such as in sustainable rural development [22], question answering [23], urban rail transportation [24], etc. CBR is extensively utilized in product design, where past similar solutions are adapted to create design solutions for new, unknown design challenges. Therefore, CBR efficiently

retrieves suitable DfRem schemas from existing DfRem databases and remanufacturing processes, ensuring quick and accurate results. Unfortunately, there are few studies on knowledge reuse for generating DfRem solutions based on CBR. Ke et al. [25] applied CBR to generate the DfRem scheme, which improved design efficiency. However, this study did not make full use of remanufacturing knowledge to generate design solutions.

Furthermore, before conducting design knowledge retrieval, it is also necessary to define the DfRem objectives to ensure the accuracy of the resulting design solutions. Remanufacturability demands determine design objectives, and it is an essential step to accurately capture design objectives by extracting the key demands from a vast amount of disorganized information. Currently, numerous techniques exist for analyzing demand information, such as clustering analysis, support vector machines, and neural networks. These methods can efficiently process unstructured demand data, but they are highly dependent on data quality. Furthermore, these approaches lack interpretability regarding their analytical principles, making it difficult to demonstrate the correlation between demand characteristics and products. Rough set theory (RST) is a mathematical approach for handling imprecise, uncertain, and incomplete data [26]. It treats demand as decision systems, using property reduction to eliminate redundant conditions while retaining the most critical demand characteristics for decision-making, thereby identifying core demand. Remanufacturability demands are often expressed colloquially by customers and cannot serve as engineering design objectives to guide product manufacturing. Therefore, key demands need to be converted into engineering terms to make them easier for technical personnel to understand. Quality function deployment (QFD) is a systematic product design and quality management approach centered on customer demand [27]. It employs structured tools to translate ambiguous customer requirements into quantifiable, actionable engineering specifications, which can effectively convert remanufacturability demand into engineering design objectives. Therefore, RST and QFD were jointly employed in this study to extract key demands and convert them into engineering features.

To improve the accuracy of DfRem solutions and the utilization rate of remanufacturing information, this paper proposes an intelligent design method for product remanufacturing based on remanufacturing information reuse. The novelties of this paper lie in its following attributes: (1) analysis of the correlation between information on remanufacturability demand, remanufacturing process, and DfRem scheme, and construction of a remanufacturing information model based on ontology technology; (2) proposal to formulate the DfRem scheme solution generation method based on CBR, which is conducive to the designers to formulate the DfRem scheme reasonably and effectively; (3) a DfRem interface application was developed to improve the operability and design efficiency. The remainder of this paper is structured as follows. Section 2 proposes the intelligent DfRem framework based on remanufacturing information reuse, which contains remanufacturability demand analysis, and the generation of DfRem solutions. Section 3 analyses remanufacturability demand and identifies key design objectives. Section 4 proposes a DfRem solution generation method based on CBR. Section 5 validates the method with a DfRem case for a lathe, and Section 6 draws conclusions for this study.

2. Intelligent DfRem Framework Based on Remanufacturing Information Reuse

Based on the function–behavior–structure (FBS) theory, product design can be divided into functional domain, behavioral domain, and structural domain. The functional domain includes planning product functions to satisfy the customer's requirements, the behavioral domain includes the method and ways to realize the function, and the structural domain encompasses the set of information of the components to realize the behavior. DfRem

considers the remanufacturability demand of the product in the customer domain and generates product design parameters in the structural domain, such as the structural parameters, material parameters, and performance parameters of components. Remanufacturing information is integrated into modeling based on ontology technology to form reusable design knowledge.

The DfRem case reasoning process involves calculating the matching degree between the remanufacturability demand and the remanufacturing information; when the matching degree exceeds the set threshold, the design knowledge will be outputted and fed back to the physical domain as the new product design parameters. Since the original design parameters of the used product have been verified through the remanufacturing process, and have satisfied the remanufacturability demand, these can avoid blind remanufacturing and improve the remanufacturing efficiency of the used product. In summary, the DfRem process mainly consists of two parts: remanufacturability demand analysis and DfRem scheme generation. The intelligent DfRem framework is shown in Figure 1.

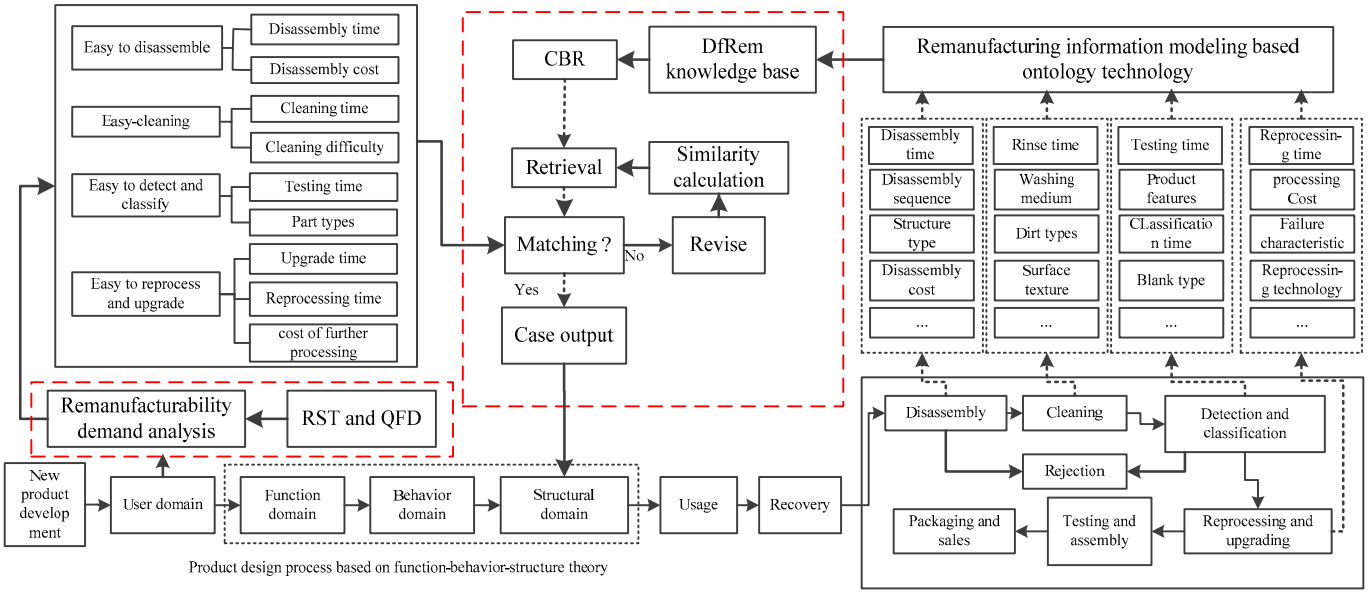


Figure 1. The intelligent DfRem framework based on remanufacturing information reuse.

