Data-driven Ecological Performance Evaluation for Remanufacturing Process

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Abstract: Remanufacturing has received extensive attention due to its advantages in material and energy saving, emission reduction and is often considered a viable approach for the realization of a circular economy. Remanufacturing ecological performance reflects the ability of an enterprise to balance economic and environmental benefits. Therefore, evaluating the remanufacturing ecological performance is of great significance for leveraging the benefits of remanufacturing and promoting the concept of sustainability and the implementation of a circular economy in the industry. To this end, a set of data-driven techniques, i.e., data envelopment analysis, R clustering and grey relational analysis, are deployed to analyze and evaluate the ecological performance of a remanufacturing process. The effectiveness and feasibility of the proposed method are illustrated via a case study of remanufacturing for hydraulic cylinder and boom cylinder. Furthermore, a number of critical factors, e.g., energy-saving rate, remanufacturing process cost and rate of remanufacturing, for end-of-life products have been identified as the key drivers impacting the remanufacturing ecological performance. So as to improve remanufacturing ecological performance, optimizing production technology, implementing lean remanufacturing and raising public acceptability over remanufacturing products are effective measures. The research results of the present work can provide support for remanufacturing enterprises to guide and improve their ecological performance and formulate better development strategies.

Keywords: remanufacturing; ecological performance; data-driven; data envelopment analysis

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Nomenclature		R_{ab}	the average correlation coefficient of subclasses *a* and *b*
CUR	comprehensive utilization rate	r_{0i}	the grey relation degree between the sequences k_0 and k_i
DEA	data envelopment analysis	s^-/s^+	the slack variables
DMU	decision-making unit	u^T	output weight coefficient
GRA	grey relation analysis	v^T	input weight coefficient
REP	remanufacturing ecological performance	X_j	the input of DMU_j
C_i	the *i*th independent subclass	X^*	the input projection value of DMU_0
h_j	the relative efficiency value of DMU_j	Y_j	the output of DMU_j
K_0	the system feature sequence	Y^*	the output projection value of DMU_0
K_i	the *i*th system behavior sequences	θ	the relative efficiency value of DMU_0
k_0	transformed system feature sequence	λ_j	the weight of DMU_j
k_i	the transformed sequences of *i*th system behavior	ξ	resolution coefficient
P_{ij}	Pearson correlation coefficient	δ_{0i}	the relation coefficient between the sequences k_0 and k_i

1 Introduction

In the past few decades, with the rapid development of the economy and the acceleration of product technology upgrades, social resources are increasingly exhausted [1]. At the same time, various waste products are also flooding our natural environment [2]. This has caused more serious problems of energy consumption [3], resource shortages and environmental pollution [4]. Remanufacturing is considered one of the best ways to handle these waste products [5]. As an outstanding selection to extend the life cycle of End-of-life (EOL) products, remanufacturing has received widespread attention [6]. In China, remanufacturing has been confirmed as an important strategy. And it has played an important role in the scrap disposal of engines, automobiles, construction machinery and other fields [7].

It is generally believed remanufacturing has great economic and environmental benefits. The remanufacturing of EOL products can not only reduce the procurement cost of raw materials, but also minimize the discharge of waste and realizes the recycling of resources [8]. In terms of improving product quality while reducing economic cost and resource consumption and decreasing the negative impact on the environment [9], these two aspects constitute the remanufacturing ecological performance [10]. Paying attention to the ecological performance of the remanufacturing process, so that the economic and environmental benefits of remanufacturing can be developed in a balanced manner [11]. It can not only scientifically and accurately reflect the operation of remanufacturing enterprises in ecological management, but also provide decision support for enterprises and properly guide the enterprise's future production behavior and performance. So as to help solve the problems of resource depletion, environmental pollution, etc [12].

Analysis and evaluation of remanufacturing ecological performance are an important means in measuring the sustainability and realizing strategic management of remanufacturing enterprise. Remanufacturing processes with higher ecological performance can achieve more economic benefits while minimizing excessive resource consumption and reducing environmental impact [13]. Through ecological performance analysis and evaluation, it can be judged whether the ecological performance management of the remanufacturing process is reasonable. And the best measures to control cost, use resources effectively, and improve ecological performance can be found. Moreover, it is also an important guarantee to help enterprises realize remanufacturing benefits and promote the sustainable development of the remanufacturing industry [14].

The focus of this study is to evaluate the remanufacturing ecological performance. To this end, a data-driven evaluation method (integrated R Clustering, DEA, Grey Relation Analysis) is proposed to quantitatively evaluate the ecological performance of remanufacturing process and then identify the key drivers impacting ecological performance. It aims to help enterprises find economic and environmental problems in the production process, and provide a basis for the government to formulate policies to regulate remanufacturing.

The rest of the paper is organized as follows. Section 2 reports on the literature review related to the research topic, and proposes the main innovations of this paper through comparative analysis. Section 3 introduces the methods deployed in this study. Evaluation system and data sources are presented in Section 4. While Sections 5 and Sections 6 respectively show the application results of the method and make discussion in detail. Finally, conclusion remarks are given in Section 7.

2 Literature review

Before proceeding further with this study, it is necessary to review literature related to remanufacturing ecological performance Evaluation. This section discusses evaluation on the remanufacturing ecological performance, methods of performance evaluation and application of data-driven modeling method in remanufacturing.

2.1 Evaluation on the remanufacturing ecological performance

Remanufacturing ecological performance includes both economic and environmental benefits. As far as know, the current literature indicates that there are few studies on the remanufacturing ecological performance evaluation. However, many researchers have studied the economic or environmental benefits of remanufacturing in a single dimension. For instance, Sabharwal and Garg [15] utilized Graph Theory to analyze the parameters affecting the economic feasibility of remanufacturing, and obtained the maximum and minimum values of cost effectiveness index. Sang et al. [16] analyzed the influencing factors of remanufacturing cost, and established a state-based remanufacturing cost prediction model using Grey Theory. In terms of environmental benefits, Sundin and Lee [17] compared the environmental performance of remanufacturing with simple material recovery and new product manufacturing through extensive literature analysis and research. Mao et al. [18] established the product life cycle based evaluation matrix for semi-quantitative analysis to obtain environmental evaluation indexes of engine remanufacturing. By analyzing the energy, materials and carbon dioxide emissions during the remanufacturing process, Xu [19] developed an assessment model of resource and environmental benefit for the remanufacturing of decommissioned construction machinery. Liu et al. [20] used Life Cycle Assessment (LCA) to analyze the environmental impact of laser cladding remanufactured cast iron cylinder head block and compared them to the manufacture of new. Furthermore, many scholars have applied different models to explore the impact of remanufacturing on environmental benefits such as resources and energy [21].

Moreover, also some experts calculate or evaluate the remanufacturing benefits from the two comprehensive dimensions of economic and environment [22]. Quariguasi and Bloemhof analyzed the eco-efficiency in remanufacturing from the perspectives of environmental impact, energy conservation, and customer purchase intentions for remanufacturing products [23]. Golinska and Kuebler [24] evaluated the sustainability of remanufacturing enterprises from the dimensions of economic, ecological and social. Liao et al. [25] and Shi [26] proposed a quantitative model to comprehensively assess the environmental benefits and cost of remanufacturing under quality uncertainty. Van et al. [27] developed a decision support tool to quickly evaluate the attractiveness of remanufacturing on economic and environmental. Diaz et al. [28] exploited the Monte Carlo method to evaluate the performance of the remanufacturing supply chain in order to help decision-makers determine the potential of remanufacturing activities. Graham et al. presented a KPI system for evaluating remanufacturing performance [29]. Deng et al. [30] and Liu [31] provided unique insights into enhancing remanufacturing benefits from the perspective of identifying key factors in remanufacturing eco-efficiency.

