An integrated design method for remanufacturing process based on performance demand

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Received: 10 May 2021 / Accepted: 20 August 2021 / Published online: 8 September 2021
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Abstract
Design for remanufacturing process (DFRP) plays a key role in implementing remanufacturing because it directly affects the performance recovery of the End-of-Life (EoL) products. Since the used parts of EoL products have various failure forms and defects, which make it hard to rapidly generate remanufacturing process scheme to satisfy the performance demand of the remanufactured products. Moreover, remanufacturing process parameters are prone to conflicts during remanufacturing processes, often leading to unsatisfactory remanufacturing processes. To accurately generate remanufacturing process scheme and solve the conflicts, an integrated design method for remanufacturing processes based on performance demand is proposed, which reuses the historical remanufacturing process data to generate the remanufacturing process scheme. Firstly, the Kansei Engineering (KE) and Quality Functional Development (QFD) are applied to analyze the performance demand data and map the demands to the engineering features. Then, Back Propagation Neural Network (BPNN) is applied to inversely generate the remanufacturing process scheme rapidly to satisfy the performance demands by reusing the historical remanufacturing process data. Meanwhile, Theory of Constraint (TOC) and TRIZ are used to identify and solve the conflicts of the remanufacturing process for the remanufacturing process scheme optimization. Finally, the DFRP of an EoL guide rail is taken as an example to demonstrate the effectiveness of the proposed method, the result of which shows the design method can quickly and efficiently generate the remanufacturing process scheme.

Keywords Remanufacturing process · Performance · BPNN · TRIZ

1 Introduction
With increasing attention to environmental pollution and energy consumption, strict legislations have been implemented by governments in many countries. The disposal of End-of-Life (EoL) products (which are called the cores) has received considerable attention over the past few decades [1]. Remanufacturing which is an industrial process of returning EoL products back to service in a condition that is like-new or better than new via a series of remanufacturing processes [2, 3] is vital to retain the inherent value of EoL products. Remanufacturing processes which refer to the specific technologies and methods for processing used products into remanufactured products directly impact the cost, recovery performance and efficiency of remanufacturing [4–6].

Used products for remanufacturing are diverse and uncertain, which makes the Design for remanufacturing process (DFRP) very complicated and time-consuming. It is also difficult to accurately restore the performance of used products to meet customer expectations. In addressing these problems, researchers have made contributions to DFRP. Jiang et al. [7] presented a remanufacturing process selection method, in which the functional relationship between remanufacturing performance and process quality characteristics is established by using QFD and fuzzy linear regression method for obtaining the optimal solution. Wang et al. proposed an
optimization method to characterize fault features for remanufacturing process planning, overcoming limitations of traditional characterization methods of fault features [8]. Shakourloo proposed a multiobjective stochastic goal programming model of remanufacturing process to optimize the remanufacturing process considering profit and cost objectives, and suggested the ratio of product quantity that should be ordered for remanufacturing processes by applying the model [9]. Li et al. proposed an analytical method, where four GERT-based RPR models are proposed to mathematically determine the time and probability of individual processes being taken in a remanufacturing system [10]. Kin et al. proposed a conceptual framework and methodology to aid in the selection of the reconditioning process sequence by analyzing the conditions of the core components [11]. Zhang et al. proposed an integrated model based on QFD, fuzzy linear regression, and zero-one goal programming model that provides the means for incorporating not only the relationships between decision objectives and decision variables but also the interactions between decision variables through adopting the QFD principles [12]. Cao et al. proposed a two-phase decision-making strategy, which was based on the experts’ assessment and fuzzy regression theory together, uncertainty was avoided in the decision-making process [13].

The current research on remanufacturing process is mainly divided into three categories: remanufacturing process generation, remanufacturing process optimization, and remanufacturing process decision-making. Undoubtedly, the above researchers have provided much useful knowledge and methodologies for remanufacturing processes, however, there is little DFRP research carried out from the perspective of the performance demand of the remanufactured products. The purpose of DFRP is to formulate a reasonable remanufacturing process scheme so that the used products can be processed into the remanufactured products that meet performance demand. Performance demand can be classified as original performance of the product (as-good-as-new) and the upgrade performance (better-than-new) which contains strength upgrade, function upgrade, and accuracy upgrade, etc. In general, customers are not professional technicians, and their demands are often vague and perceptual when describing performance demands, based on which biased and misleading design targets may be extracted. Therefore, there is a need to propose effective methods to accurately describe customer demands. Kansei Engineering (KE) which is defined as ‘translating customer sensibility into product design domain’ [14] is utilized to realize the customer’s feelings and demand for product functions and design. Hartono proposed a modified-integrated method for sustainable service design which applied Kansei Engineering to highlight the customer emotional satisfaction [15]. Jiao et al. proposed a method for Kansei knowledge extraction from the online review of the product, which can improve the design efficiency [16]. Yeh and Chen proposed a service design method that combines Kansei Engineering and data mining technology for transforming the users’ subjective feelings to the design specification [17]. It can be known from the literatures that KE is an effective method to describe the emotional demand of the customer, which is helpful for designers to extract the key performance demand of the products. Moreover, the performance demand needs to be converted into engineering features of the products, so that the designer can more accurately determine the design targets. Quality Functional Development (QFD) is a methodological tool designed to solve problems that aims to maintain customer demand throughout the design process, and promote communication between design participants [18]. Fang et al. proposed a new product model based on QFD for integrating the diverse customer demand into product design, which can realize the idea of customer-oriented design [19]. Sousa-Zomer et al. proposed an approach based on Quality Functional Development for translating the stakeholders’ demand into engineering metrics of the products and services [20]. Mistarihi et al. proposed a new enhanced model to improve the quality of the QFD method, which integrates customer demand and engineering features to achieve the optimal goal [21]. From the literatures mentioned above, it is evident that QFD can be used to translate the customer demands into the product engineering features, and determine the weights of each feature, and help designers determine the design targets of the remanufacturing processes. Thus, it is a feasible method to describe the performance demands and map them with the engineering features by using KE and QFD.