3. Remanufacturability Demand Analysis

Remanufacturability demands refer to the remanufacturing characteristic that customers or manufacturers require for new products, so as to facilitate the smooth implementation of remanufacturing in the EOL stage of the products. The main remanufacturability demands are easy disassembly, easy cleaning, easy sorting, easy processing, and easy upgrading. Since the description of remanufacturaibily demand by customers is colloquial and ambiguous, which is not conducive to the designers' extraction of DfRem objectives, there is a need for a unified and standardized description of remanufacturaibily demand. Rough set theory is used to approximate the demand information and calculate the remanufacturability demand importance to ensure the accurate extraction of key DfRem objectives; moreover, the QFD is applied to convert remanufacturability demand into engineering features, which make the design goals easier for engineers to understand.

Remanufacturability demands mainly include easy disassembly, easy cleaning, easy testing, easy processing, and easy upgrading. The types of remanufacturability demands and their corresponding engineering descriptions are shown in Table 1.

Table 1. Key remanufacturability demands.

Symbolic	Remanufacturability Demand	Engineering Description
r_1	Easy disassembly	The difficulty of disassembly can be reflected in the time required to disassemble used products.
r_2	Easy cleaning	The common cleaning methods used by remanufacturers include blowing, brushing, scrubbing, baking, washing, chemical detergent spraying, ultrasonic cleaning, and several others.
r_3	Easy classifying	Used products need to be inspected to classify the parts, and the ease of recognizing the type of features of the parts determines the classification time, so the difficulty of classification is judged by the length of the classification time.
r_4	Easy reprocessing	The ease of reprocessing can be measured by the processing time, the complexity of the process, and the cost of processing.
r_5	Easy upgrading	The structure of the product, the degree of modularity and the reserved interfaces determine how difficult it is to upgrade the product.
r_6	Low remanufacturing cost	The remanufacturing cost is the sum of the costs required to remanufacture the used product.
r_7	Short remanufacturing time	The remanufacturing time is the sum of the time spent on remanufacturing the used product.
...	...	...

3.1. Importance Analysis of Remanufacturability Demand

The remanufacturability demand information is extensive and intricate, making it imperative to analyze, simplify, and identify the core demand, the specific process is as follows:

(1) Analyzing examples of historical remanufactured products from manufacturers and evaluating the satisfaction of design solutions using the expert scoring method.

(2) Constructing a decision table for remanufacturability demand $T = (U, R, V, f)$, where $U = (u_1, u_2, \ldots, u_m)$ is a non-empty finite object representing the sample domain of remanufactured product instances and u_m is the m-th historical remanufactured product instance. $R = S \cup V$, $R = (r_1, r_2, \ldots, r_i, \ldots, r_n)$ is the set of remanufacturability demand condition attributes and r_i denotes the i-th remanufacturability demand condition attribute. $S = (s_1, s_2, s_3)$ is the set of decision attributes used to determine the satisfaction of DfRem options. s_1 indicates that the DfRem scheme is highly satisfactory, s_2 indicates that the design scheme is satisfactory, and s_3 indicates that the design program is unsatisfactory. $V = (v_1, v_2, v_3, v_4)$ denotes the set of attribute value domains, and the conditional attributes of the elements in R can be expressed in terms of importance by V. v_1 indicates very important, v_2 indicates important, v_3 indicates average, and v_4 indicates not important. $f : U \times R^{\rightarrow} V$ denotes the value of the function between U, R, and V, i.e., $u_m \in U$, $r_n \in R$, $f(u_m, r_n) \in V$.

(3) Attribute approximate simplicity. Assuming that V is a set of conditional attributes with an equivalence relation, then $ind(R)$ is an equivalence set of conditional attributes, which can partition domains through equivalence classes, quantify the discriminating power of attributes over objects, and handle uncertainty and attribute reduction. If $ind(R) = ind(R - \{r\})$, then r in the conditional attribute R is a redundant attribute that can be simplified.

Also, noting that the positive domain of the decision attribute S with respect to the conditional attribute R, i.e., the lower approximation of the set is $POS_R(S)$.

$$POS_R(S) = \bigcup_{\forall u \in U/S} \underline{R}(r) \tag{1}$$

U denotes the domain (i.e., the set of all objects being studied). U/S denotes the quotient set obtained by partitioning the domain U according to a certain classification criterion S. r is any element in the sample domain. $\underline{R}(r)$ denotes the lower approximation of the element r. $\forall u \in U/S$ denotes each equivalence class u in the set of equivalence classes U/S.

(4) Calculate the dependence of the decision attribute S on the conditional attribute R. The formula is as follows:

$$p_R(D) = \frac{card(POS_R(S))}{card(U)} \tag{2}$$

$p_R(D)$ denotes the degree of dependency and $card(U)$ denotes the number of U-set elements.

Equation (5) Calculate the importance of the remanufacturability demand condition attribute R.

The absolute importance of R is need to be calculated firstly. The calculation process is as follows:

$$imp(r_i) = p_R(D) - p_{(R-\{r_i\})}(D) \tag{3}$$

$p_{(R-\{r_i\})}(D)$ denotes the degree of dependency with element r_i. The importance of R is then normalized and calculated as follows:

$$w_i = \frac{imp(r_i)}{\sum_{i=1}^{n} imp(r_i)} \tag{4}$$

where w_i is the r_i importance of the normalized conditional attribute, as well as the importance of the i-th remanufacturability demand.

3.2. Remanufacturing Demand Engineering Feature Conversion

Data on remanufacturability demands are typically sourced from online reviews, customer interviews, and questionnaires; these data are frequently informal and inaccurate, which complicates the precise description of DfRem objectives. To accurately describe DfRem objectives, the traditional method is to use Quality Function Development (QFD) to establish the relationship between remanufacturability demand and engineering features. Subsequently, by examining the significance of remanufacturability demand and its relationship with engineering features, we can gain valuable insights. To more conveniently describe the relationship between demand and functional characteristics, a Quality Function Deployment (QFD) matrix is utilized to establish the mapping relationship between the two, as illustrated in Table 2. *RD* represents remanufacturability demand, w_j represents the weight of the j-th remanufacturability demand, v represents the absolute value of the importance of the engineering characteristic, and FR_k represents the k-th functional characteristic. These need to be assigned by the designer based on the specific product and entered into the QFD matrix table. Then, designers score the strength of the association between customer requirements and functional features, categorizing the association strength into four levels: strong, moderate, weak, unrelated, with corresponding scores of 3, 2, 1, 0, where R denotes the association strength level. Finally, the importance of functional features is ranked, and the DfRem target is selected based on the ranking.

Table 2. QFD matrix.

RD	**Weight**	FR_1	FR_2	FR_3	...	FR_k
r_1	w_1					
r_2	w_2					
r_3	w_3					
...	...					
r_j	w_j					
	v					
	R					

4. DfRem Scheme Generation

In the previous section, the remanufacturability demands were analyzed and the DfRem objectives were derived. In alignment with the DfRem objectives, CBR technology is employed to determine the most appropriate DfRem solution. First, a knowledge base is constructed with the remanufacturing information. Next, previous and target cases are defined and constructed. Finally, the GRA method is applied to search the most suitable cases that match the target case from the case base.