Most of these studies utilized qualitative methods or engineering models based on certain empirical values to evaluate economic or environmental benefits of the remanufacturing process. Although few scholars have clearly proposed the concept of “remanufacturing ecological performance”, these studies provide valuable references for further research on REP. To the best of our knowledge, there has been no research report on application in remanufacturing ecological performance evaluation. Moreover, few literatures combined key drivers of REP with performance evaluation to explore how to optimize REP. In this study, a quantitative assessment of the ecological performance of the remanufacturing process is performed by establishing a data-driven model. Combined with the evaluation results, the key drivers impacting the remanufacturing ecological performance can be identified, and the measures to improve the remanufacturing ecological performance are explored. This will benefit the sustainable development of the remanufacturing industry from the perspective of optimizing the remanufacturing environment and economic balance.

2.2 Methods for ecological performance evaluation

Performance evaluation is a tool for managers to accomplish their goals and strategies. Research on performance evaluation has received attention in many areas, such as supply chain management, renewable energy resources efficiency [32] and ecological environment, etc. The commonly used methods of ecological performance analysis mainly include Corrected Ordinary Least Square (COLS), LCA, Data Envelopment Analysis (DEA), and Key Performance Indicator (KPI). Among them, DEA has emerged as a powerful approach to analysis performance. As an effective tool for calculating relative efficiency [33], it has not only been used in evaluation on ecological performance, but also widely in power performance [34], energy and environmental efficiency [35], and supply chain performance [36].

Sarkis and Cordeiro [37] applied DEA to determine the combined ecological and technical efficiency of the 437 largest fossil fuel power plants in the United States. Cook et al. [38] developed a DEA model based on improved weight limits to assess the ecological performance of the US power industry and achieved good results. Lo Storto [39] adopted the composite index calculated by DEA crossover efficiency and Shannon entropy index to rank the urban eco-efficiency scores, the results of the case study show that the method has good discriminating ability. Xiaoping et al. [40] used DEA to explain the urban resource and environmental efficiency of 285 cities in China, and combined the evaluation results to study the factors that have the greatest impact on the spatial pattern. In addition, some improved DEA methods have also been employed in performance analysis. Liu et al. [41] proposed an improved DEA model to solve the problem of non-uniqueness of optimal weights in cross-efficiency evaluation of data envelopment analysis. To analyze environmental efficiency, Chang et al. [42] and Yang et al. [43] presented a non-radial DEA model based on slack metric (SBM) and an environmental super-efficient data envelopment analysis (SEDEA) model, respectively.

The above review indicates that DEA is a viable technique for conducting ecological performance assessments. Their work on model optimization and improvement are of great significance to the better application of DEA for performance evaluation. Nevertheless, most of the research is mainly focused on the specific methods of performance evaluation and its specific application areas, but no reasonable conclusions have been drawn in the selection of DEA model indicators and accurate analysis of performance. To fill this gap, our study proposes an improved DEA model to evaluate remanufacturing ecological performance. The R Clustering technique is used to select indicators for the DEA model, and the absolute performance value is obtained by increasing the expected DMU. The proposed model can solve the problem of insufficient data and many evaluation indicators in the remanufacturing ecological performance evaluation. Through the actual performance obtained, full ordering of all DMUs can be achieved. The presentation of this improved DEA model is one of the major contributions of this paper.

2.3 Application of data-driven modeling method in remanufacturing

Increasing studies suggest that data mining and data analysis based methods are effective approaches for knowledge discovery in various disciplines [44]. For example, Peral et al. proposed a method for obtaining specific KPIs of business objectives based on data mining techniques [45]. Torregrossa presented a data-driven methodology to support daily energy decision-making [46]. Data-driven modeling ideas are also favored by researchers in the field of remanufacturing. Ehm [47] developed a data-driven modeling method to analyze the combination problem of disassembly planning and machine scheduling in the remanufacturing process, and an industrial case was given to prove the application of the model. A big data-driven product lifecycle management framework was proposed by Zhang [48], to support optimization decisions for product lifecycle management. In order to optimize the sorting strategy of the remanufacturing system, Mashhadi and Behdad [49] used a data-driven method to evaluate the quality level of the recycled products, and then performed cluster sorting to finally complete the end of life decision. A data-driven remaining useful life assessment method based on support vector machine (SVM) was employed to realize the analysis and decision-making of remanufacturing scheme in [50]. Zhang et al. [51] presented an overall architecture for data-based product lifecycle analysis that helps product lifecycle management and cleaner production decisions. Ovchinnikov et al. [52] proposed a data-driven assessment of the economic and environmental aspects for remanufacturing.

As can be seen from the above research, various data-driven method has achieved positive results in the fields of remanufacturing disassembly planning, product life cycle management remanufacturing scheme decision and so on. However, no scholars have yet established a data-driven model to quantitatively evaluate remanufacturing ecological performance. The data-driven modeling approach is becoming a promising area, and its rapid development and widespread adoption present new opportunities and challenges for performance evaluation. The focus of this paper is to establish a quantitative evaluation model for remanufacturing ecological performance. It is different from previous research, focusing on the objective and reasonable evaluation of remanufacturing ecological performance by allowing the data itself to reflect the information. To this end, a data-driven approach of ecological performance analysis for remanufacturing process is proposed in this study. This model incorporates the techniques of R Clustering, DEA and Grey Relation Analysis. DEA is employed to calculate performance, R Clustering technique is used to determine model input/output indicators and Grey Relation Analysis (GRA) is applied to identify driving factors.

3 Proposed method

There are three main purposes of the analysis in this paper. First, assess the ecological performance of the remanufacturing process and propose optimization methods; second, horizontally compare the ecological performance of remanufacturing for different products; and third, identify key influencing factors of REP in environment, economy, society, resources and energy, etc.

By combining R Clustering, DEA, and GRA, a data-driven approach of ecological performance analysis for remanufacturing process is proposed in this study (as shown in Fig. 1). First, R Clustering technique is used to select input and output indexes for DEA model. Then, the ecological performance value of the remanufacturing process is obtained by the calculation of the DEA method. Finally, the GRA is applied to correlate ecological performance with evaluation indicators to identify key drivers. The above three main steps and related techniques of the proposed method are detailed in Sections 3.1 to 3.3, respectively.

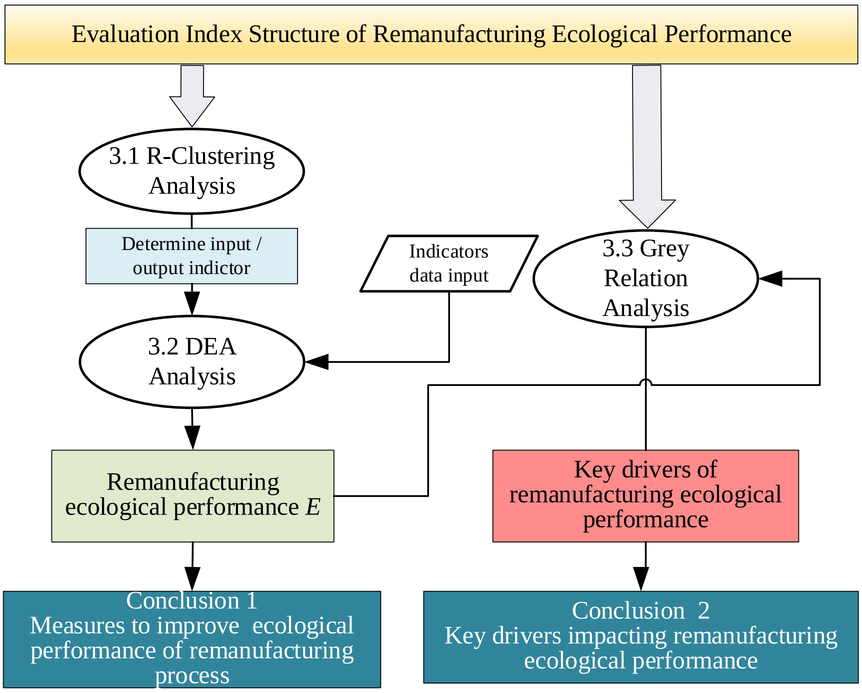

Fig. 1 Data-driven model of ecological performance analysis for remanufacturing process

