An Integrated Optimization Decision Method for Remanufacturing Process Based on Conditional Evidence Theory Under Uncertainty

ZONGKE BAO[1], WENYI LI[2], MENGDI GAO[2], CONGHU LIU[2,3], XUGANG ZHANG[4], AND WEI CAI[4,5,6]

[1]School of Accounting, Zhejiang University of Finance and Economics, Hangzhou 310018, China
[2]School of Mechanical and Electronic Engineering, Suzhou University, Suzhou 234000, China
[3]School of Economics and Management, Tsinghua University, Beijing 100084, China
[4]Hubei Key Laboratory of Mechanical Transmission and Manufacturing Engineering, Wuhan University of Science and Technology, Wuhan 430081, China
[5]College of Engineering and Technology, Southwest University, Chongqing 400715, China
[6]Faculty of Business, The Hong Kong Polytechnic University, Hong Kong

Corresponding author: Wenyi Li (szxylwy@163.com)

ABSTRACT The uncertainty of worn parts is a challenge for the remanufacturing process. Therefore, an integrated optimization decision method for remanufacturing process based on conditional evidence theory under uncertainty is proposed. On the basis of production history data of remanufacturing enterprises, prior information of the remanufacturing process is generated, and the prior evidence is constructed. Then, depending on the relationship between the parameters and the processing technology, the information of detection and evaluation of parts' characteristic parameters is transformed into evidence. The prior evidence and the evidence are fused corresponding to the parameter value. Then, the influence law among production data, characteristics of worn parts and technological process in remanufacturing is revealed. The fusion result has a one-to-one correspondence with the processing technology of worn parts. According to the decision rules, the optimal processing technology of worn parts can be obtained by judging the fusion results. The statistical data of remanufacturing worn crankshafts shows that the quality improved by 2.5%, the production cost reduced by 5.6%, and the time saved by 7.3%. This study provides theoretical and methodological support for the optimization of remanufacturing production.

INDEX TERMS Conditional evidence theory, information fusion, remanufacturing, uncertainty.

I. INTRODUCTION

With the rapid development of global economy, the contradiction between economic growth, environment and energy is increasingly prominent [1]. Remanufacturing has been recognized as an important way for the sustainable development of manufacturing industry. It is an important technology for reducing energy conservation and emission, resource consumption in the current circular economy and green manufacturing field [2]. Remanufacturing technology is to take

The associate editor coordinating the review of this manuscript and approving it for publication was Bohui Wang.

the worn part as the workpiece, to obtain the remanufactured parts after remanufacturing process [3], and the requirement is that the quality of the remanufactured products is not lower than the original products. Different from original manufacturing, the remanufacturing worn parts have greater uncertainty [4], which makes the remanufacturing process have more difficulties. Because of the above reasons, it is a challenge to control remanufacturing quality, and to optimize remanufacturing production management benefits [5].

In order to improve the production control and management of remanufacturing process, many experts have studied that:

In terms of remanufacturing technology, the main aspects of a holistic approach to assess and improve remanufacturing processes were shown by Butzer [6]. An overall process method for remanufacturing process planning of worn parts is proposed by Kin [7], which includes some key steps such as damage analysis of waste parts, selection of remanufacturing repair process, remanufacturing process sequencing, risk and reliability assessment of remanufacturing scheme. A remanufacturing process technology that can restore the original performance of the toque converters for passenger car 6-speed automatic transmissions is developed [8]. A reverse engineering based approach is proposed to aid remanufacturing process for worn components [9]. The microstructure formation in the near-net-shape tip-remanufacturing process of SX superalloy is studied through LAM experiments and simulation [10].

In remanufacturing process evaluation, a sustainability evaluation of remanufacturing machining systems emergy-based is proposed by Liu [11]. An uncertain remanufacturing process routings model for used parts based on Graphical Evaluation and Review Technique network is studied by Li [12]. Through a comprehensive study of more than 2000 engines of caterpillar remanufacturing company in the UK, it is found that enhanced pre-treatment inspection can improve remanufacturing efficiency [13]. The environmental benefits and costs assessment model for remanufacturing process under quality uncertainty is built by Liao [14]. The data-driven ecological performance evaluation for remanufacturing process is built by Jiang [15].

In the aspect of multi-objective optimization of remanufacturing process, an integrated model based on quality function deployment, fuzzy linear regression and zero-one goal programming is proposed by Zhang [16]. A mixed integer optimization model to optimize the batch, route and type of remanufacturing process from the perspective of cost is proposed by Kernbaum [17]. An optimization model for remanufacturing process routes oriented toward eco-efficiency is proposed by Peng [18]. There are also many studies on remanufacturing process planning and scheduling, the multi-objective stochastic goal programming model for more efficient remanufacturing process is studied by Shakourloo [19]. The linear optimization model to optimize the processing capacity, processing time and processing equipment in the remanufacturing process is established by Franke, and the optimization results are verified by simulation technology [20]. The coupling mechanism of reassembly quality with uncertainty of remanufactured parts is presented [21]; A cost-driven process planning method for hybrid additive–subtractive remanufacturing is proposed [22].