4.1. Knowledge Base Construction

During the processes of DfRem and remanufacturing, a substantial amount of knowledge is generated. Yet this knowledge exists as isolated fragments, with no connections forged between them, resulting in low levels of relevance and reusability. To manage this knowledge effectively and enhance its sharing and reuse capabilities, it is crucial to develop knowledge bases that are based on standardized knowledge representation. The development of such knowledge bases comprises three main elements: the establishment of knowledge structures, remanufacturing process knowledge support for DfRem, and construction of ontologies for the knowledge bases.

4.1.1. Knowledge Structures Establishment

Knowledge base construction contributes to the management and retrieval of design knowledge. First, remanufacturing information must be collected and classified. Then, intrinsic links between remanufacturing information and DfRem need to be established. Finally, ontology technology is used to standardize the expression of remanufacturing information, thereby forming reusable design knowledge.

The remanufacturing process mainly includes the disassembly process, cleaning process, reprocessing process, and functional upgrading process, etc. The remanufacturing information contains both remanufacturing-related information and the original information of the used products, and the remanufacturing information mainly includes disassembly time, disassembly tools, cleaning time, and reprocessing technology, etc. The original information of the used product mainly includes the product structure, connection mode, material type, and dimensional accuracy, etc. Additional remanufacturing information is also available, as shown in Table 3.

Table 3. Remanufacturing information.

Symbolic	Remanufacturing Process	Information
ri_1	Disassembly process	Select appropriate disassembly tools, disassembly sequences, disassembly time, and cost based on product structure and connection methods.
ri_2	Cleaning process	Select appropriate cleaning media, cleaning equipment, cleaning time, and cost information based on the surface material and pollution situation of the product.
ri_3	Inspection and classification	Classify components based on their category characteristics; determine the number and duration of classification.
ri_4	Reprocessing	Select appropriate processing equipment, process routes, processing time, and cost information based on the performance, structural type, and accuracy level of the components.
ri_5	Function upgrade	Select appropriate accessory models, functional parameters, and installation tools based on the product structure, reserved interfaces, and functional requirements.
...	...	...

Remanufacturing knowledge can be divided into two categories: explicit knowledge and implicit knowledge. Explicit knowledge includes knowledge related to recycling, dis-

mantling, and reprocessing, while implicit knowledge is not easily discovered and requires analysis and extraction through technologies such as data mining and cluster analysis. It mainly includes design experience, operational skills, and management experience. The specific knowledge structure is shown in Figure 2.

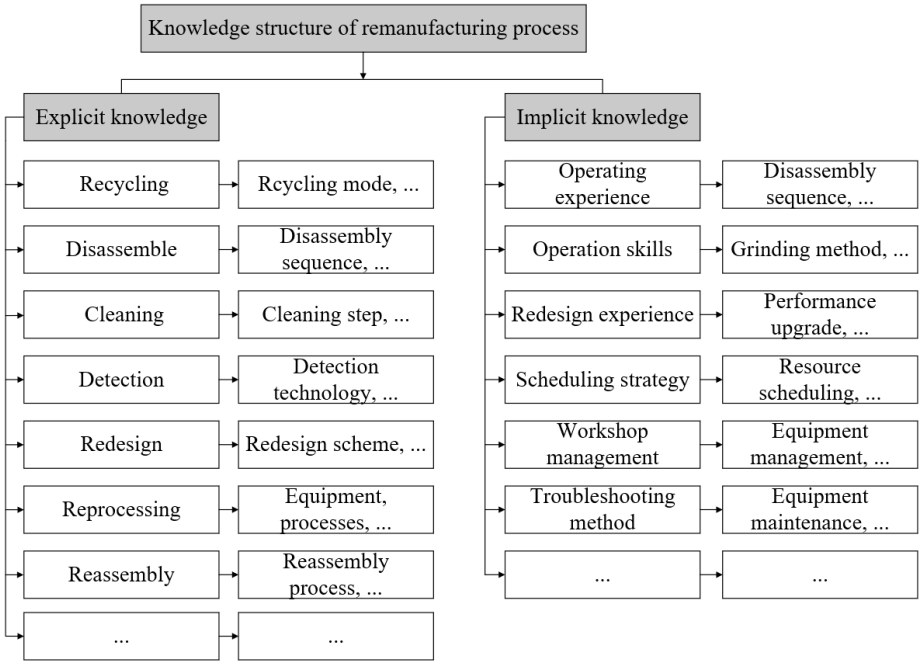


Figure 2. Remanufacturing knowledge structure.

4.1.2. Remanufacturing Knowledge Support DfRem

The remanufacturing process contains a large amount of information that is beneficial to DfRem. The remanufacturing information and DfRem parameters are not only one-to-one correspondences, but may also be one-to-many mappings, which is shown in Figure 3. It is crucial to establish internal correlations between different types of remanufacturing information and design parameters, analyzing the transmission mechanism from remanufacturing information to design parameters, and achieving accurate mapping from remanufacturing information to design parameters.

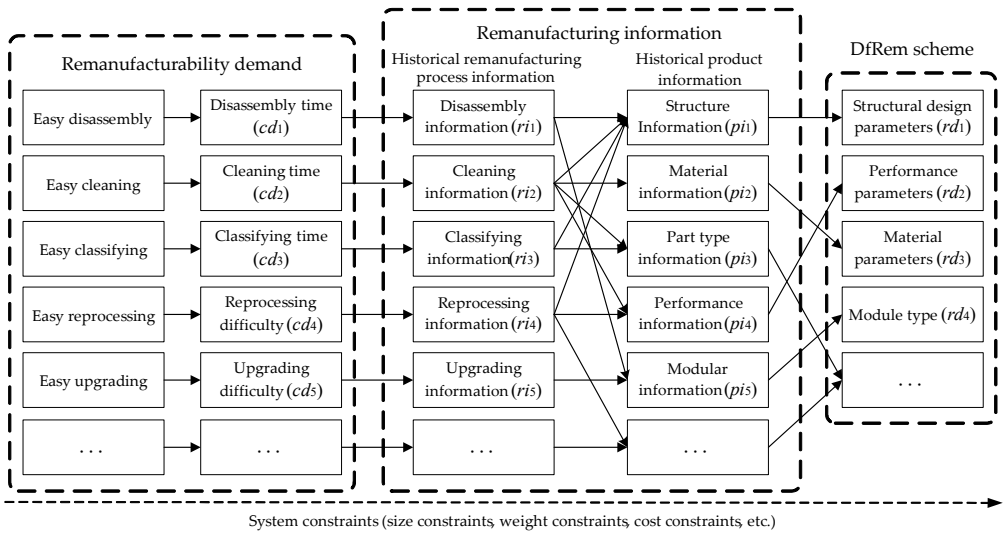


Figure 3. Mapping relationship between remanufacturing information and DfRem.

The design for remanufacturing (DfRem) process comprises three core phases: conceptual design, general design, and detailed design. Within each phase, overarching design objectives are systematically broken down into actionable tasks, guiding critical scheme decision-making. A fundamental requirement across all stages is the integration of product remanufacturability considerations; leveraging practical remanufacturing process knowledge directly enhances the eventual success of product remanufacturing.