Moreover, DFRP is very complicated, and many factors have to be considered, such as damage features of the cores, process route, and technical parameters. It is hard to generate a suitable remanufacturing process scheme rapidly. To address these, Back Propagation Neural Network (BPNN) is proposed to solve the problems for DFRP by reusing the existing remanufacturing process data. BPNN has arbitrarily complex pattern classification capabilities and excellent multidimensional function mapping capabilities, which has been widely used. Huynh presented a model for predicting the detects to assist shop floor operations, for which BPNN was applied to predict the detects at each stage of the manufacturing process [22]. Chang et al. proposed an improved BPNN method to establish the relationship between the penetration quality and the welding process parameters, which can be used to predict the penetration quality based on the welding data [23]. Feng et al. proposed a data-driven learning algorithm to improve the prediction capacity of fatigue life by considering stochastic parameters of structures, and BPNN is used to predict the fatigue life based on the stochastic parameters database [24]. Kwon developed an integrated performance measurement and prediction model, in which BPNN was employed to predict an efficiency score and corresponding target output for each
decision-making unit of the railroads [25]. From the literatures mentioned above, BPNN has an excellent multidimensional function mapping the ability to establish the prediction model between the target variables and the influence variables. To improve the efficiency of DFRP, BPNN is used to establish the prediction model between performance demand and remanufacturing process scheme, for which the performance variables and failure features and the remanufacturing process parameters are used as input parameters. The BPNN is trained with these historical remanufacturing process data, when the BPNN model reaches the set prediction error threshold, the remanufacturing process scheme can be predicted according to the performance demand.

Although the BPNN model has high prediction accuracy, unreasonable remanufacturing process scheme may still be produced due to process conflicts which have not been considered in the model. To address the process conflicts, TRIZ, which is a whole set of systemized theory for solving invention-related problems [26] and has been used widely in various fields to solve design problems, is proposed. Hsieh et al. proposed a decision-making trial and evaluation laboratory-based analytic network process (DANP) and the TRIZ is the innovative design of machine tools, for which TRIZ provided several techniques to facilitate problem-solving [27]. Bao et al. applied TRIZ to solve the innovation issue in the active remanufacturing design process, which improved the efficiency and success rate of the structural green design for active remanufacturing [28]. From the literatures mentioned above, conflict problems are solved, and innovative design schemes are generated by using TRIZ. In addition, the conflicts of the remanufacturing process scheme are not easy to be detected, it is necessary to identify conflicts in the implementation of the remanufacturing process. Theory of Constraints (TOC) can help designers find the key factors that affect the actual production system [29]. Besides, TOC is mainly composed of five logical diagrams, which is used to solve and correct errors in conflict problems [30]. In TOC approach, the current reality tree (CRT) is used to put forward the possible causes of the conflicts [31], and the contradiction resolution diagram (CRD) is applied to express the relationship among one target, two basic requirements and two prerequisites of the system, which can determine the relevant factors in the conflicts and find ways to resolve the conflicts [32]. Hence, in this paper, TOC is employed as an effective method to find the conflicts and determine the direction to solve the problems, and TRIZ is utilized to provide innovative solutions to the problems.

To improve design efficiency and solve the conflicts for DFRP, an integrated design method for remanufacturing process based on performance demand is presented in this study. In short, the main contributions of this study is composed of three aspects: (1) an integrated design framework for remanufacturing process based on performance demand is established, which can reuse the historical remanufacturing process data to generate remanufacturing process scheme; (2) BPNN is used to build the predictive model between the performance demand and the remanufacturing process scheme, simultaneously, the failure features of the used products are considered in the input parameters, which can improve the predictive accuracy; (3) TOC and TRIZ theory are used to identify and resolve the conflicts of the remanufacturing process scheme, which can optimize the remanufacturing process scheme and improve the success rate of remanufacturing.