With the development of big data technology and knowledge engineering, there are more and more researches on comprehensive application of remanufacturing production data for remanufacturing processing. An ontology-based method for knowledge modeling for remanufacturing process planning is proposed for leading to considerable time and cost saving [23]. A hybrid method integrating blockchain and case-based reasoning for remanufacturing process planning is presented, which can take full advantage of the remanufacturing knowledge by cross enterprises knowledge sharing [24]. The impact of human resources experience and its training level on key process indicators, perceived quality of core, and internal complexity of remanufactured metal-mechanic products is assessed [25]. A knowledge-based method for remanufacturing process planning is proposed as part of the efforts in upgrading eco-efficiency which also aims to improve the efficiency of process planning and realize the inheritance and evaluability of the process planning knowledge [26].

The above researches of remanufacturing process is studied from perspective of cost, quality, resources, environment and other aspects [27], and many models are used to evaluate the processing decision-making, optimize the processing path, and improve the efficiency of remanufacturing process [25]. However, due to the large uncertainty of worn parts [28], it is difficult to describe the remanufacturing process accurately and clearly by using the models [29]. The remanufacturing process is a step-by-step process. How to apply the uncertainty characteristics of worn parts, optimize the remanufacturing process, and improve the remanufacturing efficiency is important for the remanufacturing enterprises [30], [31]. At the same time, in view of the advantages of evidence theory: (i) the required prior data is more intuitive and easier to obtain than in the probability reasoning theory; (ii) it can integrate a variety of data and knowledge; and (III) it has the ability to directly express ''uncertainty'' and ''unknown'', which are expressed in the *mass* function and retained in the process of evidence synthesis [32]. The method of remanufacturing process optimization based on conditional evidence theory is proposed. The historical experience of remanufacturing is expressed in the form of prior evidence, and it is combined with the evidence corresponding to the worn parts' parameter using conditional evidence theory. The remanufacturing process is optimized according to the fusion results. It provides theoretical and methodological support for the optimization of remanufacturing production.

In order to achieve the above research objectives, the remainder of this paper is organized as follows. In Section 2, the integrated optimization method of remanufacturing process is outlined. In Section 3 case application is carried out using the proposed approach in this paper. Finally, concluding remarks and discussions are summarized in Section 4.

II. METHODOLOGY

The crack, fatigue and other damage forms of worn parts are different, so the way of repair should be determined according to the damage situation. To complete the remanufacturing process of a worn part, it needs multiple stations, and each station has different processing technology to choose, which makes the decision of processing technology more complex. At the same time, the repair process itself may bring new

variables, resulting in temporary changes in the processing technology, thus increasing the uncertainty and control difficulty of the process. Due to the particularity of remanufacturing process, it will inevitably bring more complexity of work arrangement, material buffer capacity, and processing progress. It is one of the urgent problems to be solved in the field of remanufacturing process. The theory of conditional evidence is an effective method to deal with uncertain information. Therefore, the conditional evidence theory is used to solve the decision-making problem of remanufacturing process integration optimization.

A. INTEGRATION OPTIMIZATION MODEL OF REMANUFACTURING PROCESS

1) CONDITIONAL EVIDENCE THEORY

Suppose $M = \sum_{S \subseteq U} b_S S$ and $N = \sum_{T \subseteq U} c_T T$ are two independent evidences on frame Θ. $\Pi = \sum_{j=1,\ldots,k} p_i F_i$ is the prior evidence on set Θ. The fusion steps and formulas of conditional evidence theory are as follows [32]

1) The conditional consent of M, N based on Π is

$$\alpha_\Pi(M, N) = \sum_{S,T \subseteq \Theta} b_S c_T \alpha_\Gamma(S, T) \quad (1)$$

where, $\alpha_\Pi(S, T) = \begin{cases} \frac{\beta_\Pi(S \cap T)}{\beta_\Pi(S)\beta_\Pi(T)}, \beta_\Pi(S) \neq 0 \neq \beta_\Pi(T) \\ 0 \quad , other \end{cases}$

$\beta_\Pi(S)$ is the probability assignment functions based on Π.

2) The conditional product of M, N based on Π is

$$M \cdot_\Pi N = \sum_{S,C \subseteq U} b_S c_T \alpha_\Pi(S, T)(S \cap T) \quad (2)$$

3) The conditional evidence combination of M, N based on Π is

$$M *_\Pi N = \frac{M \cdot_\Pi N}{\alpha_\Pi(M, N)}(\alpha_\Pi(B, C) \neq 0) \quad (3)$$

$M *_\Pi N$ is the fusion result, if there are other evidences, the above formula $M *_\Pi N$ can be used again to fuse other evidences.

Based on the conditional evidence theory, we can generate the prior information of remanufacturing process according to the enterprise production history data, and construct the prior evidence by using the prior information. According to the corresponding relationship between the parameter characteristics and the processing technology of the worn parts, the detection and evaluation information of the feature parameters of the parts is transformed into the corresponding evidence of the parameter values. Finally, the conditional evidence theory is used to fuse the prior evidence and the corresponding evidence of parameter value, and the fusion result has one-to-one correspondence with the remanufacturing processing technology of worn parts (Fig 1).

2) INTEGRATION OPTIMIZATION MODEL

In order to achieve the goal of remanufacturing process optimization and maximize its production efficiency, time, cost and dimensional tolerance should be considered comprehensively.