Due to the distinct targets and tasks inherent to each DfRem stage, the specific content and depth of remanufacturing knowledge required for design decisions vary significantly. Early conceptual stages may focus on modularity principles, while detailed design demands precise insights into material recovery or component repair techniques. These stage-specific knowledge variations are illustrated in detail in Figure 4.

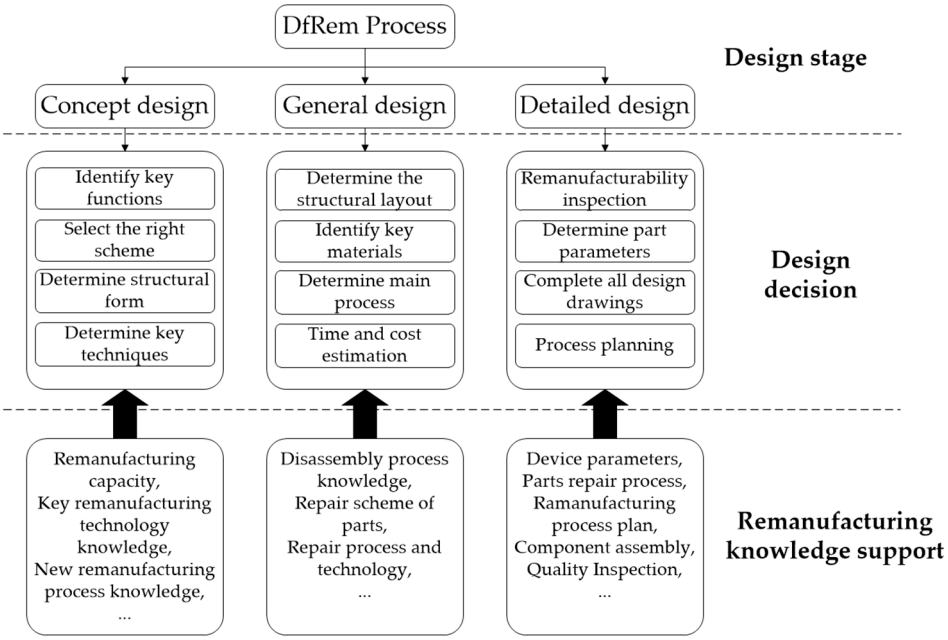


Figure 4. Remanufacturing knowledge supporting DfRem.

4.1.3. Remanufacturing Knowledge Construction for DfRem

The remanufacturing information not only includes performance recovery or upgrading information but also includes the physical information of the used products. To construct the mapping relationship between remanufacturing information and DfRem parameters, it is necessary to establish the relationship between remanufacturability demand and remanufacturing information, as well as between remanufacturing information and DfRem parameters.

For characterizing the remanufacturing information transfer process, ontology technology facilitates the mapping of relationships between remanufacturing demand information, remanufacturing data, and DfRem parameters. The ontology is mainly composed of five parts, namely $O = \{I, AI, R, AR, C\}$, representing concepts, concept attributes, relationships, concept relation attributes, and instances, respectively.

$I = \{i_1, i_2, \ldots, i_m\}$ represents a collection of various things, such as lathes, guide rails, and gearboxes.

AI encompasses a set of attributes for various concepts. For instance, the remanufacturing process attributes of parts typically include equipment number, process route, and process parameters.

$R = \{r_1(i_1, i_2), r_2(i_2, i_3), \ldots\}$ represents the set of relationships between two concepts, primarily encompassing inheritance, global and local associations, as well as reference connections.

AR denotes the attribute set of conceptual relationships, which refers to the attributes of a specific concept in relation to another concept. For instance, the material of a guide rail is considered a sub-attribute of the guide rail itself.

C represents instances of remanufacturing processes, such as disassembly instances, cleaning instances, and remanufacturing instances.

The remanufacturing demand includes easy disassembly, easy cleaning and easy upgrading, etc. The realization degree of remanufacturability demand is mainly based on the value of various parameters of the remanufacturing process, i.e., the difficulty of remanufacturing technology, the performance of remanufactured products and remanufacturing time, etc., and the object of realizing remanufacturing is the structure, material and performance of the product. When the matching degree between remanufacturability demand and remanufacturing information exceeds a set threshold, the historical used product information including structural dimensions, material type, and strength, will be passed to the DfRem process. Therefore, it is necessary to construct remanufacturing knowledge based on ontology for DfRem, which can improve design efficiency and information reuse rates. The specific mapping process is shown in Figure 5.