The rest of the paper is organized as follows. In section 2, the integrated design framework for the remanufacturing process is proposed. Section 3 analyzes the performance demand based on the KE and QFD, and establishes the prediction model based on BPNN. In section 4, the TOC and TRIZ theory are used to identify and resolve the conflicts of the remanufacturing process scheme. Then, a case study is presented to verify the feasibility of the proposed method in section 5. Finally, conclusions are given in section 6.

2 The implementation framework of DFRP

The remanufacturing process scheme needs to determine whether the performance of the product can be restored to or exceeds the original product performance. In addition, a sound remanufacturing process scheme can reduce remanufacturing costs and improve remanufacturing efficiency. Therefore, it is necessary to develop a design method for remanufacturing process which can restore the performance of used products to satisfy the performance demands. This paper proposes an integrated design method for remanufacturing process which mainly contains remanufacturing process scheme generation and optimization, and the process framework of DFRP is shown in Fig. 1. The first part is the performance demand analysis which contains performance upgrade demand and performance restoration demand, the second part is the remanufacturing process scheme prediction based on the performance demand by using BPNN. Then, the TOC and TRIZ theory are used to identify the conflicts of the remanufacturing process scheme and resolve the conflicts. Finally, the improved remanufacturing process schemes are feedback to the remanufacturing process scheme database.

3 Remanufacturing process scheme generation

3.1 Performance demand analysis

Performance demand mainly includes performance upgrade demand and performance restoring demand, the former is
mainly to improve the original performance of the EoL product, such as improving strength, hardness, and flatness, the latter is mainly the demand to restore the original performance of the product. In order to standardize the expression of performance demand information, the Likert tables are used to collect demand information. Table 1 shows the five-point Likert scale for performance demands for the case study.

The five-point Likert table is used to perceptually describe the performance demand of customers, and score the intensity of the demand, so as to more accurately describe the performance demand and tendencies. The demand intensity is divided into five levels: {strongly disagree, disagree, uncertain, agree, and strongly agree}, with a corresponding score is {1, 2, 3, 4, and 5}. After collecting the performance demand information, QFD is used to map the performance demand to the engineering features and quantify the engineering feature value, which can be described as shown in Table 2 in which PD represents the performance demand, $w_{pj}$ is the j-th weight of the performance demand, $E_k$ indicates the strength of the correlation between engineering features and performance demand, which is divided into four levels: {strong, general, weak, and irrelevant}, with a corresponding score is {3, 2, 1,
3.2 Remanufacturing process prediction model based on BPNN

After extracting the performance value of the used products, it is necessary to build the relationship between the performance and the remanufacturing process scheme, and develop a method to deduce the remanufacturing process parameters. Therefore, this study proposes a remanufacturing process prediction model based on the inversion theory. Firstly, the mathematical models between performance and the remanufacturing process scheme are established, then, BPNN is used to predict the remanufacturing process scheme based on the performance demand.

3.2.1 Mathematical model establishment

The target of the remanufacturing process is to obtain remanufactured products that meet the performance demand. Therefore, in the mathematical model, the performance demand is the objective function, and the remanufacturing process is a functional variable. It is a reverse process to solve the remanufacturing process parameters according to the product performance. Inversion is the derivation of unknown model parameters from known observations, in this paper, the performance demand is the known observations, and the remanufacturing process parameters are required to solve for unknown values. Hence, we can use the inversion theory to establish the relationship between the product performance and remanufacturing process parameters. It is assumed that the design variables contain the remanufacturing process \( P_r \) to achieve original performance (as-good-as new), remanufacturing upgrading process \( P_u \) (better-than-new). It is assumed that an accurate forward model of the process design is existing, which is expressed as follows:

\[
U^{\text{expect}} = f(P)
\]  
(1)

where \( U^{\text{expect}} = \{u_{e1}, u_{e2}, \ldots, u_{em}\} \), composed of the performance target vectors, is the performance that the customers or designers expect the remanufactured product to have, \( P = \{p_1, p_2, \ldots, p_n\} \) is the remanufacturing processes that are conducted on the products to achieve the performance targets. \( f \) represents the functional relationship between the performance targets and the process parameters.