The dimensional tolerance D is the weighted sum of each part tolerance:

$$D = \sum_{i=1}^{n} \zeta_{D_i} D_i \quad (4)$$

where, D_i is the dimensional tolerance, ζ_{D_i} is the corresponding coefficient, where $i = (1, 2, \cdots\cdots, n)$ is the ith tolerance, and n is the total of measurements. The time tolerance T includes the weighted sum of the processing time of each station:

$$T = \sum_{i=1}^{m} \zeta_{T_i} T_i \quad (5)$$

where, T_i is the processing tolerance, ζ_{T_i} is the corresponding coefficient, i is the ith tolerance, where m is the total of processing station. And the cost C includes the algebraic sum of material cost of each station:

$$C = \sum_{i=1}^{m} \zeta_{C_i} C_i \quad (6)$$

where, C_i is the material cost tolerance, where ζ_{C_i} is the corresponding coefficient, i is the ith tolerance, and m is the total of processing station. Then the overall optimization goal is to take the minimum value:

$$P = T + D + C \quad (7)$$

When formula (8) takes the minimum value, it shows that our process path is optimal. Due to the uncertainty of worn parts, the complexity of processing technology and the diversity of processing paths, it is difficult to minimize formula (8). It is assumed that there exist k routes $\{F_1, F_2, \ldots, F_k\}$ to process the worn parts, and the processing route of a worn part is determined by the parameters of the worn part. It is assumed that there exist quantitative parameters $\alpha_i \in U_i (i = 1, 2, \cdots, r)$, and qualitative parameter $\beta_j \in U_j (j = r + 1, 2, \cdots, p)$, where U_i is the value range of α_i, and U_j is the value range of β_j.

Different worn parts adopt different machining paths according to the different properties of parameter. The worn parts should be processed using different processing route.

There exist k machining paths, recorded as set $F_1, F_2, \ldots\ldots F_k$. The machining path $F_l = \{F_1, F_2, \ldots\ldots F_k\}$ of a worn part is a multivariable function of parameters. Suppose the function is

$$f : U_1 \times U_2 \times \ldots \times U_r \times T_{r+1} \times \ldots \times T_p$$
$$\rightarrow \{F_1, F_2, \ldots, F_k\} \quad (8)$$

Suppose the parameter of a worn part is $x \in U_1 \times U_2 \times \ldots \times U_r \times T_{r+1} \times \ldots \times T_p$.
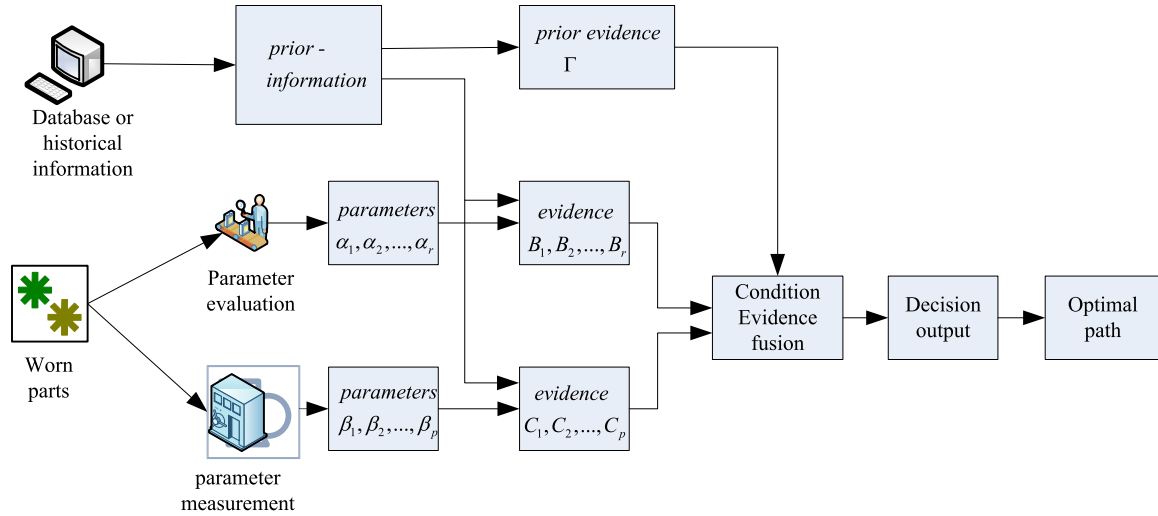
$$f(x) = F_i \quad (9)$$

FIGURE 1. Method framework.

Formula (9) shows that worn part x is processed by route F_l ($l \in \{1, 2, \ldots k\}$).

Experienced technicians firstly evaluate and measure the worn parts, and then select the appropriate processing path according to the evaluation and measure results. After a long time of accumulation of these processing experiences, it has a positive guiding role for the subsequent of remanufacturing process. Assume the historical processing experience is Ξ, Under the condition Ξ, the functions (8) form is

$$f(x) = f(x|\Xi) = F_l \qquad (10)$$

where $j = 1, \ldots, k$ and $f(x|\Xi)$ is considered as a fixed condition function.

Deal to the uncertainty of the parameters and the complexity of the process path, it is difficult to get the specific expression of the function $f()$, and it makes the remanufacturing processing path difficult to optimal.

Conditional evidence theory can effectively deal with the prior information and nonlinear problems. If the prior information is regarded as the prior evidence, and the each parameter information of worn parts is considered as characteristic parameter evidence; so the prior information and characteristic parameter evidence can be effectively integrated using conditional evidence theory. Thus the optimal remanufacturing process path can be obtained using the appropriate decision method.