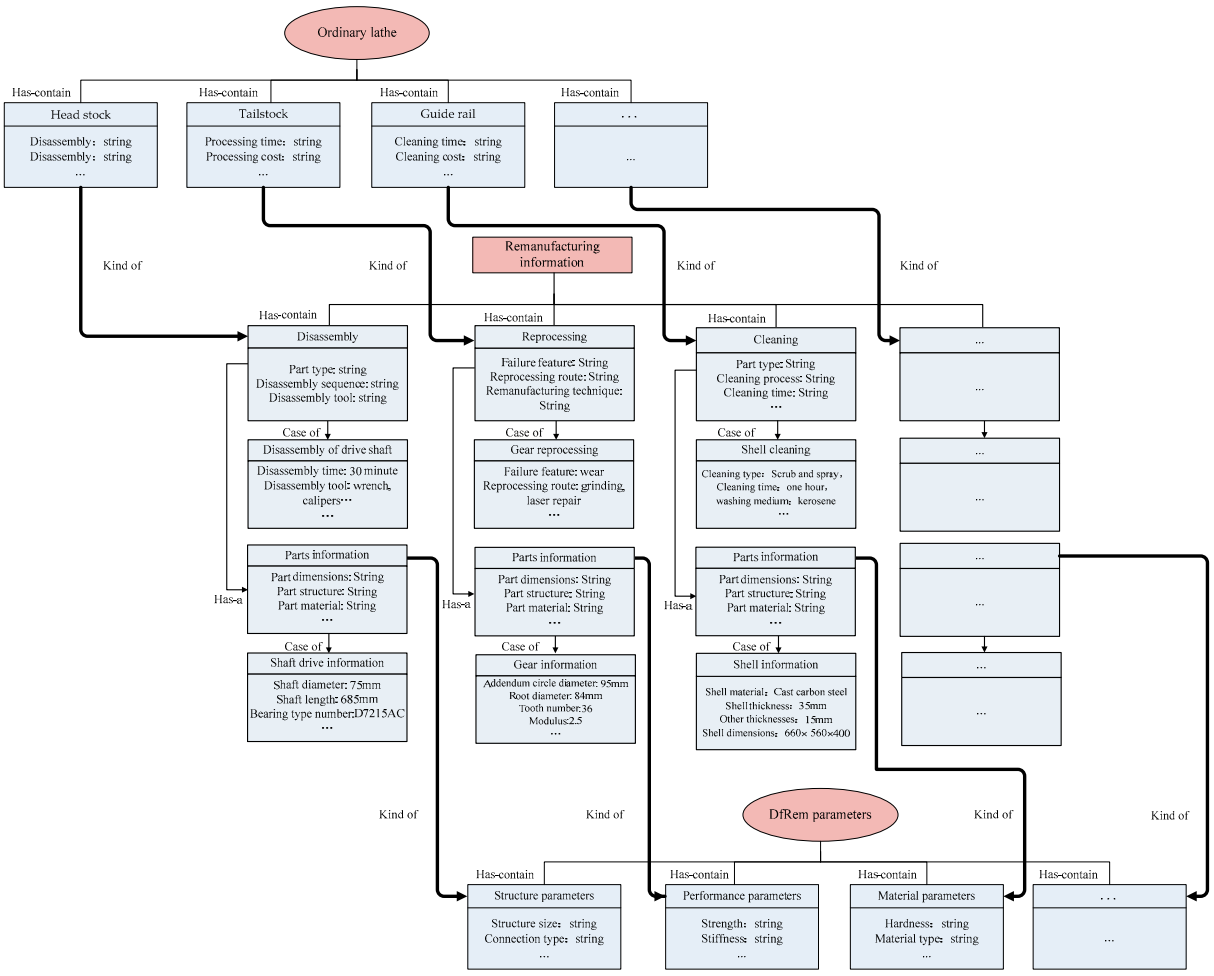


Figure 5. Remanufacturing knowledge structure for DfRem based on ontology.

In Figure 5, at the top of remanufacturing knowledge structure, an "Ordinary lathe" is the main object, which consists of components like "Head stock", "Tailstock", "Guide rail",

etc. Each component has associated attributes. For example, "Head stock" has attributes such as "Disassembly" (with details like disassembly time and tools). The diagram centers on "Remanufacturing information", which is categorized into aspects like "Disassembly", "Reprocessing", and "Cleaning". Each of these categories further contains specific attributes and "Case of" instances. For "Disassembly", there is a "Case of disassembly of drive shaft", with details like disassembly time (30 min) and tools (wrench, calipers). Also, there are "Parts information" sections under each remanufacturing category, providing details like part dimensions, structure, and material. For instance, "Case of shaft drive information" under "Parts information" provides the shaft diameter (75 mm) and length (68 mm). At the bottom, "DRem parameters" (presumably remanufacturing parameters) are divided into "Structure parameters", "Performance parameters", and "Material parameters", each with respective attributes like structure size, strength, and hardness.

4.2. DfRem Solution Generation Based on CBR

The development of the DfRem scheme is a complex process that requires consideration of the product's function, behavior, structure, and remanufacturability. Historical knowledge is created and verified during the design and remanufacturing processes; utilizing this existing knowledge to develop DfRem solutions can boost design efficiency. CBR is an intelligent approach to solving new problems by quickly retrieving the most similar past solution cases from knowledge bases. The CBR-based DfRem solution process primarily involves case representation, case retrieval, and case evaluation, with the following details.

4.2.1. Case Representation

In a CBR system, cases are divided into two categories: previous cases and target cases. A previous case refers to a historical instance that includes both the DfRem problem description and its corresponding solution. Conversely, the target case refers to a new instance that solely comprises the new DfRem problem description. In the DfRem case, the notation H stands for the case number, R indicates the product feature description that meets customer requirements, and S represents the solution, commonly known as the DfRem scheme. The detailed description of the DfRem case is provided in Table 4.

Table 4. The detailed description of the DfRem case.

Case number(H)	
Product feature(R)	
Product feature for remanufacturing:	Wear, surface corrosion, difficult to disassemble, product upgrade, etc.
DfRem scheme(S)	
Product structure parameters:	Product structure parameters include size specifications, connection formats, and material details, etc.
Process parameters:	Machine type, tool type, process parameters, etc.
Production information:	Emissions information, scheduling information, etc.

Therefore, DfRem case can be described as follows. The DfRem case is a triplet $CD = \{H, R, S\}$, where H represents the case number. $R = \{R_1, R_2, \ldots, R_n\}$ is the product feature description and S is DfRem parameter solution. Each product feature R_i is represented as $R_i = \{N_i, w_{R_i}, V_i\}$, where R_i denotes the i-th product feature, w_{R_i} denotes the relative weight of the feature, and V_i denotes the true value of the feature.

Moreover, A target case is defined as a two-tuple $CT = \{H, R\}$, where H denotes the case number and $R = \{R_1, R_2, \ldots, R_n\}$ represents the set of product features. Each product feature R_i is characterized by a triplet $R_i = \{N_i, w_{R_i}, V_i\}$, where N_i is the feature name, w_{R_i} is the relative weight of the feature, and V_i is the true value of the feature.

4.2.2. Case Retrieval

After constructing the cases and simplifying the case attributes, the gray correlation analysis algorithm is utilized to determine the similarity between the target case and historical cases. The similarity calculation method is shown as follows:

$$\zeta_j(k) = \frac{\min\limits_j \min\limits_k |v_{0K} - v_{jK}| + \rho \max\limits_j \max\limits_k |v_{0K} - v_{jK}|}{|v_{0K} - v_{jK}| + \rho \max\limits_j \max\limits_k |v_{0K} - v_{jK}|} \quad (5)$$

Among them, $\zeta_j(k)$ is the similarity between the design target case and the historical case characteristics, v_{0K} is the k-th characteristic value of the target case, v_{jK} is the kth characteristic value of the historical case, and ρ is the discrimination coefficient, which is generally within (0,1).

Once the similarity of each feature attribute between cases has been calculated, the overall similarity is calculated as follows:

$$s_j = \sum_{k=1}^{n} w_k \zeta_j(k) \quad (6)$$

Among them, s_j represents the overall similarity between the target case and the historical case, while the weight of the k-th feature, denoted as w_k, can be determined using the Analytic Hierarchy Process (AHP).

4.2.3. Case Evaluation

Since the concept of confidence is subjective, it is difficult to avoid human interference. The calculated similarity indicates the degree of match between new cases and existing cases. Although it has a certain degree of objectivity, it is also easily affected by noise data. In order to improve the accuracy and interference resistance of case matching, a comprehensive evaluation method combining similarity and confidence is proposed. Based on similarity and confidence, the comprehensive evaluation factor E is defined as

$$E(P_j) = (1 - \psi)\varepsilon(P_j) + \psi Sim(X, P_j) \quad (7)$$

Among them, $\varepsilon(P_j)$ is the confidence level for the j-th source case and ψ represents the proportional factor of the degree to which similarity and confidence level affect the comprehensive confidence factor E. To ensure the objectivity of the proportional factor ψ, it is generally set to 0.7. After searching through the cases, the comprehensive credibility coefficient of each case can be calculated. The results are sorted in ascending order, and then the maximum value of E is determined.

5. Case Study

5.1. Demand Analysis for DfRem

The feasibility of the proposed method is verified by taking the DfRem for a certain type of ordinary lathe as an example. The lathe is required to be a horizontal lathe, and the maximum cutting rotation diameter is 400 mm. The ordinary lathe is mainly composed of a gearbox, guide rail, bed body, tool holder, and tailstock. First, it is necessary to construct the topological structure network of the lathe, as shown in Figure 6.

Then, by collecting and analyzing customer demand information, the main remanufacturability demands of the lathe are determined, and the specific demand information is shown in Table 5.