3.1 R Clustering Analysis

There are many aspects in the criterion layer of REP evaluation, and there are a large number of indicators in each aspect of the criterion layer. For small sample sets, substantial independent attributes make it difficult for samples to form clusters in high-dimensional spaces [53]. According to the characteristics of the remanufacturing process, selecting the evaluation indicators. These indicators can correctly describe, reflect, and measure the operational characteristics and posture of remanufacturing ecological performance. It is the premise and basis for scientifically conducting remanufacturing ecological performance evaluation.

In most of the current performance evaluation, the selection of indicators is often determined qualitatively or through the quantitative analysis of expert scoring. Generally speaking, there are more qualitative analysis and less quantitative analysis in the construction of ecological performance index structure. Quantitative selection method is also more subjective, lack of effectiveness test. This has a subjective impact on the final evaluation results. R Clustering is a multivariate statistical analysis technique based on similarity to group targets. Therefore, R Clustering technology is utilized to select the impactful indicators for evaluation model in this study. That is, the purpose of screening indicators can be achieved through the selection of similar indicators. The R clustering technique has proven to be a great advantage in the selection of indicators. It can cluster the indicators into several categories according to the similarity relationship between them and then find the main indicators that affect the remanufacturing ecological performance.

R Clustering is a hierarchical algorithm on data mining. It is a way to cluster the variables and classify the characteristics of the sample set in order to reduce the number of variables and achieve the purpose of dimensionality reduction. The indicators selection process based on the R Clustering technique is shown in fig. 2. The correlation coefficient $R_{a,b}$ of the two classes C_a, C_b is calculated as follows:

$$R_{a,b} = \frac{1}{|C_a||C_b|} \sum_{s_i \in c_a} \sum_{s_j \in c_b} P_{ij} \tag{1}$$

$$P_{\mathrm{ij}} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \tag{2}$$

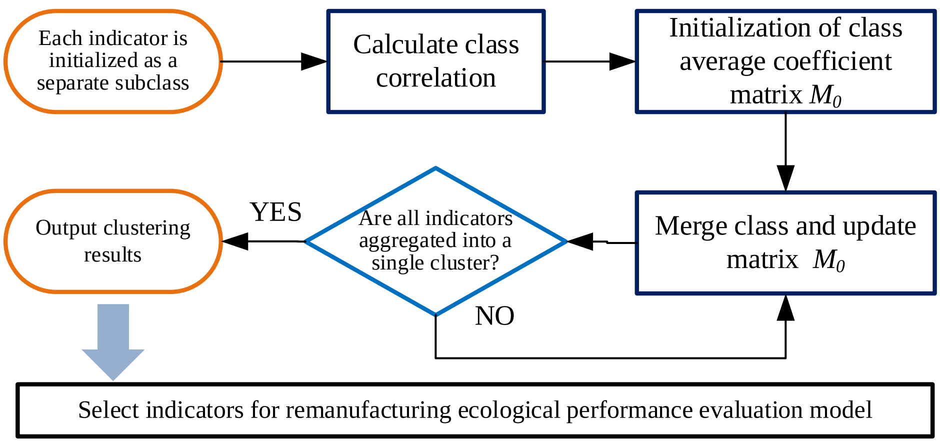

Fig. 2 Flow chart of indicator selection bases on R Clustering

3.2 DEA method

DEA is an efficiency evaluation method based on the concept of relative efficiency, which is used to deal with multi-objective decision making. It evaluates the strengths and weaknesses of

Decision-Making Unit (DMU) based on a set of input and output data, i.e., evaluates the relative efficiency of each unit. DEA method relies on input and output indicator data and evaluates the efficiency of each unit from the point of relative efficiency. It does not need to set the specific input/output function of the decision unit in advance. In determining the relative efficiency of several DMUs, the emphasis is on optimizing each DMU to obtain the maximum relative efficiency and the optimal weight. The DEA method does not require any weighting assumptions, but mathematically plans the actual input/output data of DMU to obtain the optimal weight. It does not require user subjective weighting and has strong objectivity. Therefore, the DEA method can avoid the complexity of input/output indicators and the difficulty in measuring the ecological performance of the remanufacturing process.

There are many factors to be considered in the remanufacturing ecological performance evaluation. And there is a multi-directional interaction among many evaluation indicators. This complex internal relationship is difficult to accurately express from a microscopic perspective with a certain function analytic. In addition, the units of each indicator in the remanufacturing ecological performance evaluation are often not uniform. When using other methods for evaluation, the indicators need to be compared to the same unit for comparison. The DEA method does not need to consider whether the dimension is unified, or the weight of the indicators is assigned. It can better reflect the information and characteristics of the evaluation object. Therefore, this method has its unique advantages in remanufacturing ecological performance evaluation.

3.2.1 Traditional DEA model

The C^2R model of DEA technology is the most commonly used in efficiency evaluation. Suppose there are n comparable DMUs, the input and output of the DMU$_j$ are recorded as $X_j = (x_{1j}, x_{2j,} \cdots, x_{sj})^T$ and $Y_j = (y_{1j}, y_{2j,} \cdots, y_{mj})^T$ respectively, then the efficiency evaluation index of DMU$_j$ is:

$$h_j = \frac{u^T Y_j}{v^T X_j} \tag{3}$$

The meaning of h_j is the ratio of output to input when input is X_j and output is Y_j. Each DMU has a corresponding efficiency evaluation index, and there are always appropriate u and v, making $h_j \le 1$. The C^2R efficiency evaluation model is:

$$\max h_{j_0} = \frac{u^T Y_0}{v^T X_0}$$
$$s.t.\begin{cases} \dfrac{u^T Y_j}{v^T X_j} \le 1,\ j = 1,2,\cdots,n \\ u \ge 0, v \ge 0 \end{cases} \tag{4}$$

By using the duality principle of linear programming and introducing relaxation variables, the dual linear programming model of C^2R can be obtained as follows:

$$\min \theta$$
$$s.t.\begin{cases} \sum_{j=1}^{n+1} X_j \lambda_j + s^- = \theta X_0 \\ \sum_{j=1}^{n+1} Y_j \lambda_j - s^+ = Y_0 \\ \lambda_j \ge 0,\ j = 1,2,\cdots,n \end{cases} \tag{5}$$

In this study, θ is employed to represent REP; the slack variables s^- and s^+ are the input redundancy and the output deficiency, reflecting the way to improve the performance of DMU_0.