The block diagram of integrated optimization model of remanufacturing process using conditional evidence theory is shown in Figure 1.

Different remanufacturing processes constitute the identification frame $\Theta = \{F_1, F_2, \ldots, F_k\}$. Firstly, historical data (information in database and experience information) is transformed into prior evidence Γ. The parameters of the worn parts are evaluated and measured, and then qualitative and quantitative parameters $\alpha_i (i = 1, \ldots, r)$, $\beta_j (j = r+1, \ldots, p)$ are transformed into corresponding evidence according to

workers' experience, which is recorded as $C_i (i = 1, \ldots, r)$ and $B_j (j = r+1, \ldots, p)$. Finally, conditional evidence theory is used for fusion, and then the remanufacturing process path is selected (decision output).

B. IMPLEMENTATION STEPS

Suppose a batch worn part has n pieces of processing history information and every worn part has 5 attributes. C_1, C_2, C_3 are quantitative parameters, and the value ranges are U_1, U_2, U_3 respectively. C_4, C_5 are qualitative parameters, whose value range is {none, slight, medium, serious}. According to the different parameter values and the restriction of the processing conditions of the enterprise, there are 4 processing paths $\{F_1, F_2, F_3, F_4\}$.

The number of the processing paths F_1, F_2, F_3 and F_4 used in historical data is $n_I, n_{II}, n_{III}, n_{IV}$ respectively. Then the frame of the evidence theory is $\Theta = \{F_1, F_2, F_3, F_4\}$. The frequency of using route F_1, F_2, F_3, F_4 is:

$$\begin{cases} P_I &= n_I/n \\ P_{II} &= n_{II}/n \\ P_{III} &= n_{III}/n \\ P_{VI} &= n_{VI}/n \end{cases} \qquad (11)$$

Then, $\Gamma = \{P_i, P_{II}, P_{III}, P_{IV}\}$ is a random number set, and $\beta_\Gamma()$ is a confidence function based on Γ, where $\beta_\Gamma()$ is the prior evidence. According to the value range of parameters C_1, C_2, C_3, C_4, C_5, each value range can be divided into 4 different categories I, II, III and IV, as shown in Tab 1.

The range of quantitative parameter U_1, U_2, U_3 is divided into 4 parts without overlap (Tab 1), The second column of Tab1 shows the optimal processing paths of different categories.

$$\begin{cases} U_{11} \cup U_{12} \cup U_{13} \cup U_{14} = U_1 \\ U_{21} \cup U_{22} \cup U_{23} \cup U_{24} = U_2 \\ U_{31} \cup U_{32} \cup U_{33} \cup U_{34} = U_3 \\ U_{41} \cup U_{42} \cup U_{43} \cup U_{44} = U_4 \end{cases} \qquad (12)$$

TABLE 1. Parameters of worn parts.

category	Processing paths	C	C	C	C_4	C_5
I	F_1	U_{11}	U_{21}	U_{31}	None	None
II	F_2	U_{12}	U_{22}	U_{32}	Slight	Slight
III	F_3	U_{13}	U_{23}	U_{33}	Medium	Medium
IV	F_4	U_{14}	U_{24}	U_{34}	Severe	Severe

If a worn part's parameter $C_1 \in U_{11}$, then it belong to class I. If the parameter $C_1 \in U_{12}$, then it belong to class II. If the parameter $C_1 \in U_{13}$, then it belong to class III. If the parameter $C_1 \in U_{14}$, then it belong to class VI. C_2 and C_3 are classified according to the same method.

Transforming quantitative parameters into evidence: The construction method of mass function is illustrated using the feature C_1 as an example. The midpoint and length of the four intervals $U_{11}, U_{12}, U_{13}, U_{14}$ of feature C_1 are $\delta_{11}, \delta_{12}, \delta_{13}, \delta_{14}$ and $|U_{11}|, |U_{12}|, |U_{13}|, |U_{14}|$ respectively. The mass function is determined according to the actual measured value of the feature.

The mass function is depending on the actual measurement value x of C_1.

$$
\begin{cases}
if \ x \in U_{11}, \ m_1(F_1) = \eta e^{-\frac{|\delta_{11}-x|}{|U_{11}|}}, \ m_1(\Theta) = 1 - m_1(F_1) \\
if \ x \in U_{12}, \ m_1(F_2) = \eta e^{-\frac{|\delta_{12}-x|}{|U_{12}|}}, \ m_1(\Theta) = 1 - m_1(F_2) \\
if \ x \in U_{13}, \ m_1(F_3) = \eta e^{-\frac{|\delta_{13}-x|}{|U_{13}|}}, \ m_1(\Theta) = 1 - m_1(F_3) \\
if \ x \in U_{14}, \ m_1(F_4) = \eta e^{-\frac{|\delta_{14}-x|}{|U_{14}|}}, \ m_1(\Theta) = 1 - m_1(F_4)
\end{cases}
\tag{13}
$$

$\eta \in [0, 1]$ is a variable parameter. $m_1(F_i)$ is the possibility using F_i as the processing route, and $m_1(\Theta)$ represent the uncertainty of the process route F_i. C_2, C_3 are transformed into evidence m_2 and m_3 using the same method.