However, the original performance value of the used product is known, and upgrade performance value needs to be obtained based on the customer demand analysis, and a suitable remanufacturing process scheme for performance repair or performance upgrade is to be selected. Thus, remanufacturing process solution based on product performance is a reverse remanufacturing process design process, which can be described as follows:

\[
P_r = f_1(U_{o,\text{actual}}, F) 
\]  
(2)

\[
P_u = f_2(U_{d,\text{actual}}, F) 
\]  
(3)

where \( U_{o,\text{actual}} \) and \( U_{d,\text{actual}} \) are the actual original performance and upgrade performance. \( F = \{F_1, F_2, \ldots, F_n\} \) represents the failure features of the used products, which is the input constraint of selecting remanufacturing process. \( P_r \) and \( P_u \) are the remanufacturing processes that can achieve the performance demand. In addition, the remanufacturing process needs to meet the constraint scope which includes the remanufacturing cost, time, and the environmental indicators which are expressed as follows:

\[
P_r = \{p_{r1}, p_{r2}, \ldots, p_{rn}\}, P_r \in D_1, D_2, D_3
\]  
(4)

\[
P_u = \{p_{u1}, p_{u2}, \ldots, p_{un}\}, P_u \in D_1, D_2, D_3
\]  
(5)

where \( D_1 \) represents the range of remanufacturing costs, \( D_2 \) represents the range of remanufacturing time, \( D_3 \) represents the environmental indicators.

![Fig. 2 The structure of BPNN](image)
3.2.2 The establishment of the prediction model

Back Propagation Neural Network (BPNN) is an intelligent algorithm that can build the mapping relationship between performance and remanufacturing process based on the historical remanufacturing data. BPNN contains the input layer, hidden layer, and output layer. The input layer contains the performance demand data and failure feature data. The hidden layer is the internal information processing layer, which responds to information transformation, the output layer is the output of the remanufacturing process scheme, the BPNN can be constructed as Fig. 2.

In Fig. 2, $U_n$ represents the $n$-th performance demand, $F_n$ represents the $n$-th failure feature, $w_{ij}$ represents the connection weight between the input layer and the hidden layer, $w_{jk}$ represents the connection weight between the output layer and the hidden layer, $P$ represents the predictive value of remanufacturing process scheme, $T$ represents the actual value of remanufacturing process scheme, $e$ represents the error between predictive value and actual value, the error can be feed backed to the connection weights which are adjusted based on the error. The process is iterated until the error reaches the expected value.

**Table 3** Design features of remanufacturing process

| Design feature | Feature description |
|----------------|---------------------|
| **Size parameters (M)** | | |
| Geometry size ($m_1$) | Size of each component |
| Shape ($m_2$) | Appearance shape of each component |
| Dimensional tolerance ($m_3$) | Material type of each component |
| ... | ... |
| **Process scheme (P)** | | |
| Heat treatment process ($p_1$) | Acquiring Performance Requirements |
| Assembly process ($p_2$) | Reasonable assembly process |
| Machining process ($p_3$) | Process method for obtaining part size |
| ... | ... |
| **Technical solution (T)** | | |
| Additive technology ($t_1$) | Parts for rapid prototyping |
| Brush plating technology ($t_2$) | Remanufacturing of workpiece surface |
| Deposit welding technology ($t_3$) | Enhancing metal surface property |
| ... | ... |
BPNN can feed back the error of the output result to each connection weight until the prediction error reaches the desired value, which represents the remanufacturing process prediction accuracy, the specific algorithm process is as follows.

### Table 4 The 39 standard parameters of TRIZ

| No. | The 39 standard parameters of TRIZ | No. | The 39 standard parameters of TRIZ | No. | The 39 standard parameters of TRIZ |
|-----|-----------------------------------|-----|-----------------------------------|-----|-----------------------------------|
| 1   | the weight of the moving object   | 11  | stress or pressure                | 21  | power                             |
| 2   | the weight of the stationary object | 12  | shape                            | 22  | loss of capacity                  |
| 3   | the length of the moving object   | 13  | structural stability             | 23  | material loss                     |
| 4   | the length of the stationary object | 14  | strength                         | 24  | information loss                  |
| 5   | the area of the moving object     | 15  | movement time of moving objects  | 25  | time loss                         |
| 6   | the area of the stationary object | 16  | action time of stationary objects | 26  | quantity of matter or thing       |
| 7   | the volume of the moving object   | 17  | temperature                       | 27  | reliability                       |
| 8   | the volume of the stationary object | 18  | brightness                        | 28  | test accuracy                     |
| 9   | velocity                          | 19  | energy of moving objects          | 29  | manufacturing accuracy            |
| 10  | force                             | 20  | energy of stationary objects      | 30  | sensitivity to the effects of harmful external factors |

### Table 5 The 40 principles of invention and innovation

| No. | The 40 principles of invention and innovation of TRIZ |
|-----|-------------------------------------------------------|
| 1   | principle of segmentation                             |
| 2   | extraction principle                                  |
| 3   | local quality principle                               |
| 4   | asymmetry principle                                   |
| 5   | combination principle                                 |
| 6   | principle of pluralism                                |
| 7   | nesting principle                                     |
| 8   | weight compensation principle                         |
| 9   | pre-reaction principle                                |
| 10  | pre-action principle                                  |
| 11  | principles of preset prevention                       |
| 12  | equipotential principle                               |
| 13  | reverse action principle                              |
| 14  | principle of curve and surface                        |
| 15  | dynamic principle                                     |
| 16  | principle of phase change                             |
| 17  | principle of thermal expansion                        |
| 18  | principle of gradual oxidation                        |
| 19  | principle of inert environment                        |
| 20  | principle of composite materials principle            |