When θ=1 and s^-=s^+=0, it means that DMU_0 is DEA efficient; when θ=1 and s^-≠0 or s^+≠0, DMU_0 is weak DEA efficient; when θ<1, DMU_0 is non-DEA efficient. When the DMU is non-DEA efficient, the input and output are adjusted by equation (6).

$$X_0^* = \theta X_0 - s^-, Y_0^* = Y_0 + s^+ \tag{6}$$

3.2.2 Improved DEA model considering the expected goal

While the traditional DEA approach is beneficial in evaluating remanufacturing ecological performance, it also has the following limitations: (1) The DEA method only evaluates the relative efficiency of the DMU, rather than the absolute efficiency evaluation. Therefore, DEA cannot completely replace the analysis of absolute efficiency by the traditional ratio analysis method; (2) Due to the weight change of the traditional DEA model is too flexible, it is easy to cause an excessive number of effective DMUs. To some extent, this limits the ability of sorting method to distinguish DMU.

In order to solve the above problems, a virtual optimal decision unit is introduced. If the optimal value of each indicator can be determined in advance, and the optimal virtual DMU containing all the best values can be simulated, the efficiency of these DMUs can be calculated and sorted by DEA method. The efficiency value of the virtual optimal DMU is 1, it can be regarded as the expected efficiency, and that of the real DMU is between 0 and 1. The efficiency value obtained can be regarded as the comparison result with the standard efficiency, and basically can be regarded as absolute efficiency. In this way, the full ranking of DMUs can be realized.

By using the DEA method, the virtual expected optimal DMU is included in the actual DMU for sorting. And the obtained efficiency value of the actual DMU can be regarded as the actual efficiency, and the actual efficiency value can reflect the degree of expected efficiency that can be achieved. The closer the actual efficiency is to the expected efficiency, i.e, the closer to 1, the higher the level of ecological performance of the remanufacturing process.

Among the many indicators for evaluating remanufacturing ecological performance, not all data are objective data generated in actual production activities, but there are standards when evaluating them. Compared with the manufacture of new products, remanufactured products can save 50% of cost, 60% of energy saving, 70% of material saving, and hardly produce solid waste. This can be regard as an expected goal for remanufacturing ecological performance. Incorporating the virtual DMU into the real DMU, the following improved DEA model is available:

$$\max h_{j0} = u^T Y_0$$
$$s.t.\begin{cases} v^T X_0 = 1 \\ u^T Y_j - v^T X_j \le 0,\ j = 1,2,\cdots n+1 \\ u \ge 0, v \ge 0 \end{cases} \tag{7}$$

The DEA analysis process for remanufacturing ecological performance is shown in Fig. 3. The model has the following main steps:

Step 1: Selects input and output indicators via R Clustering.

Step 2: Calculate the ecological performance of the remanufacturing process by using the C^2R models of improved DEA model.

Step 3: The optimal measure to improve the REP is obtained by projection analysis of relaxation variables. The sensitivity analysis is carried out to further optimize the index set and the verification algorithm.

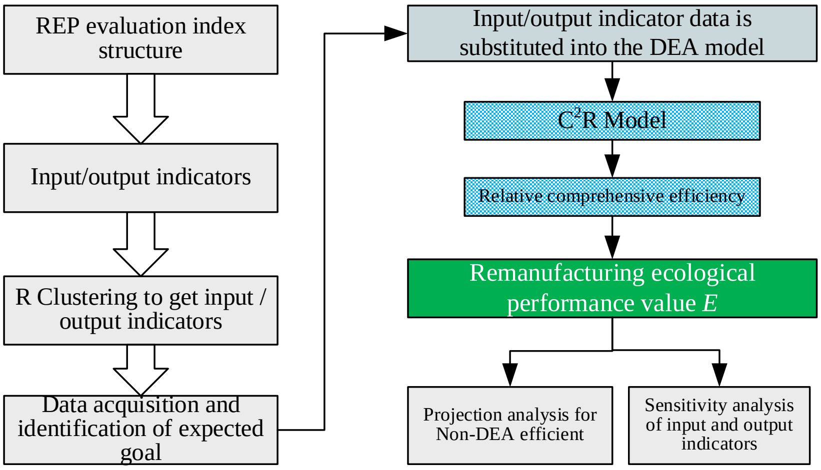

Fig. 3 The calculation process of improved DEA model

3.3 Grey Relation Analysis

The remanufacturing ecological performance value can be obtained by the DEA method, then the driving factor identification should be carried out in order to further explore the factors affecting the remanufacturing ecological performance. Owing to the amount of data in remanufacturing ecological performance evaluation is too small and its distribution law cannot be known, it is difficult to use the traditional correlation analysis method to identify the driving factors. GRA is a method to measure the degree of influence of factors on the object of study. The Grey Relation Analysis method does not require too much sample size, nor does it require a typical distribution law, and the calculation amount is relatively small. The results are in good agreement with the qualitative analysis results. Therefore, Grey Relation Analysis is employed to determine the key factors affecting the remanufacturing ecological performance in this study.

Grey Relation Analysis is mainly used to analyze the dynamic relationship between the various factors of the system and its characteristics, so as to find the main factors of the system [54]. In the process of system development, if the situation of the two factors changes is basically same, they are considered to be highly correlated. Thus, the correlation degree is a quantitative description on relativity among the factors of the system. In this study, GRA is adopted to identify key drivers impacting REP. The calculation process is as follows:

(1) Let the system feature sequence be $K_0=(K_{0(1)},K_{0(2)},\cdots,K_{0(n)})$, and there are m system behavior sequences as $K_i=\left(K_{i(1)},K_{i(2)},\cdots,K_{i(n)}\right)(i=1,2,\cdots,m)$.

(2) The system feature sequence and the system behavior sequence are transformed by the initial value operator. The transformed initial valued image sequences are $k_0 = (k_0(1), k_0(2), \cdots, k_0(n))$ and $k_i = \left(k_i(1), k_i(2), \cdots, k_i(n)\right)$, respectively.

(3) Calculate the grey relation coefficient between the initialized image sequences k_0 and k_i :

$$\delta_{0i}(l) = \frac{\min_i \min_k \left|k_0(l) - k_i(l)\right| + \xi \max_i \max_k \left|k_0(l) - k_i(l)\right|}{\left|k_0(l) - k_i(l)\right| + \theta \max_i \max_k \left|k_0(l) - k_i(l)\right|}, \quad l = 1,2,\cdots,n \tag{8}$$

Where $\theta \in (0,1)$, the general value of θ is 0.5.

(4) Calculate the grey relation degree between the system feature sequence and the system behavior sequence.

$$r_{0i} = \frac{1}{n}\sum_{l=1}^{n} \delta_{0i}(l) \tag{9}$$

When θ=0.5, if r >0.6, it indicates that the factor is closely related to the system.

(5) Sort each factor according to the grey relation degree.

4 Evaluation indicators and data

Constructing a scientific and reasonable evaluation index structure is the first step for remanufacturing ecological performance evaluation. In this section, on the basis of referring to a large number of documents, the remanufacturing ecological performance evaluation index structure is established. Then the input/output indicators of the evaluation model are determined by using the R clustering technique proposed in Section 3.2. Section 4.3 describes the data sources and data lists.

4.1 Evaluation index structure

The remanufacturing ecological performance evaluation index structure is composed of many indicators. It is used to scientifically evaluate the ecological level and effect achieved by the remanufacturing process. Ecological performance indicators include many aspects such as economy, environment, etc., with a focus on converting environmental information into quantifiable numbers. The ecological performance is considered as the ratio of input to output, which is measured by converting environmental impact into value. The goal is to obtain the maximum value of the product or service with minimal environmental impact.