Then transform the qualitative of a worn part into evidence. If the qualitative $C_4 = $ "None", then it belongs to class I. If the qualitative $C_4 = $ "Slight", then it belongs to class II. If the qualitative $C_4 = $ "Medium", then it belongs to class III. If the qualitative $C_4 = $ "Severe", then it belong to class VI. C_5 is classified according to the same method.

Suppose the number of worn parts with $C_4 = $ "None", "Slight", "Medium", "Severe" is $n_{None}, n_{Slight}, n_{Midium}, n_{Severe}$ respectively.

Transforming qualitative parameters into evidence:
Convert C_4 to evidence according to the following rules:

$$
\begin{cases}
if \ C_4 = \text{"None"}, \quad m_4(F_1) = n_{None}/n, \\
\quad m_4(\Theta) = 1 - m_4(F_1) \\
if \ C_4 = \text{"Slight"}, \quad m_4(F_2) = n_{Slighte}/n, \\
\quad m_4(\Theta) = 1 - m_4(F_2) \\
if \ C_4 = \text{"Medium"}, \ m_4(F_3) = n_{Medium}/n, \\
\quad m_4(\Theta) = 1 - m_4(F_3) \\
if \ C_4 = \text{"Severe"}, \quad m_4(F_4) = n_{Severe}/n, \\
\quad m_4(\Theta) = 1 - m_4(F_4)
\end{cases}
\tag{14}
$$

$m_4(F_i)$ is the possibility using the process route F_i, $m_4(\Theta)$ represents the uncertainty of the process route F_i, where $i \in \{1, 2, 3, 4\}$. Transform C_5 into evidence m_5 using the same method.

Suppose S is a worn part to be remanufactured The specific steps of optimizing the remanufacturing routes using conditional evidence theory are as follows:

STEP 1: Transforming quantitative parameters C_1, C_2, C_3 of S into corresponding evidence m_1, m_2, m_3 respectively.

STEP 2: Transforming qualitative parameters C_4, C_5 of S into corresponding evidence.

STEP 3: Fuse the prior evidence Γ and the evidence m_1, m_2, m_3, m_4, m_5 of different features of the worn parts, using the condition evidence rule.

STEP 4: Decision rules of the fusion results as follows

(i) The optimal processing path have the largest mass function, and the value of the function should be greater than 0.5.

(ii) The uncertainty of fusion results $m(\Theta)$ is less than 0.1.

If the fusion result does not meet the above conditions, it cannot be used for decision-making and needs to be processed manually.

III. APPLICATION EXAMPLES
A. BACKGROUND
The optimization experiment of the remanufactured crankshaft machining process route was carried out. The parameters of remanufactured crankshaft include physical shape, surface quality, physical and chemical properties, etc. According to the detection technology and machining conditions of the remanufacturing enterprise, combined with the actual experience in the remanufacturing process and the evaluation of the industry experts, 8 quantitative parameters and 2 non-quantitative parameters are selected as the actual evaluation indexes of worn crankshaft. The quantitative parameters include: the maximum wear of crankshaft main journal C_1, the maximum wear of connecting rod journal C_2, the roundness of main journal C_3, the cylindricity of main journal C_4, the curvature C_5, the twist C_6, the axial clearance C_7 and the roughness C_8; the qualitative indexes include: the crack degree C_9 and the ablation degree C_{10}. Considering test value of remanufactured crankshaft and the actual production requirements of the enterprise, the worn crankshaft is divided into four levels, and the classification standard is shown in Table 2.

TABLE 2. Classification standard of worn crankshaft.

Class	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
I	(0,0.03]	(0,0.03]	(0,0.04]	(0,0.04]	(0,0.15]	(0,0.1]	(0.08,0.25]	(0.2,0.4]	No	No
II	(0.03,0.75]	(0.03,0.75]	(0.04,0.08]	(0.04,0.08]	(0.15,0.3]	(0.1,0.2]	(0.25,0.50]	(0.4,0.6]	slight	slight
III	(0.75,1.5]	(0.75,1.5]	(0.08,0.12]	(0.08,0.12]	(0.3,0.5]	(0.2,0.3]	(0.50,1.00]	(0.6,0.8]	medium	medium
IV	(1.5,3.0]	(1.5,3.0]	(0.12,0.20]	(0.12,0.20]	(0.5,1.2]	(0.3,0.5]	(1.00,3.00]	(0.8,1.0]	severe	severe

TABLE 3. Available process paths for worn crankshaft.

routes	processing techniques
route1	Cleaning → grinding → preheating → roughening → metal powder plasma spraying → straightening → grinding
route2	Cleaning → alignment → grinding → preheating → roughening → metal powder flame spraying → straightening → grinding
route3	Cleaning → alignment → grinding → preheating → oil plugging → roughening → metal powder flame spraying → straightening → grinding
route4	Recycling of materials.

The goal of integrated optimization is to maximize the benefit of the enterprise, which involves processing time, production costs, and dimensional tolerance of each remanufactured routes. Since the number P (formula 8) is difficult to express in an analytical form, it is difficult to select an optimized processing route by a conventional method. And experienced workers will choose the appropriate processing route based on the maximum benefit of the product. Therefore, processing experience of workers is chosen as an indirect optimization goal. The overall benefits of enterprises adopting different processing technologies for the same kind of worn parts can be divided into three different situations: high, medium and low. For the experienced workers, the machining process paths in Table 3 for Class I, II, III and IV crankshafts are respectively adopted. The benefits of using different processing technologies for four different types of worn parts are shown in the Table 4.