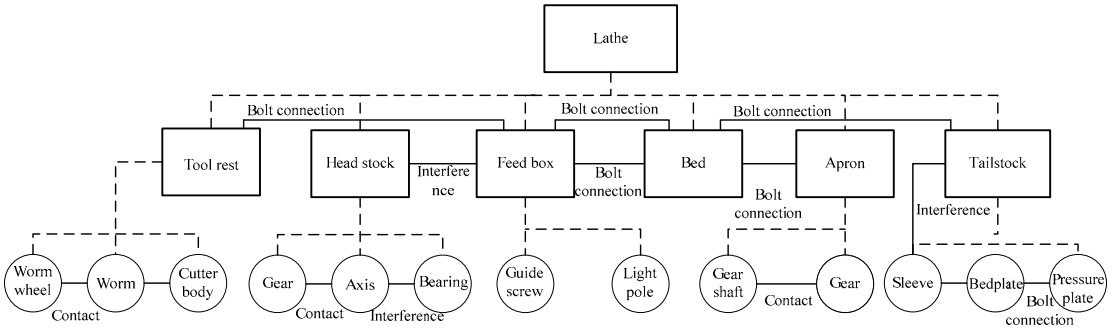


Figure 6. Topological structure network of ordinary lathe.

Table 5. Lathe-related remanufacturability demands.

Element (a_i)	Name	Remanufacturability Demand (r_i)	Engineering Description
a_1	Head stock	The structure is easy to disassemble (r_1)	The complete disassembly time is not more than 1 h, and the disassembly cost is not more than CNY 300.
		Tractability (r_2)	The spindle can realize stepless speed regulation and reduce cutting energy consumption.
		Easy classification (r_3)	The gear has obvious feature identification, and the classification time of a single gear is not more than 1 min.
a_2	Guide rail	High reusability (r_4)	The surface hardness is high and not easy to wear.
		Easy classification (r_5)	The guide rail has obvious feature identification, and the classification time is no more than 30 s.
a_3	Guide screw	High reusability (r_6)	The surface hardness is high and not easy to wear.
		Easy classification (r_7)	The screw has obvious feature identification, and the classification time is no more than 30 s.
a_4	Bed	The structure is easy to disassemble (r_8)	The complete disassembly time is not more than 1 h, and the disassembly cost is not more than CNY 200.
		Tractability (r_9)	The weight is not more than 1400 kg.
a_5	Tailstock	The structure is easy to disassemble (r_{10})	Add hydraulic motion module to reduce mechanical moving parts.
		High reusability (r_{11})	Enhance the surface hardness of the sleeve and improve the wear resistance.

Taking the manufacturer's historical remanufacturing case $U = \{u_1, u_2, \ldots, u_{12}\}$ as the decision sample, the remanufacturability demand decision table is established, and the attribute reduction and importance calculation are carried out. The details are as follows.

According to the definition of attribute reduction, the decision-making samples are classified. The results are as follows:

$$\begin{aligned} U/r_1 &= \{\{u_1, u_5, u_{12}\}, \{u_2, u_7\}, \ldots, \{u_3, u_9\}\}; \\ U/r_2 &= \{\{u_1, u_2\}, \{u_4, u_5, u_7\}, \ldots, \{u_3, u_{12}\}\}; \\ U/r_3 &= \{\{u_1, u_2, u_{12}\}, \{u_4, u_5\}, \ldots, \{u_3, u_8\}\}; \\ &\cdots \\ U/r_{11} &= \{\{u_1, u_2, u_3\}, \{u_5, u_8\}, \ldots, \{u_9, u_{12}\}\}; \end{aligned} \tag{8}$$

Meanwhile, the set satisfying the attribute $\boldsymbol{R}$ is

$U/ind(R) = \{\{u_1, u_5\}, \{u_4, u_6, u_8\}, \{u_2, u_9, u_{12}\}\}$. Among them,

$U/ind(R - r_{11}) = \{\{u_1, u_5\}, \{u_4, u_6, u_8\}, \{u_2, u_9, u_{12}\}\} = U/ind(R)$. Therefore, the remanufacturability demand attribute r_{11} can be reduced. Then the calculation of the basic set of all $\boldsymbol{S}$ decision attributes of the universe U is achieved as follows:

$U/ind(S) = \{\{u_1, u_8, u_{12}\}, \{u_2, u_5, u_7, u_3\}, \{u_4, u_6, u_{10}, u_9, u_{11}\}\}$, calculating the lower approximation set of decision attribute S relative to R entails

$\underline{R}(\{u_1, u_8, u_{12}\}) = \{u_1, u_{12}\}$; $\underline{R}(\{u_2, u_5, u_7, u_3\}) = \{u_2\}$; $\underline{R}(\{u_4, u_6, u_{10}, u_9, u_{11}\}) = \{u_9\}$, By combining the lower approximation sets of each sub-decision attribute, it can be obtained that $POS_R(S) = \{u_1, u_2, u_9, u_{12}\}$. According to Formula (2), the dependence of decision attribute S on condition attribute R can be calculated as $p_R(D) = \frac{1}{3}$.

The lower approximation set and dependence degree after removing each sub-condition attribute are calculated, respectively. The calculation results are as follows:

$$\begin{aligned} &POS_{(R-r_1)}(S) = \{u_2, u_{12}\}, p_{(R-r_1)}(D) = \tfrac{1}{6} \\ &POS_{(R-r_2)}(S) = \{u_1, u_5\}, p_{(R-r_2)}(D) = \tfrac{1}{6} \\ &POS_{(R-r_3)}(S) = \{u_1, u_4, u_8\}, p_{(R-r_3)}(D) = \tfrac{1}{4}, \\ &\qquad\qquad \cdots \\ &POS_{(R-r_{10})}(S) = \{u_1, u_5\}, p_{(R-r_{10})}(D) = \tfrac{1}{6} \end{aligned} \tag{9}$$

Finally, according to Formulas (3) and (4), the importance of each remanufacturability demand condition attribute is solved, and the calculation results are as follows.

It can be seen from Table 6 that the importance of r_3, r_5, and r_7 is relatively small. In order to reduce the remanufacturing workload of used products r_3, r_5, and r_7 are discarded. Therefore, the key remanufacturability demand information is $R = (r_1, r_2, r_4, r_6, r_8, r_9, r_{10})$ (Table 7).

Table 6. Remanufacturability demand decision table.

U	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	S
u_1	v_1	v_1	v_3	v_1	v_2	v_1	v_3	v_2	v_1	v_1	v_3	s_1
u_2	v_2	v_1	v_3	v_1	v_3	v_1	v_3	v_2	v_1	v_2	v_3	s_3
u_3	v_3	v_2	v_2	v_1	v_3	v_1	v_3	v_2	v_1	v_2	v_3	s_3
...	...	...	...	...	...	...	...	...	...	...	...	...
u_{12}	v_1	v_2	v_3	v_1	v_3	v_1	v_3	v_1	v_1	v_1	v_2	s_1

Table 7. Importance of remanufacturability demand.