### Table 6 The conflict resolution matrix

| DEP | IEP | AM₁ | AM₂ | AM₃ | AM₄ | ... | AM₃₇ | AM₃₈ | AM₃₉ |
|-----|-----|-----|-----|-----|-----|-----|------|------|------|
| 1   | AM₁ | 15,8,29,34 |     | 28,29,26,32 | 26,35,18,19 | 35,3,24,37 |
| 2   | AM₂ | 10,1,29,35 | 25,28,17,15 | 2,26,35 | 1,28,15,35 |
| 3   | AM₃ | 8,15,29,34 | 35,1,26,24 | 17,24,26,16 | 14,4,28,29 |
| 4   | AM₄ | 35,28,40,29 |     | 26 | 30,14,7,26 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 37  | AM₃₇ | 27,26,28,13 | 6,13,28,1 | 16,17,26,24 | 26 | 34,21 | 35,18 |
| 38  | AM₃₈ | 28,26,18,35 | 28,26,35,10 | 14,13,17,28 | 23 | 34,27,25 | 5,12,35,26 |
| 39  | AM₃₉ | 35,26,24,37 | 28,27,15,3 | 18,4,28,38 | 30,7,14,26 | 35,18,27,2 | 5,12,35,26 |
Step 1: Network initialization. Each connection weight is assigned a random number in the interval \((-1,1)\), and the error function value \(e\), calculation accuracy value \(\varepsilon\), and maximum learning times \(M\) are set.

Step 2: Input and output layer design. The number of the nodes in the input layer is determined based on the performance demand and the number of failure features. The performance is the main remanufacturing targets and the failure features are the constraint targets. The node of the output layer is 1, which is the remanufacturing process scheme. Meanwhile, the performance demand value and failure feature value need to be normalized in \((0,1)\), the conversion process is as follows.

\[
y = \frac{2^n(x-\text{min})}{(\text{max}-\text{min})-1}
\]

where \(y\) is the value after normalization, \(x\) is the input value.

Step 3: Hidden layer design. The number of hidden layer nodes is an important factor in fitting the nonlinear relationship function, which can be determined by Eq. (7).

\[
l = \sqrt{n + m + a}
\]

where \(l\) is the node number of the hidden layer, \(n\) represents the node number of the input layer, \(m\) represents the node number of the output layer, \(a\) is a constant which is in \([1, 10]\). The calculation process of the hidden layer input and output is as Eq. (8).

\[
H_j = f \left( \sum_{i=1}^{n} w_{ij} x_i - a_j \right)
\]

\[
P_k = \sum_{j=1}^{l} w_{jk} H_j + b_k
\]

where \(f\) is the activation function of the hidden layer, \(a_j\) is the initialization threshold of the hidden layer, \(b_k\) the threshold of the output layer. \(H_j\) represents the output of the hidden layer, \(P_k\) is the prediction value of the output layer.

Step 4: Predictive model parameters selection. The sigmoid function is used as the incentive function of the network, the tangent function (tansig) is used as the activation function of the hidden layer, the logarithmic function (logsig) is used as the excitation function of the output layer. The expressions of the three functions are as follows.

Table 7 The performance demand data collection of the guide rail

| Number | Object                | Perceptual evaluation | Demand intensity |
|--------|-----------------------|-----------------------|------------------|
| 1      | Guiderail surface     | Smooth                | √                |
| 2      | Surface hardness      | Hard                  | √                |
| 3      | Guide rail straightness| Upright               |                   |
| 4      | Guiderail Stiffness   | Steady                | √                |
| 5      | Size tolerance        | Small                 | √                |

Table 8 The weight of each demand

| PD   | P₁ | P₂ | P₃ | P₄ | P₅ |
|------|----|----|----|----|----|
| Quantity | 8  | 17 | 16 | 4  | 5  |
| Weight  | 0.16 | 0.34 | 0.32 | 0.08 | 0.10 |

Table 9 Engineering feature mapping by QFD

| PD   | E₁ | E₂ | E₃ | E₄ | E₅ |
|------|----|----|----|----|----|
| P₁   | 0.16 | 3   | 0  | 1  | 0  |
| P₂   | 0.34 | 0   | 3  | 0  | 2  |
| P₃   | 0.32 | 1   | 0  | 3  | 0  |
| P₄   | 0.08 | 0   | 2  | 0  | 3  |
| P₅   | 0.10 | 1   | 0  | 1  | 0  |

In Table 9, five engineering features are determined by the technician analysis, which are listed as follows.