Therefore, the path 1, 2, 3 and 4 can be used to process the class I, II, III and IV parts respectively to maximize the profits of the enterprise.

B. RESULTS

Taking the 4102QB crankshaft repaired by a remanufacturing workshop as the research object, 200 sets of crankshaft blanks are selected as test samples. The characteristic properties are shown in Tab. 5.

The historical data are used to get $P_I = 0.24$, $P_{II} = 0.35$, $P_{III} = 0.31$, $P_{IV} = 0.1$, $\Gamma = \{P_I, P_{II}, P_{III}, P_{IV}, \}$ then the prior evidence is : $\beta_\Gamma(R_1) = 0.24$, $\beta_\Gamma(R_2) = 0.35$, $\beta_\Gamma(R_3) = 0.31$, $\beta_\Gamma(R_4) = 0.1$.

STEP 1: Let $\eta = 0.7$, and use step 1 of section II.A to translate $C_1, C_2, \cdots, C_8$ into evidence $m_1, m_2, \cdots m_8$

STEP 2: Use step 2 of section II.A to translate C_9, C_{10} into evidence m_9, m_{10}.

STEP 3: Use condition evidence theory of section II.A to fuse the prior evidence Γ and the evidence $m_i(i = 1, \cdots, 10)$.

STEP 4: The fusion results are determined according to the following rules.

TABLE 4. Corresponding income of different process paths of remanufacturing Crankshaft.

Crankshaft category	Technological route	Enterprise benefit
I	route 1	high
	route2	medium
	route3	low
	route4	low
II	route 1	medium
	route2	high
	route3	medium
	route4	low
III	route 1	low
	route2	medium
	route3	high
	route4	low
IV	route 1	low
	route2	low
	route3	low
	route4	higt

I. The optimal processing path determined should have the largest mass function and be greater than 0.5.

II. The uncertainty of fusion results $m(\Theta)$ is less than 0.1.

When η is different values, the accuracy of the optimal processing process path obtained by the method in this paper compared with the actual processing process is shown in Table 6.

It can be seen from table 6 that the accuracy of fusion results vary with the parameter values. When the values are large or small, the accuracy of fusion results is not the best. The above experiments show that the accuracy of fusion results reaches 95% - 93% when $\eta = 0.7$ and 0.9.

TABLE 5. The characteristic properties OF the 4102QB crankshaft.

sample	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
X_1	1.7	1.5	0.15	0.15	0.09	0.15	0.26	0.9	slight	medium
X_2	0.45	0.61	0.09	0.10	0.16	0.10	0.41	0.6	Slight	slight
X_3	0.48	0.50	0.07	0.11	0.08	0.10	0.33	0.5	No	slight
X_4	0.02	0.04	0.05	0.05	0.07	0.00	0.50	0.7	slight	medium
X_5	0.30	0.35	0.06	0.06	0.20	0.20	0.30	0.5	medium	medium
X_6	2.10	2.00	0.11	0.12	0.31	0.40	0.45	0.7	slight	medium
X_7	1.20	1.30	0.07	0.07	0.42	0.20	0.50	0.5	slight	No
X_8	1.40	1.40	0.10	0.11	0.35	0.10	0.30	0.4	No	slight
X_9	1.90	2.00	0.10	0.15	0.6	0.10	0.35	0.8	medium	slight
X_{10}	0.25	0.30	0.05	0.05	0.18	0.00	0.20	0.3	severe	slight
X_{11}	0.45	0.45	0.03	0.03	0.22	0.20	0.28	0.4	slight	slight
X_{12}	0.03	0.03	0.04	0.04	0.10	0.00	0.10	0.3	No	slight
X_{13}	0.85	0.90	0.07	0.09	0.40	0.10	0.70	0.8	medium	slight
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
X_{199}	1.4	1.5	0.12	0.12	0.4	0.3	0.75	0.6	severe	medium
X_{200}	0.50	0.55	0.07	0.08	0.40	0.20	0.35	0.5	slight	medium

TABLE 6. Accuracy of fusion results.

Different value of η	0.1	0.3	0.5	0.7	0.9	1
Accuracy of fusion results	21%	34%	73%	95%	93%	87%

Analysis of the reasons for the above phenomenon: when η is small, it gives a larger value to the identification framework Θ. At this time, the uncertainty information is large, while the accuracy of the fusion result with less deterministic information is low. For example, when $\eta = 0.1$, the accuracy of the fusion result is 21%. When η is large, the deterministic information is large, and the uncertain information is small, the evidence corresponding to different characteristic parameters may produce greater conflicts, so the accuracy of the fusion results will be reduced.

C. DISCUSSION

This method can accurately guide the remanufacturing process of waste crankshaft, and has achieved good application effect. It improves the utilization rate of waste crankshafts and improves the remanufacturing quality of waste crankshafts from 93.1% to 95.6%. The unit cost of worn crankshaft in remanufacturing workshop decreased from 664 *CNY/p* to 627 *CNY/p*. The average remanufacturing time decreased from 1.64 *h/p* to *1.52 h/p*. This method has been recognized and promoted in the remanufacturing workshop of the remanufacturing enterprise.