In order to select a scientific and comprehensive evaluation index of ecological performance, a large number of domestic and foreign literature related to ecological performance evaluation were consulted by the author. Many scholars and institutions have published ecological performance evaluation standards for application reference [30]. Among them, ISO14031 Environmental Performance Evaluation Standard [55] and WBCSD Eco-efficiency Index Structure [56] have the most reference. Referring to the existing ecological performance evaluation system and considering the characteristics of the remanufacturing process, the evaluation index structure is constructed, as shown in Table 1. In this indicator structure, 14 first-level performance indicators (includes 52 sub-indicators) are reorganized into four categories: economy, economy, environment, resource & energy, and society. It can provide a detailed analysis of remanufacturing ecological performance.

4.2 Indicator selection

As can be seen from Table 1, there are a total of 52 relevant indicators in the established evaluation system. Too many variables and high correlation between variables bring great inconvenience to performance evaluation. The R Clustering method proposed in Section 2.2 is employed to select input/output indicators for the DEA model in this study. For instance, the economic indicators are clustered by R-cluster, and the results of indicator classification is shown in Fig. 3. It can be seen from Fig. 4, that the *Remanufacturing processing cost* is highly correlated with the *cost of purchasing EOL products*, *inventory cost*, *cost of purchasing replace parts*, and *management service cost*, and the *Remanufacturing processing cost* can effectively represent other indicators. A lot of other indicators can be similarly processed.

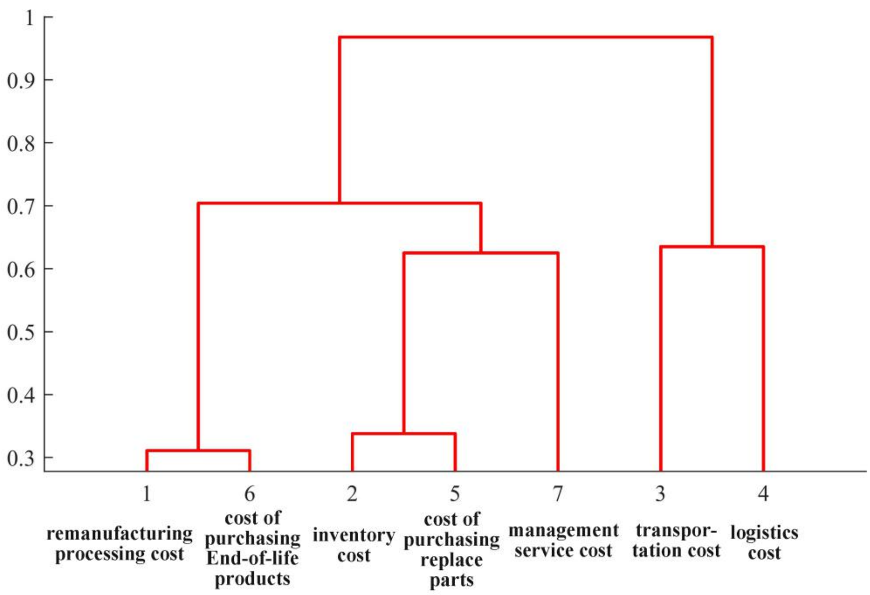

Fig. 4 Dendrogram of R-Clustering based outputs

According to the principle that the redundancy between input indicators/output indicators is as small as possible, and the correlation between input and output is as large as possible. Meanwhile, in the DEA model, the ratio is generally not directly applicable to input/output indicators. Finally, combined with the results of the R Clustering analysis, and considering the data availability, the input and output of the DEA model are determined as shown in Fig. 5.

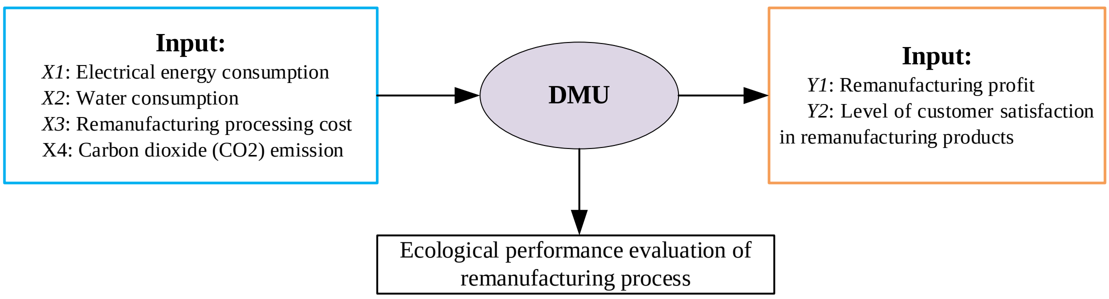

Fig. 5 Input and output indicators of the evaluation model

Table 1 Evaluation index structure of remanufacturing ecological performance

Category	Indicator		Indicator Subgroup
Economy	C1	Remanufacturing cost	Cost of purchasing End-of-life (EOL) products, transportation cost, inventory cost, remanufacturing processing cost, cost of purchasing replace parts
	C2	Remanufacturing income	Remanufacturing profit, parts reuse income, waste disposal income, government incentive income, total asset utilization, net asset yield
	C3	Environmental protection fund investment	Environmental management investment, pollution control investment, environmental rehabilitation investment
	C4	Production input	Management service cost, logistics cost, cost of supplemental material, depreciation for plant assets, waste management cost
Environment	C5	Environmental benefit	Energy saving rate, comprehensive utilization rate (CUR) of industrial wastewater, CUR of industrial exhaust fumes, CUR of industrial solid waste, the utilization rate of environmentally friendly materials, rate
	C6	Exhaust fumes emissions	Carbon dioxide (CO_2) emission, sulfur dioxide (SO_2) emission, compounds of nitrogen and oxygen emission
	C7	Sewage discharge	Wastewater discharge, COD emission, ammonia nitrogen emission
	C8	Waste discharge	Solid waste, non-recyclable waste
Resource & energy	C9	Original energy consumption	Coal consumption, crude oil consumption, natural gas consumption
	C10	Water consumption	Water consumption
	C11	Electrical energy consumption	Electrical energy consumption
	C12	Resource utilization	Rate of material reuse, rate of material recovery, other material resource consumption
Society	C13	Service level	Level of customer satisfaction in remanufacturing products, level of customer dissemination for remanufacturing information, level of remanufacturing quality management, market response time, recovery
	C14	Social responsibility	Corporate green image, degree of cleaner production, meet emission standards, comply with the laws and regulations, market share of remanufacturing products

4.3 Data

The remanufacturing data of different products from two remanufacturing enterprises in China have been chosen as the object of empirical study. These mainly include the remanufacturing of hydraulic cylinder and boom cylinder. The data used is from the on-the-spot investigation of relevant enterprises. The collected data includes not only the data recorded in the enterprise database, but also the multi-lifecycle inventory data. The production data comes from enterprise investigation. The raw material processing data is collected from Chinese Life Cycle Database (CLCD), which is the life cycle basic database suitable for Chinese enterprises.

Key statistics of the data are summarized in Table 2. Decision making unit H1-H12 are data on remanufacturing of hydraulic cylinder, obtained from W mechanical remanufacturing company. B1-B12 are the K company's data of remanufacturing for boom cylinder. Different DMU represents different remanufacturing batch, that is, different remanufacturing time. The acquisition of data on electrical energy consumption and water consumption refers to the CLCD, on the other hand, comes from the detailed account records of remanufacturing enterprises. Data of Carbon dioxide emissions are mainly obtained from the corporate waste disposal list. Remanufacturing processing cost/profit are calculated based on the enterprise investigation data combined with material cost and labor cost. The level of customer satisfaction in remanufacturing products is the score obtained by the questionnaire. The higher the score, the more satisfied the customer is with the remanufacturing products.