(\(E₁\)) surface finish ≤Ra 0.5µm.
(\(E₂\)) surface hardness ≥60 HRC.
(\(E₃\)) straightness ≤0.10/1000 mm.
(\(E₄\)) stiffness ≥8000 N/µm.
(\(E₅\)) size tolerance ≤0.02 mm.
Step 5: Network prediction error is calculated as Eq. (13).

\[ E = \frac{1}{2} \sum_{k=1}^{n} (T_k - P_k) \]  
\[ (13) \]

where \( E \) is the total network prediction error, \( T_k \) is the actual value of the output layer. Supposing that \( e \) represents the error value between the actual value and the predictive value of the output, which is expressed by Eq. (14).

\[ e_k = T_k - P_k \]  
\[ (14) \]

Then the total network error can be simplified as Eq. (15).

\[ f_1(x) = \frac{1}{1 + e^{\beta x}}, \beta > 0 \]  
\[ (10) \]

\[ f_2(x) = \frac{2}{1 + \exp(-2n)} - 1 \]  
\[ (11) \]

\[ f_3(x) = \frac{1}{1 + e^{-n \sigma}} \]  
\[ (12) \]

Step 6: Adjust the weights of the BPNN. The update formula for the connection weights from the hidden layer to the output layer is as Eq. (16).

\[ w_{jk} = w_{jk} + \eta H_j e_k \]  
\[ (16) \]

where \( \eta \) represents the learning rate of the network.

The update formula for the connection weights from the input layer to the hidden layer is shown in Eq. (17).

\[ w_{ij} = w_{ij} + \eta H_j (1-H_j) x_i \sum_{k=1}^{m} w_{jk} e_k \]  
\[ (17) \]

Step 7: Judge whether the network error value meets the set expected error value, if it is satisfied, output the remanufacturing process scheme, if not, then return to the third step and repeat step 3 until the network error reaches the expected value.

### 4 Remanufacturing process scheme optimization

#### 4.1 Conflicts identify based on TOC theory

In the previous section, the remanufacturing process scheme can be obtained based on BPNN. However, due to the errors in prediction accuracy and differences in the working...
conditions, the remanufacturing process scheme will produce conflicts during the implementation process. To address that, the current reality tree (CRT) and contradiction resolution diagram (CRD) of TOC theory are used to determine the conflict problems in remanufacturing process scheme, and establish the solution model, respectively. Firstly, CRT is used to describe the actual situation of remanufacturing process design, and identify the core problems of the remanufacturing process scheme, which is described in Fig. 3.

CRT is used to describe the actual situation of a given system, which can reflect the causal relationship chain of the given system in certain specific environments, infer the root cause from the bad results of the system and determine the core problem. In the CRT, the core problems of the system should be determined, then the factors that caused the problem...
are determined, and the root causes of the problem are analyzed. Finally, the bad results caused are analyzed by the problem according to the influencing factors and root causes. After identifying the problems of the system, the main conflicts are determined by using CRD, which is described in Fig. 4.

As shown in Fig. 4, A and B are prerequisites for achieving the target, but A and B are contradictory problems. If A and B exist at the same time, the target cannot be achieved. After the CRD design system combing, what needs to be improved is clarified, and conflicts can be identified in the remanufacturing process scheme. However, CBD is effective in identification of the conflict problems, but itself is incapable of providing an effective solution, thus it is necessary to apply TRIZ theory to effectively solve the conflicts.

### 4.2 Conflicts resolution based on TRIZ

TRIZ is a systematic tool that can assist in solving problems and recommending inventive and effective solutions [33]. For establishing the relationship between feature parameter and TRIZ, each feature parameter of DFRP is mapped with the engineering parameter of the conflict matrix. The design features of the remanufacturing process are shown in Table 3.

There are 39 standard parameters in TRIZ theory as shown in Table 4, in which each technical conflict is represented by a pair of standard parameters. Meanwhile, the corresponding technical conflict can be solved by the 40 principles of invention and innovation, which are shown in Table 5. The problem can be solved only by mapping the feature parameters to the standard parameters in TRIZ theory.

The process parameters can be described by the set of feature parameters of the design process as shown in Eq. (18):

\[
PL = \{M, P, T\}
\]  

where \(PL\) represents the set of feature parameters, \(PL\) is composed of sub-parameters which include size parameter \(M\), process scheme \(P\) and technical solution \(T\).

Standard parameters in TRIZ theory are represented by sets:

\[
TR = \{AM_1, ..., AM_i, ..., AM_{39}\}
\]  

where \(TR\) represents the standard parameter set in TRIZ theory, \(AM_i\) indicates standard parameters. As shown in Eq. (20), each \(PL\) parameter has a corresponding \(TR\) parameter. The mapping relationship between \(PL\) and \(TR\) is constructed based on TRIZ as follows:

\[
TR = f(PL)
\]  

\(f\) denotes the mapping relationship between \(TR\) and \(PL\), the parameters in \(TR\) set represent the corresponding parameters in \(PL\) set, and the elements in \(PL\) set are called the object of elements in \(TR\) set about \(f\). Each technical conflict consists of a pair of feature parameters, which can be represented by a pair of standard parameters in TRIZ, the description is as follows:

\[
CT_{ij} = \{AM_i, AM_j\}
\]  

\(CT_{ij}\) represents the conflict in DFRP, \(i\) and \(j\) represent the serial numbers of any two in the thirty-nine standard parameters.