In conclusion, compared with similar research results [6], [16]–[18], the integrated optimization decision method for remanufacturing process based on conditional evidence theory under uncertainty has the following advantages:

First of all, for remanufacturing operators, this method can guide them to a more efficient and accurate remanufacturing production operation.
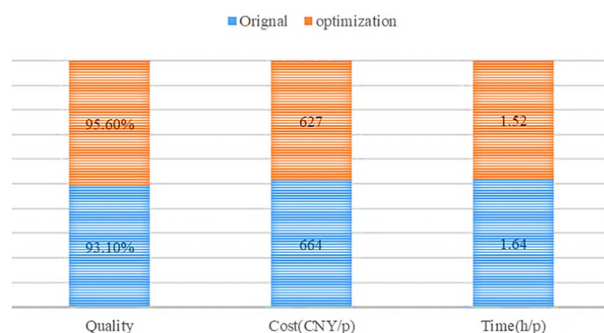

FIGURE 2. The effect of the method.

Second, for remanufacturing production manager, this method can help them reduce the cost, improve quality and improve production efficiency of remanufacturing process.

Third, for remanufacturing enterprises, this method can effectively expand the utilization efficiency of worn parts, improve the quality of remanufacturing products, and further condense the core competitiveness of remanufacturing enterprises.

Last but not least, this method provides a meaningful reference for the data mining and application of remanufacturing production management, as well as intelligent remanufacturing, and has a positive promoting significance for the sustainable development of remanufacturing industry.

IV. CONCLUSION

Uncertainty is the most critical difficulty in remanufacturing enterprise management. How to reduce the impact of uncertainty and improve the comprehensive benefits of remanufacturing process is the challenge of remanufacturing production management. Aiming at this problem and challenge, an integrated optimization decision method for

remanufacturing process based on conditional evidence theory under uncertainty is studied.

The main innovations are as follows: (i) the method of transforming quantitative and qualitative parameters into evidence is proposed; (ii) the influence law among production data, characteristics of worn parts and technological process in remanufacturing is revealed; and (iii) an integrated optimization decision method for remanufacturing process under uncertainty is studied considering the comprehensive benefits of quality, cost and time. Finally, an example of remanufacturing crankshaft is given to verify the effectiveness and feasibility of the method.

With the increasing scale of remanufacturing industry, research on the efficient application of remanufacturing production data to promote the development of intelligent remanufacturing is a broad direction to enhance the core competitiveness of remanufacturing enterprises. It has a good research prospect and practical value for promoting the sustainable development of remanufacturing industry.

REFERENCES

[1] Q. Zhu, J. Sarkis, and Y. Geng, "Green supply chain management in China: Pressures, practices and performance," *Int. J. Oper. Prod. Manage.*, vol. 25, no. 5, pp. 449–468, May 2005.

[2] C. Liu, "A review on remanufacturing assembly management and technology," *Int. J. Adv. Manuf. Technol.*, vol. 105, no. 11, pp. 4797–4808, Dec. 2019.

[3] B. Xu, E. Li, H. Zheng, F. Sang, and P. Shi, "The remanufacturing industry and its development strategy in China," *Strategic Study Chin. Academy Eng.*, vol. 19, no. 3, pp. 61–65, 2017.

[4] M. Ferguson, V. D. Guide, E. Koca, and G. C. Souza, "The value of quality grading in remanufacturing," *Prod. Oper. Manage.*, vol. 18, no. 3, pp. 300–314, May 2009.

[5] B. Xu, S. Dong, and P. Shi, "States and prospects of China characterised quality guarantee technology system for remanufactured parts," *J. Mech. Eng.*, vol. 49, no. 20, pp. 84–90, 2013.

[6] S. Butzer, S. Schötz, and R. Steinhilper, "Remanufacturing process assessment—A holistic approach," *Procedia CIRP*, vol. 52, pp. 234–238, Aug. 2016.

[7] S. T. M. Kin, S. K. Ong, and A. Y. C. Nee, "Remanufacturing process planning," *Procedia CIRP*, vol. 15, pp. 189–194, May 2014.

[8] Y. Seo, S. Hong, D. Jung, and N. Chung, "A study on the performance restoration of torque converters for passenger car 6-Speed automatic transmissions with remanufacturing process technology," *Int. J. Automot. Technol.*, vol. 21, no. 4, pp. 1061–1070, Aug. 2020.

[9] L. Li, C. Li, Y. Tang, and Y. Du, "An integrated approach of reverse engineering aided remanufacturing process for worn components," *Robot. Comput.-Integr. Manuf.*, vol. 48, pp. 39–50, Dec. 2017.

[10] Z. Liu and J. Shu, "Control of the microstructure formation in the near-net-shape laser additive tip-remanufacturing process of single-crystal superalloy," *Opt. Laser Technol.*, vol. 133, Jan. 2021, Art. no. 106537.

[11] C. Liu, W. Cai, O. Dinolov, C. Zhang, W. Rao, S. Jia, L. Li, and F. T. S. Chan, "Emergy based sustainability evaluation of remanufacturing machining systems," *Energy*, vol. 150, pp. 670–680, May 2018.

[12] C. Li, "Uncertain remanufacturing process routings model for used components based on GERT network," *Comput. Integr. Manuf. Syst.*, vol. 18, no. 2, pp. 298–305, 2012.