Table 2 Input and output indicator data of the decision-making unit collected

DMU	X1	X2	X3	X4	Y1	Y2
	Electrical energy consumption (kwh)	Water consumption (kg)	Remanufacturing processing cost (yuan)	CO_2 emission (kg)	Remanufacturing profit (yuan)	Level of customer satisfaction in remanufacturing products
H1	325	451	802	133	2,895	82
H2	212	424	776	102	3,247	76
H3	303	397	974	126	2,972	85
H4	271	484	1,040	78	2,409	90
H5	198	407	841	94	3,143	88
H6	245	362	926	105	3,200	84
H7	339	328	1,120	82	2,571	94
H8	206	441	991	113	3,023	87
H9	317	342	874	93	3,340	74
H10	182	377	1,290	89	2,509	92
H11	253	290	940	97	2,876	91
H12	212	346	889	107	2,910	85
B1	14.5	667	1,860	76.3	9,212	91
B2	18.0	724	2,436	81.2	8,816	92
B3	24.2	584	2,879	70.4	8,240	89
B4	30.8	612	3,200	68.5	7,955	79
B5	44.5	528	4,200	51.3	7,734	81
B6	36.8	561	4,050	49.6	8,545	80
B7	48.7	710	2,560	70.1	9,010	75
B8	32.3	642	3,120	64.6	8,204	86
B9	27.9	505	3,454	48.2	7,800	81
B10	41.2	577	4,109	53.7	7,209	95
B11	34.6	692	2,704	55.3	9,364	90
B12	37.5	624	2,570	69.0	8,902	88

5 Results

Based on the proposed method above, a systematic study has been performed, and the results are presented as follows. While Sections 5.1 presents the results of the performance analysis, Section 5.2 shows the results of the comparison experiment and sensitivity analysis. And Section 5.3 identifies the key drivers impacting remanufacturing ecological performance.

5.1 DEA analysis results

The REP of hydraulic cylinder and boom cylinder derived with the DEA method is shown in Fig. 6. Since the expected optimal DMU is added to the model, all actual DMUs are DEA invalid (ie, the efficiency value is less than 1.000). The performance value in Fig. 6 can be regarded as the absolute efficiency of the DMUs.

Through the DEA analysis, the REP of the two remanufacturing enterprises can be compared and analyzed. There are two main findings that can be drawn. In the evaluation of REP for hydraulic cylinder, the efficiency value of all DMUs is above 0.65, and the DMU with performance value higher than 0.8 accounts for 41.7%. This shows that the ecological management of remanufacturing process of hydraulic cylinder has reached a relatively good state. In addition, out of all 12 DMUs on the remanufacturing process for boom cylinder, all DMUs had a performance value of less than 0.8 and the lowest is only 0.5711. Thus, it can be seen K company should pay attention to the ecological performance of the remanufacturing process and strive to improve the efficiency value.

Table 3 shows the performance value ranking and slack variable values for REP of hydraulic cylinder and boom cylinder. As can be seen from Table 3, the reasons that affect the REP vary in different decision-making unit (i.e., different batches of remanufacturing products). By using slack improvement analysis, the key elements of invalid DMU can be locally adjusted, so that invalid DMU can reach a strong and effective state. This reflects the specific ways to improve ecological performance.

From the perspective of input variables, electrical energy consumption, water consumption, and CO2 emission are the important reasons why W company does not reach the ecological performance envelope, and are the weak links that affect the ecological performance. W company should improve production efficiency and utilization of energy. For boom cylinder remanufacturing, electrical energy consumption and remanufacturing processing cost affect its ecological performance level. K company can adopt more advanced technologies and strengthen production management to reduce remanufacturing cost. From the point of view of output variables, the social recognition of the remanufacturing products of two enterprises reached a high level, indicating that they have made achievements in terms of service level and social responsibility. However, remanufacturing profit needs to be improved under the existing resource input and technology level.

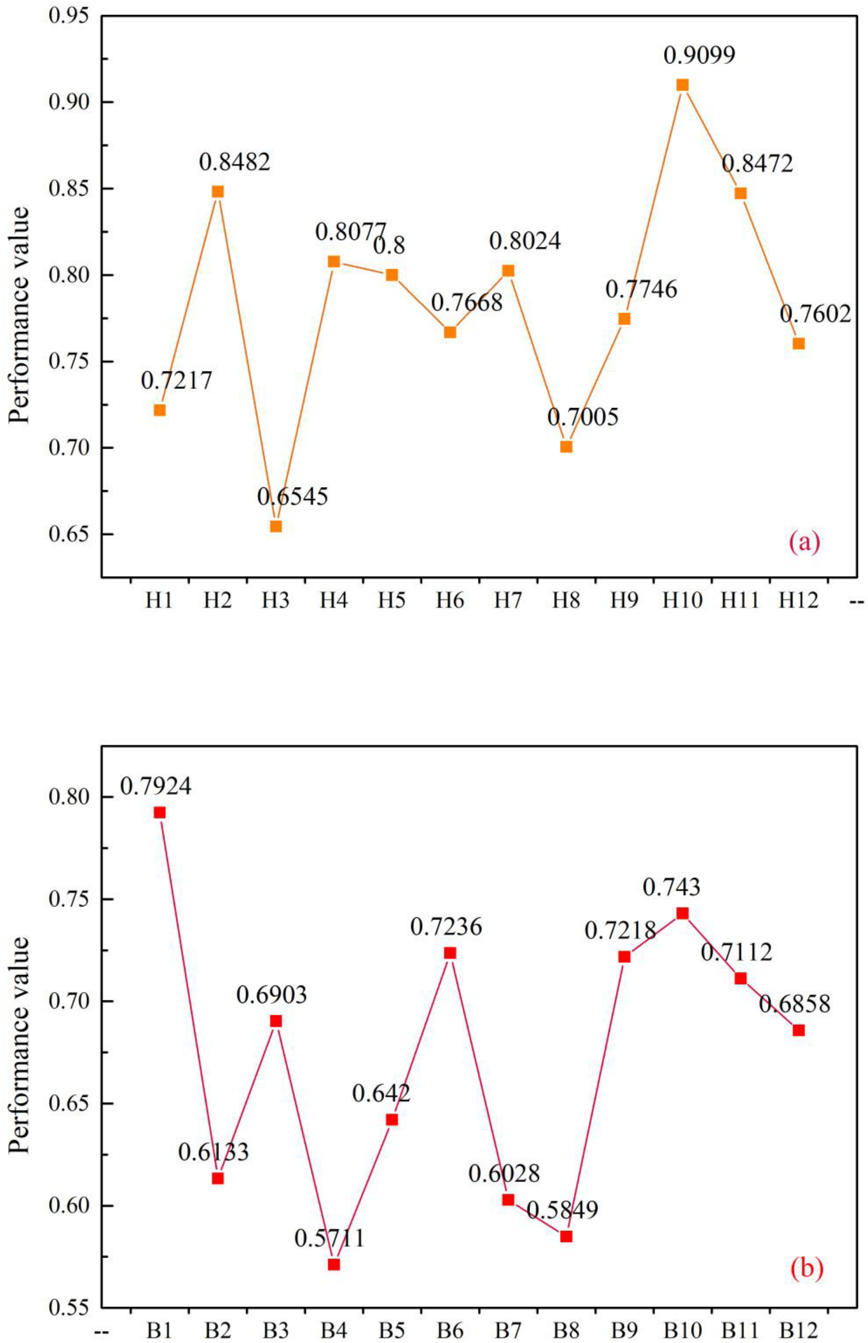

Fig. 6 The results of REP analysis of hydraulic cylinder (a) and boom cylinder (b)