After mapping the technical conflicts to the TRIZ standard parameters, the solutions of conflicts can be found by referring to the conflict resolution matrix, which is shown in Table 6, in which DEP indicates the deteriorating engineering...
parameters, and IEP indicates the improved engineering parameters. The solutions are usually heuristic, and designers can optimize the remanufacturing process scheme based on the solution.

5 Case study

This study takes the guide rail from a machine tool as an example to verify the feasibility of the remanufacturing process design method. The guide rail that is an important part of the machine tool, is subject to failures such as wear, creep, crack, and deformation during the service, which influences the precision, size, and strength of the part. Therefore, it is necessary to design a suitable remanufacturing process scheme for the used guide rail, which can restore the performance of the used guide rail to the like-new one or even to a condition that surpass the new one (upgrade).

In the case study, 100 pieces of remanufacturing process data have been collected by the remanufacturer, and 50 pieces of performance demand data are collected by using the Likert scale, which mainly contain hardness improvement, flatness recovery, smooth guide rail surface, steady guide rail stiffness, and size tolerance, the demand information is described as Table 7.

For accurately extracting the performance demand targets, the performance demand is mapped to product features by using QFD, the weights are determined according to the proportion of the demand data, which is the value of the individual demand quantities divided by the total demand quantity. The calculation results are shown in Table 8, and the mapping process is described in Table 9.

By calculating the absolute weight value of the engineering feature, the importance ranking of the engineering feature is obtained, therefore, according to the performance demand, the first four engineering features are determined as the remanufacturing targets. The failure features of the guide rail are wear (F_5) and crack (F_6), the corresponding value are 5.5 mm and 3.1 mm, which can be measured by the 3D laser scanner.

Then, the BPNN needs to be trained based on the remanufacturing process data. Moreover, hardness, straightness, surface finish, and stiffness of the guide rail are used as the input parameters in the BPNN, and the remanufacturing process scheme is the output data. Firstly, 100 pieces of remanufacturing process data are divided into training data sets and test data, the first 80 sets of data are used to train BPNN, and the remaining 20 sets of data are used for testing the predictive model, the data classification is shown as Table 10, and the 50 corresponding remanufacturing schemes are shown in Table 11.

| Table 12 Application process of the TRIZ |
|------------------------------------------|
| Technical parameters of TRIZ | Invention principle |
| Parameters that need to be improved | 29-Manufacturing accuracy | 25-Self-service principle |
| Deteriorating parameters | 8-Volume of the stationary object | 10-Preaction principle |
| | | 35-Principle of changing physical or chemical parameters |
After determining the training samples and test samples, parameter values of BPNN need to be set. According to Eq. (7), the number of the hidden nodes is 10, the number of the input nodes is 8, and the output node is 1. Therefore, the BPNN model can be selected with an 8–10–1 structure containing a hidden layer. Besides, the number of network iterations $M$ is set to 5000, the expected error $\varepsilon$ is set to $10^{-2}$, and the learning rate $\eta$ is set to 0.01.

The number of training and the error value are shown in Fig. 5. The comparison between the actual output value and the predictive output value is shown in Fig. 6. From Fig. 5 and 6, when the training reaches 259 steps, the error reaches $10^{-2}$, which meets the network setting requirements. For solving the remanufacturing process scheme, $E_1$, $E_2$, $E_3$, and $E_4$ are the performance demand input, $F_5$ and $F_6$ are the failure feature input, the remanufacturing process scheme 8 can be obtained which can meet the performance demand based on BPNN, the solution is shown in Fig. 7.

As shown in Fig. 7. Quenching the failure guide rail can improve the hardness of the guide rail, then the surface grinding is carried out with the guide grinder. Finally, the laser repairing method is used to restore the damaged parts for the guide rail. Although in theory, these remanufacturing processes can restore performance for the remanufactured product, there are conflicts in the implementation of the process. After grinding, the size of the guide decreases and it may not be aligned with the center of the chuck, which could lead to errors in parts processing.

The key concept of TOC is to manage the constraint of the system, which can determine the conflicts of the remanufacturing process scheme. CRD and CRT are used to identify the core conflict and problem respectively. CRT is used to sort out the remanufacturing process problems, as shown in Fig. 8.