[13] S. J. Ridley, W. L. Ijomah, and J. R. Corney, "Improving the efficiency of remanufacture through enhanced pre-processing inspection—A comprehensive study of over 2000 engines at caterpillar remanufacturing, U.K.," *Prod. Planning Control*, vol. 30, no. 4, pp. 259–270, Mar. 2019.

[14] H. Liao, Q. Deng, Y. Wang, S. Guo, and Q. Ren, "An environmental benefits and costs assessment model for remanufacturing process under quality uncertainty," *J. Cleaner Prod.*, vol. 178, pp. 45–58, Mar. 2018.

[15] Z. Jiang, Z. Ding, H. Zhang, W. Cai, and Y. Liu, "Data-driven ecological performance evaluation for remanufacturing process," *Energy Convers. Manage.*, vol. 198, Oct. 2019, Art. no. 111844.

[16] X. Zhang, H. Zhang, Z. Jiang, and Y. Wang, "An integrated model for remanufacturing process route decision," *Int. J. Comput. Integr. Manuf.*, vol. 28, no. 5, pp. 451–459, May 2015.

[17] S. Kernbaum, S. Heyer, S. Chiotellis, and G. Seliger, "Process planning for IT-equipment remanufacturing," *CIRP J. Manuf. Sci. Technol.*, vol. 2, no. 1, pp. 13–20, Jan. 2009.

[18] H. Peng, H. Wang, and D. Chen, "Optimization of remanufacturing process routes oriented toward eco-efficiency," *Frontiers Mech. Eng.*, vol. 14, pp. 422–433, Dec. 2019.

[19] A. Shakourloo, "A multi-objective stochastic goal programming model for more efficient remanufacturing process," *Int. J. Adv. Manuf. Technol.*, vol. 91, nos. 1–4, pp. 1007–1021, Jul. 2017.

[20] C. Franke, B. Basdere, M. Ciupek, and S. Seliger, "Remanufacturing of mobile phones—Capacity, program and facility adaptation planning," *Omega*, vol. 34, no. 6, pp. 562–570, Dec. 2006.

[21] C. Zhang, C. Liu, J. Chen, Q. Li, K. He, M. Gao, and W. Cai, "The coupling mechanism of reassembly quality with uncertainty of remanufactured parts," *Assem. Autom.*, vol. 39, no. 4, pp. 548–555, Sep. 2019.

[22] Y. Zheng, J. Liu, and R. Ahmad, "A cost-driven process planning method for hybrid additive–subtractive remanufacturing," *J. Manuf. Syst.*, vol. 55, pp. 248–263, Apr. 2020.

[23] Y. He, C. Hao, Y. Wang, Y. Li, Y. Wang, L. Huang, and X. Tian, "An ontology-based method of knowledge modelling for remanufacturing process planning," *J. Cleaner Prod.*, vol. 258, Jun. 2020, Art. no. 120952.

[24] S. Li, H. Zhang, W. Yan, and Z. Jiang, "A hybrid method of blockchain and case-based reasoning for remanufacturing process planning," *J. Intell. Manuf.*, pp. 1–11, Jul. 2020.

[25] K. C. Arredondo-Soto, A. Realyvasquez-Vargas, A. A. Maldonado-Macías, and J. García-Alcaraz, "Impact of human resources on remanufacturing process, internal complexity, perceived quality of core, numerosity, and key process indicators," *Robot. Comput.-Integr. Manuf.*, vol. 59, pp. 168–176, Oct. 2019.

[26] D. Chen, Z. Jiang, S. Zhu, and H. Zhang, "A knowledge-based method for eco-efficiency upgrading of remanufacturing process planning," *Int. J. Adv. Manuf. Technol.*, vol. 108, no. 4, pp. 1153–1162, May 2020.

[27] J. Esquer, J. A. Arvayo, C. R. Alvarez-Chavez, N. E. Munguia-Vega, and L. Velazquez, "Cleaner production in a remanufacturing process of air compressors," *Int. J. Occupational Saf. Ergonom.*, vol. 23, no. 1, pp. 83–91, Jan. 2017.

[28] B. Xu, P. Shi, H. Zheng, B. Liu, and X. Zhou, "Engineering management problems of remanufacturing industry," *Frontiers Eng. Manage.*, vol. 2, no. 1, pp. 13–18, 2015.

[29] S. Peng, T. Yang, and T. Li, "Environmental benefits of engine remanufacture in China's circular economy development," *Environ. Sci. Technol.*, vol. 53, no. 19, pp. 11294–11301, 2019.

[30] C. Liu, Q. Zhu, F. Wei, W. Rao, J. Liu, J. Hu, and W. Cai, "An integrated optimization control method for remanufacturing assembly system," *J. Cleaner Prod.*, vol. 248, Mar. 2020, Art. no. 119261.

[31] J. Gönsch, "A note on a model to evaluate acquisition price and quantity of used products for remanufacturing," *Int. J. Prod. Econ.*, vol. 169, pp. 277–284, Nov. 2015.

[32] Y. Tang and J. Zheng, "Generalized Jeffrey's rule of conditioning and evidence combining rule for a priori probabilistic knowledge in conditional evidence theory," *Inf. Sci.*, vol. 176, no. 11, pp. 1590–1606, Jun. 2006.

● ● ●