Table 3 Performance values and slack variable of DEA performance analysis

DMU	Performance value	Rank	S^-_1	S^-_2	S^-_3	S^-_4	S^+_5	S^+_6
H1	0.7217	10	-101.62	-124.44	0.00	-44.59	139.00	0.00
H2	0.8482	2	-21.85	-122.68	0.00	25.08	0.00	11.76
H3	0.6545	12	-45.32	-30.34	0.00	-22.97	173.00	0.00
H4	0.8077	4	-56.88	-147.92	-165.00	0.00	921.00	0.00
H5	0.8000	6	0.00	-88.00	-12.80	-13.60	113.00	0.00
H6	0.7668	8	-15.94	-20.06	0.00	-13.01	0.00	2.49
H7	0.8024	5	-102.83	-9.40	-193.73	0.00	907.00	0.00
H8	0.7005	11	0.00	-100.35	-100.85	-25.00	196.00	0.00
H9	0.7746	7	-83.07	-21.19	0.00	-8.85	0.00	16.27
H10	0.9099	1	0.00	-94.63	-483.76	-16.58	895.00	0.00
H11	0.8472	3	-50.55	0.00	-113.91	-18.48	491.00	0.00
H12	0.7602	9	0.00	-20.21	-4.09	-17.72	235.00	0.00
DMU	**Performance value**	**Rank**	S^-_1	S^-_2	S^-_3	S^-_4	S^+_5	S^+_6
B1	0.7924	**1**	-0.4	-114.0	0.0	-21.8	0.0	1.1
B2	0.6133	9	0.0	-30.1	-22.1	-11.2	384.0	0.0
B3	0.6903	6	-5.9	0.0	-550.4	-10.9	660.0	0.0
B4	0.5711	12	-8.5	0.0	-599.0	-6.7	0.0	0.6
B5	0.6420	8	-21.0	0.0	-1603.4	-1.4	366.0	0.0
B6	0.7236	3	-16.4	-21.4	-1563.3	0.0	0.0	5.5
B7	0.6028	10	-17.0	0.0	-20.3	-2.2	0.0	15.1
B8	0.5849	11	-9.2	0.0	-504.7	-2.8	396.0	0.0
B9	0.7218	4	-10.4	0.0	-1197.0	-0.8	300.0	0.0
B10	0.7430	2	-19.2	-1.2	-1533.1	0.0	2291.0	0.0
B11	0.7112	5	-13.4	-70.8	-424.8	0.0	0.0	3.6
B12	0.6858	7	-13.4	0.0	-225.5	-6.9	0.0	1.0

5.2 Comparison experiments and sensitivity analysis

In order to verify the effectiveness of the proposed method, both the traditional DEA model and DEA-TRIS model [57] were used to compare in this work. The comparison experiments were carried out with 12 sets of data of the hydraulic cylinder, and the results are shown in Table 4. It can be seen from Table 4 that the three models are basically consistent in the ranking of remanufacturing ecological performance of hydraulic cylinder. Compared with the traditional DEA model, the improved DEA model proposed in this paper can effectively achieve the full ordering of all DMUs. And compared with DEA-TRIS model, the proposed model can obtain absolute performance values and simplify the calculation process. It further illustrates the feasibility and rationality of the proposed model.

In order to ensure the stability of the DEA results, sensitivity analysis is also required. Take the 12 sets of data of the boom cylinder as an example. On the basis of the original model, one input indicator or output indicator was omitted at a time to generate six DEA models. Fig. 7 shows the results of the sensitivity analysis. The performance value obtained by the four models is basically unchanged from the original model. The performance value of Model 2 and Model 6 are slightly fluctuating, but the ranking is consistent with the original model. It can be concluded that the proposed method is robust based on the obtained evaluation results. This method is feasible and effective. In addition, the results show that the samples are sensitive to indicators X2 and Y2, reflecting that the remanufacturing ecological performance of boom cylinder has an advantage in these two indicators.

Table 4 Comparison results of the three models

	The proposed model		Traditional DEA model		DEA-TRIS model	
DMU	Performance value	Rank	Performance value	Rank	Sort index	Rank
H1	0.7217	10	0.9771	10	0.7634	10
H2	0.8482	2	1.0000	1	0.9213	2
H3	0.6545	12	0.8754	12	0.7512	11
H4	0.8077	4	1.0000	1	0.8418	4
H5	0.8000	6	1.0000	1	0.8249	6
H6	0.7668	8	1.0000	1	0.8022	8
H7	0.8024	4	1.0000	1	0.8352	5
H8	0.7005	11	0.9371	11	0.7224	12
H9	0.7746	7	1.0000	1	0.8117	7
H10	0.9099	1	1.0000	1	1.0000	1
H11	0.8472	3	1.0000	1	0.9024	3
H12	0.7602	9	0.9963	9	0.7881	9

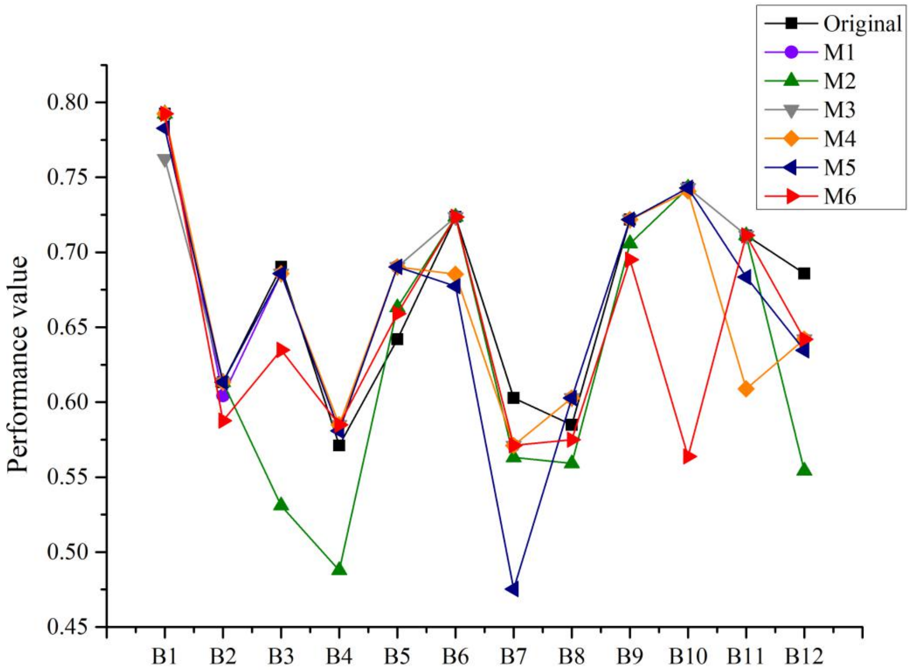

Fig. 7 The results of sensitivity analysis for 6 experiments

5.3 Results of key drivers identification

Since evaluation index structure of remanufacturing ecological performance (as shown in section 3.1) provides a comprehensive evaluation of 52 performance indicators in major performance aspects (economy, environment, resource & energy and society) of remanufacturing process, this section investigates the impacts of detailed performance indicators on REP. The 14 first-level indicators related to the above four kinds of factors are taken as the system behavior series, and the grey relation degree with ecological performance value as the system characteristic sequence is calculated. The results are shown in Fig. 8. The analysis has shown that remanufacturing cost (C1), environmental benefit (C5), electrical energy consumption (C11) and resource utilization (C12) group indicators have the most influence on REP. Obviously, those four indicators can help improve remanufacturing ecological performance.