As shown in Fig. 8, despite the quenching can improve the hardness of the guide rail, it is not conducive to grind the guide rail for improving the surface accuracy. Meanwhile, grinding can improve the accuracy of the guide rail, but it will reduce the size of the guide rail, which cannot guarantee machining accuracy. Therefore, there are conflicts in the remanufacturing process scheme, and the core problems need to be determined and optimized.

To address this, CRD is used to identify conflicts in the remanufacturing process, as shown in Fig. 9 and 10. By constructing the CRD of the remanufacturing process scheme, the problems are sorted out and the contradictions in the process of guide rail remanufacturing process are determined. Grinding technology can improve the accuracy and surface roughness of the guide rail, but it will reduce the size of the guide rail, which is a pair of contradictions. Besides, quenching can improve the hardness of the guide rail, but it is not conducive to improve the surface accuracy of the guide rail, which is a pair of contradictions.

After determining the conflicts of the remanufacturing process scheme, TRIZ theory is used to solve the conflicts. Firstly, for building the relationship between process problems and TRIZ, process problems need to be mapped to engineering parameters in the TRIZ conflict matrix. As accuracy and size is a pair of conflict, the accuracy of guide rail is associated with manufacturing accuracy, and the size of guide rail is related to the volume of the stationary object in TRIZ engineering parameters. Then the corresponding inventive principles are found according to the conflict matrix table, and the application process is shown in Table 12.

Finally, by analyzing the principles of each invention, the 10-preaction principle can resolve process conflicts, that the laser casting is performed before griding, and the solutions are shown in Fig. 11.

The repaired guide rail is shown in Fig. 12.

It was found that the proposed method is feasible to generate the remanufacturing process scheme by reusing the historical remanufacturing process data, and resolve the conflicts of
remanufacturing process scheme based on TOC and TRIZ theory. The specific remanufacturing process scheme shown in Fig. 12 is as follows. The guide rail of the lathe used for the case study has wear failure. For remanufacturing, in order to improve machining accuracy and the performance of the guide rail, the guide rail is cleaned by diesel and wiped clean firstly. Then, laser casting is used to restore the geometry of the worn part of the guide rail. After the restoration, the grinder is used to grind the guide rail plane so that the surface roughness of the guide rail reaches Ra 0.5 μm and the straightness reaches 0.08/1000 mm, which can be detected by the three-coordinate measuring machine. The process sequence should take place in the right order, laser casting should take place firstly to restore the geometry, and grinding should be placed after the laser casting to achieve machining accuracy and the angle grinder is used to remove burr on guide rails.

Quenching should be undertaken after the laser casing and grinding to achieve good surface hardness. For the case study, high-frequency quenching is used to enhance the hardness of the guide rail to 65 HRC, which can be detected by the hardness tester. If the order of remanufacturing processes is not followed, the roughness and flatness of the restored part may not meet the demand. Therefore, through remanufacturing process scheme prediction and conflict resolution, the optimal remanufacturing process scheme can be obtained. The guide rail after remanufacturing is shown in Fig. 11. It can be seen in Fig. 11, the wear of the guide rail has been restored, and the smooth surface of the guide rail has been achieved. The case study showed that BPNN reached the error requirement and produced the remanufacturing process scheme as the output within 1 sec, which greatly improved the efficiency of DFRP.

(1) TOC and TRIZ can resolve the conflicts of the remanufacturing process schemes, but they cannot intelligently provide solutions to conflicts, in future work, case-based reasoning, rule-based reasoning, and k-Nearest Neighbor may be applied to resolve the conflicts and make the solution process more intelligent; (2) remanufacturing process design tool may be developed to make the design method more integrated and user friendly, which contains performance demand analysis, remanufacturing process scheme generation, and remanufacturing process scheme optimization.

Funding This research paper is supported by the National Natural Science Foundation of China (Grant No. 52075396, Grant No. 51905392). These financial contributions are gratefully acknowledged.

Declarations

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee or comparable ethical standards.

Consent to participate Informed consent was obtained from all individual participants included in the study.

Consent to publish The participants provided informed consent for publication of their statements.

Disclaimer The use of the commercial software systems identified in this paper to assist the progress of design, development, and understanding does not imply that such systems are necessarily the best available for the purpose.

Conflict of interest No potential conflict of interest was reported by the authors and the stakeholders.

6 Conclusions

This study proposes an integrated design method for remanufacturing process based on performance demand, which could provide both theoretical and practical insights for generating and optimizing the remanufacturing process scheme. The main contributions to knowledge could be concluded as follows: (1) Kansei Engineering and QFD are integrated to analyze the performance demand, which can accurately describe the demand and map the performance demand to the engineering features; (2) the predictive model based on BPNN is established which can reuse the historical remanufacturing process data to rapidly generate the remanufacturing process scheme that is more in line with performance demand; (3) TOC and TRIZ are applied to identify and resolve the conflicts of the remanufacturing process scheme, under this method, the remanufacturing process scheme can be optimized.

The future work requires efforts in the following aspects:

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