Remanufacturability Demand	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}
$imp(r_i)$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{12}$	$\frac{1}{6}$	0	$\frac{1}{6}$	$\frac{1}{12}$	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{6}$
w_i	$\frac{1}{9}$	$\frac{1}{9}$	$\frac{1}{18}$	$\frac{1}{9}$	0	$\frac{1}{9}$	$\frac{1}{18}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{9}$

In order to accurately describe the design objectives, QFD was used to map remanufacturability demands to product characteristics. The analysis results are shown in Table 8.

Table 8. QFD matrix table.

RA	Weight	FR_1	FR_2	FR_3	FR_4	FR_5	FR_6	FR_7
r_1	0.111	3	1	0	0	0	0	0
r_2	0.111	0	0	0	0	0	3	0
r_4	0.055	0	0	0	3	0	0	0
r_6	0.111	0	3	0	0	0	0	0
r_8	0.167	0	0	0	0	1	0	3
r_9	0.167	0	0	0	0	3	0	1
r_{10}	0.111	0	0	3	0	0	0	0
v		0.333	0.444	0.333	0.165	0.668	0.333	0.668
R		4	3	5	7	2	6	1

In Table 8, based on technical advice from the lathe manufacturing company, seven general engineering characteristics can be summarized as follows:

(FR_1) Transmission disassembly time $\leq$ 1 h;
(FR_2) Gear hardness $\geq$ 60 HRC;
(FR_3) Hydraulic clamping module is used;
(FR_4) Surface hardness of the guideways $\geq$ 55 HRC;
(FR_5) Capable of expanding the CNC system;
(FR_6) Capable of achieving stepless speed regulation;
(FR_7) Bed disassembly time $\leq$ 1 h.

5.2. DfRem Scheme Generation for Ordinary Lathe

The engineering characteristics of product design were determined through remanufacturability demand analysis. According to the product design process, functional unit knowledge matching was first retrieved from the remanufacturing knowledge base. The retrieval content mainly included component concept names, functional feature concepts, and functional feature attribute values. When the similarity exceeded 0.8, the functional knowledge information was output.

The main design objectives include easy disassembly of the gearbox and stepless speed regulation, wear resistance of the guide rails and gears, easy disassembly and expandability of the bed, and easy disassembly of the tailstock. H(x) is the target case and H(1)–H(5) are the existing cases in the case base. Designers need to retrieve the most relevant design cases from existing examples based on the target case.

To facilitate similarity calculations, numerical calculations need to be performed based on attribute types. The knowledge information for each unit is as follows (Table 9).

Table 9. Functional knowledge attribute values.

Case Number	Transmission Disassembly Time	Gear Hardness	Surface Hardness of Guide Rails	CNC Device	Hydraulic Module	Gearbox Stepless Speed Regulation	Bed Disassembly Time
H(x)	0.8 h	60 HRC	55 HRC	Better	1	1	0.7 h
H(1)	1 h	55 HRC	58 HRC	General	1	0	1 h
H(2)	0.8 h	58 HRC	60 HRC	Better	0	1	0.9 h
H(3)	0.8 h	60 HRC	55 HRC	General	0	0	0.8 h
H(4)	1 h	56 HRC	53 HRC	Better	1	1	1 h
H(5)	1 h	61 HRC	52 HRC	General	0	0	1 h

The overall similarity between the existing functional cases and the target functional cases was calculated using MATLAB 2024 based on Formulas (5) and (6), the calculation results are shown in Table 10. As can be seen from the table, case $H(1)$ has a similarity greater than 0.8 and the highest similarity value, indicating that it is most similar to the target functional case. The detailed information of functional case $H(1)$ is shown in Table 11.

Table 10. Functional knowledge attribute values.

Case Number	$H(1)$	$H(2)$	$H(3)$	$H(4)$	$H(5)$
Overall similarity	0.8038	0.8033	0.7986	0.7960	0.7953

Table 11. Functional knowledge attribute values.

Number	Part Name	Functional Concept Name	Functional Attribute Name	Functional Attribute Value
1	Gearbox	Easy disassembly	Disassembly time	Bolted connection
2	Gear	High reusability	Hardness	Carbon content of 0.14%
3	Rail	High reusability	Hardness	Carbon content of 3.3%
4	Body	Easy expansion	CNC device	FANUC-0i-TF model extension interface
5	Tailstock	Easy disassembly	Disassembly time	Screw connection
6	Gearbox	Easy reprocessing	Operation mode	This feature is not available
7	Lathe body	Easy disassembly	Disassembly time	Bolted connection

To ensure the objectivity of the case, a comprehensive evaluation of the functional case is required, with the calculation process as follows:

$$E(P_1) = (1-\psi)\varepsilon(P_1) + \psi Sim(X, P_1)$$
$$= (1-0.7) \times 0.9 + 0.7 \times 0.8038 = 0.833$$

If the comprehensive evaluation factor of Case 1 exceeds the threshold of 0.8, it is considered reliable. Then, the historical product design information is output, which corresponds to the functional knowledge. The details of the design case are shown in Table 12.

Table 12. Product design information of Case 1.

Serial Number	Part Name	Design Concept Name	Design Attribute Name	Design Attribute Value
1	Gearbox	Nut and bolt specifications	Screw thread profile	Triangular thread
			Screw major diameter	10 mm
			Screw material	Low-carbon alloy steel
2	Gear	Carburizing heat treatment of 45 steel	Carbon layer depth	0.4 mm
			The duration of carburizing	2 h
			Carburizing temperature	900 °C
3	Guide rail	45Cr solid carburizing heat treatment	Carbon layer depth	2.3 mm
			The duration of carburizing	2 h
			Carburizing temperature	930 °C
4	Bed	FANUC-0i-TF model extension interface	Interface model	9-pin extension port
			Communication methods	RS232 communication interface
5	Tailstock	Bolt specification	Screw thread profile	Triangular thread
			The major diameter of a thread	40 mm
			Screw material	Q235 low-carbon steel
6	Lathe body	Bolt specification	Screw thread profile	Triangle
			The major diameter of a thread	6 mm
			Screw material	Q235 low-carbon steel

Table 12 covers the design information of components such as the gearbox, gear, guide rail, bed, tailstock, and lathe body. The setting of each parameter is based on the remanufacturability demand, material properties, and process requirements of the components. For the nut and screw of the gearbox, triangular threads, a major diameter of 10 mm, and low-carbon alloy steel are selected to ensure self-locking performance, strength, and wear resistance; meanwhile, threaded connections are beneficial for gearbox disassembly and improve disassembly efficiency. The gear is made of 45 steel with carburizing treatment, featuring a carburized layer depth of 0.4 mm, a treatment duration of 2 h, and a temperature of 900 °C, aiming to enhance surface hardness and wear resistance. The guide rail is made

of 45Cr with solid carburizing, having a carburized layer depth of 2.3 mm, a treatment duration of 2 h, and a temperature of 930 °C. Since it needs to bear large loads and friction, a thicker hardened layer is more suitable. The FANUC-0i-TF extended interface of the machine bed uses a 9-pin and RS232 communication, which is adapted to the system's function upgrading and equipment communication. Triangular threads are selected for the bolts of the tailstock and the lathe body, which is beneficial for disassembly between them. The tailstock uses a 40 mm major diameter to cope with large loads, while the lathe body uses a 6 mm major diameter to match small loads or space constraints. Moreover, the tailstock and lathe body are made of Q235 low-carbon steel, balancing strength, toughness, and cost; this is beneficial for their end-of-life remanufacturing, reducing remanufacturing time and costs.

In conclusion, the parameter settings of each component are reasonable choices after comprehensively considering various factors such as function, material, and process, so as to ensure the performance and reliability of the component. The design case can provide reliable design parameters for the DfRem of new lathes, improve the remanufacturability of lathe, and facilitate the remanufacturing implementation of the lathe at its EOL stage. The new lathe manufactured according to the DfRem scheme is shown in Figure 7.



Figure 7. The new ordinary lathe based on the DfRem scheme.

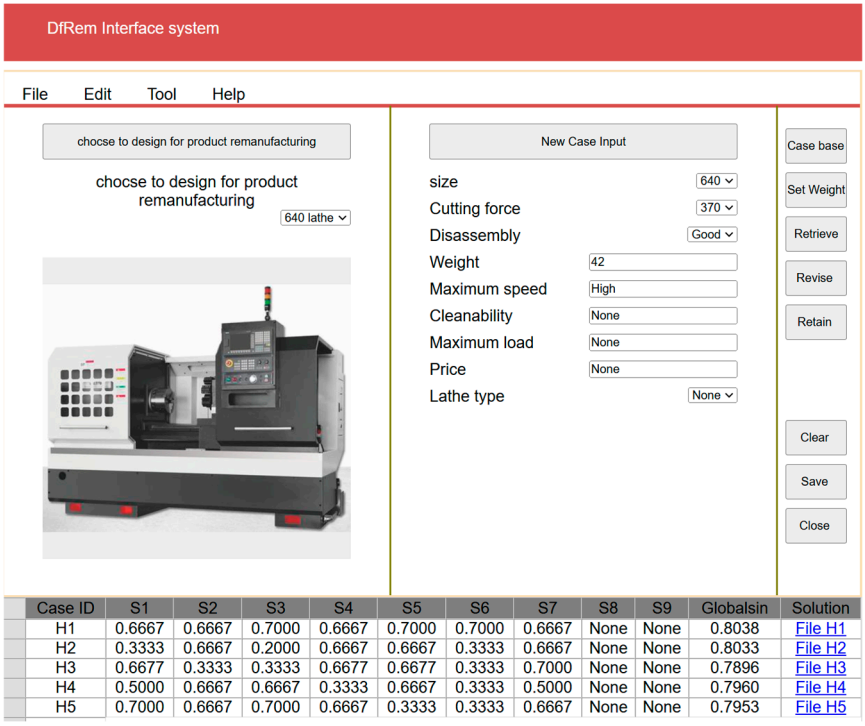
In comparison with other DfRem research, such as [25], the latter employed intelligent technologies to analyze customer demand and generate DfRem scheme, which promote the DfRem efficiency. However, it failed to establish an inherent link between remanufacturing information and DfRem. Moreover, it did not construct reliable DfRem knowledge.

Consequently, this current research not only enhances the efficiency of DfRem but also establishes a connection between remanufacturing information and DfRem. This not only improves the feasibility of design solutions but also better promotes the implementation of product remanufacturing.

5.3. DfRem Interface Application Construction

To expedite DfRem scheme generation, a case-based reasoning (CBR) application was implemented using Visual Studio and SQL Server. This application automates the retrieval of similar cases, as illustrated in Figure 8. The process begins with the selection of a candidate product for DfRem and the inputting of corresponding attribute values for each remanufacturability demand. Users subsequently assign weight values to each attribute. The system then queries the case base for similar cases based on these weighted attribute values. The retrieval process contains three parts, outlined as follows. (1) If the similarity

score falls below 0.8, the existing case requires modification until it exceeds this threshold before being saved to the knowledge base. (2) If no similar case is identified, a new case can be created and stored for future reference. (3) When the similarity score exceeds 0.8, the case is directly applicable and saved to the case base. Continuously archiving successful or revised cases enhances the diversity of case types, thereby improving case retrieval success rates. Compared to traditional DfRem methods, such as the two-stage QFD model, which necessitates labor-intensive manual processing of extensive failure data to identify product features and DfRem criteria, this intelligent approach processes demand analysis more efficiently, enabling the more rapid generation of the DfRem scheme.



Case ID	S1	S2	S3	S4	S5	S6	S7	S8	S9	GlobalsIn	Solution
H1	0.6667	0.6667	0.7000	0.6667	0.7000	0.7000	0.6667	None	None	0.8038	File H1
H2	0.3333	0.6667	0.2000	0.6667	0.6667	0.3333	0.6667	None	None	0.8033	File H2
H3	0.6677	0.3333	0.3333	0.6677	0.6677	0.3333	0.7000	None	None	0.7896	File H3
H4	0.5000	0.6667	0.6667	0.3333	0.6667	0.3333	0.5000	None	None	0.7960	File H4
H5	0.7000	0.6667	0.7000	0.6667	0.3333	0.3333	0.6667	None	None	0.7953	File H5

Figure 8. DfRem interface application.

6. Conclusions

This paper proposes an intelligent design method for product remanufacturing based on remanufacturing information reuse, which constructs the mapping relationship between remanufacturing information and DfRem parameters. Moreover, RST and QFD are applied to analyze the remanufacturability demand and extract the intelligent design goal. Ontology technology is used to construct the remanufacturing information model, which can support the DfRem process. Then, CBR is applied to retrieve the most similar design case from the DfRem case base that match the design target. Meanwhile, gray relational analysis (GRA) is used to calculate the similarity between pieces of design knowledge. Finally, a DfRem interface application is constructed to improve design efficiency and operability. Finally, the DfRem of an ordinary lathe is used as an example to verify the feasibility of the proposed method.

Compared to existing DfRem methods, this method offers three key advantages. (1) This method establishes a correlation between remanufacturing information and product design parameters, thereby improving the reuse rate of remanufacturing information and design accuracy. (2) CBR is utilized to create the DfRem scheme, which effectively shortens the design cycle and enhances the utilization of remanufacturing information. (3) A comprehensive set of DfRem interface applications have been developed, facilitating the rapid generation of design schemes.

The prospective research needs to work in the following directions. (1) Remanufacturing information is extensive and fragmented, posing significant challenges for ontology technology to structurally integrate diverse types of remanufacturing information and establish precise relationships among them, ultimately leading to decreased utilization rates and accuracy. In future research, knowledge graph technology will be used to construct a remanufacturing information integration model, which is beneficial for building semantic relationships between different information, improving the accuracy of knowledge retrieval, and increasing knowledge reuse rate. (2) The reliability of the design implementation needs to be improved. In the future, digital twin technology will be considered to construct the virtual–physical model for the DfRem process, and the design parameters can be dynamically adjusted based on remanufacturing process data, which is conducive to verifying the reliability of the DfRem scheme in real time, thereby reducing manufacturing process consumption.

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

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