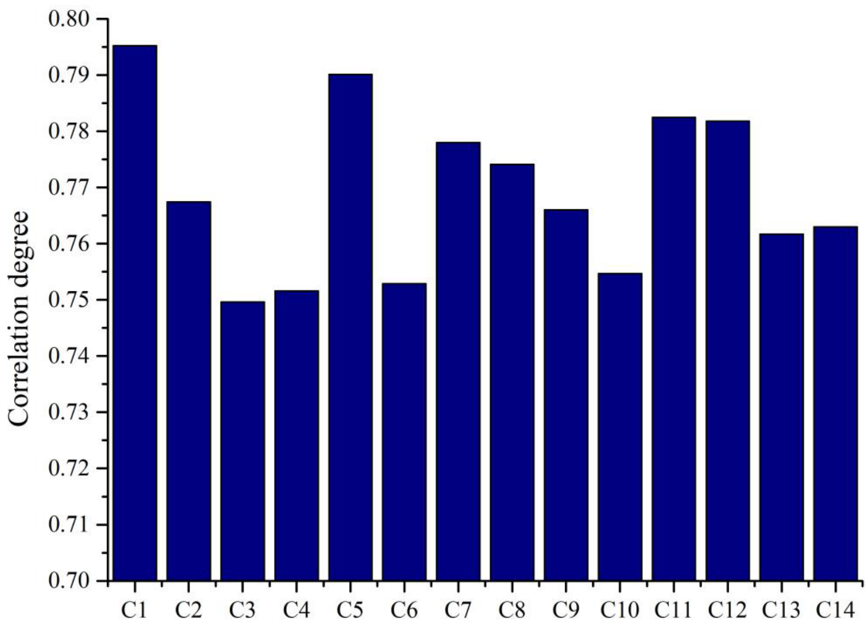

Fig. 8 Correlation degree between remanufacturing ecological performance and primary indicators

Through the above grey relation analysis, indicators in the above four groups have been found to be correlated with REP. To further identify key drivers for remanufacturing ecological performance, the grey relation analysis for 15 sub-indicators of those four group indicators is performed. Fig. 9 shows the final result.

From Fig. 9. Among the ‘economy’ related indicators, cost of purchasing EOL products, remanufacturing processing cost and cost of purchasing replace parts are the most important factors. It can be seen that low cost given higher performance scores in the REP evaluation. This could be explained from the following perspectives. As an input resource, the cost is an important indicator for measuring the REP. And among all the remanufacturing cost, the three types of cost mentioned above determine more than 80% of the total cost. Among the ‘environment’ related factors, energy-saving rate and rate of remanufacturing for EOL products are more important than other factors. Finally, among the ‘resource & energy’ group indicators, electrical energy consumption is the top important factors. This suggests that in remanufacturing process, the electrical energy consumption is a significant measure of resource & energy saving ability. Since in the process of reprocessing for EOL products, electrical energy consumption is much greater than other resources.

Overall, remanufacturing processing cost, energy saving rate and rate of remanufacturing for EOL products are found to be the most important factors. They are considered to be the key drivers impacting remanufacturing ecological performance. In contrast, CUR of industrial exhaust fumes, the utilization rate of environmentally friendly materials, transportation cost, etc. are found to be less important.

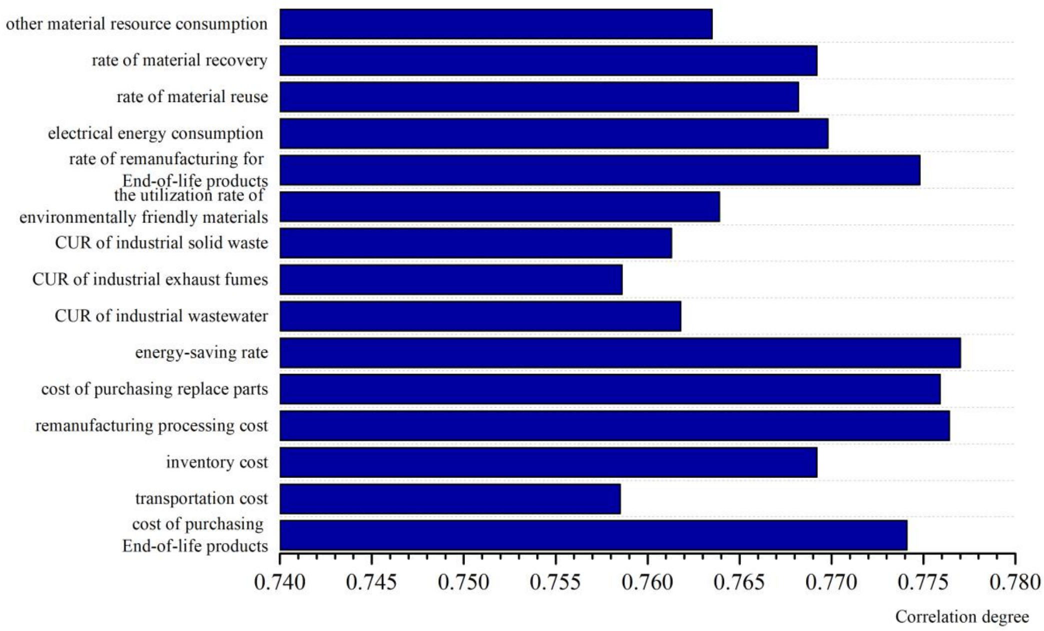

Fig. 9 Correlation degree between remanufacturing ecological performance and impact factors

6 Discussion

Ecological performance emphasizes the balanced development of economic and environmental benefits. Remanufacturing ecological performance evaluation is of great significance for achieving the sustainable development goal of enterprises and promoting the sustainable implementation of remanufacturing engineering. In this work, we present a data-driven approach (integrated R-Clustering analysis, DEA and GRA) to evaluate the ecological performance of the remanufacturing process. The results of the case study have demonstrated the effectiveness of the method. In addition, on the basis of the evaluation results, the key drivers impacting the remanufacturing ecological performance were identified. To the best of our knowledge, this study is the first to propose a remanufacturing ecological performance evaluation, and to link remanufacturing evaluation with impact factors to explore how to improve remanufacturing ecological performance.

Based on the proposed method, we evaluated the remanufacturing ecological performance of boom cylinders and hydraulic cylinders. As can be seen from Fig. 6, there is no significant difference in the remanufacturing ecological performance of an identical product. The overall ecological performance of the remanufacturing industry is in good shape. On the other hand, in terms of horizontal comparison, the REP of hydraulic cylinder is higher than that of the boom cylinder. This is mainly due to different product types. This result is consistent with previous experience-based assessments. Therefore, the government should focus on how to improve the institutional design of the ecological performance evaluation system. In order to guide and encourage the remanufacturing enterprises with relatively low levels of ecological performance, enhance the initiative of ecological performance management.

From the results of DEA analysis in Section 5.1, it can be seen that the REP of different products is quite different, and factors impacting on the REP of different batches for the same product will be different. Reducing remanufacturing cost and electricity consumption, decreasing carbon emissions; and improving technical efficiency while effectively utilizing resources. These are impactful measures to improve the REP. According to the analysis of this study, carbon emissions are not the only contributors to REP, and may not even be the most important factor. Therefore, reducing carbon emissions should not be considered as a comprehensive solution. Moreover, remanufacturing process with high sustainability does not necessarily have high energy efficiency, in other words, pursuing sustainability does not mean improving remanufacturing ecological performance, although they are relevant.

To further explore important factors impacting the remanufacturing ecological performance, key drivers identification was performed. It can be seen from the results of identification for REP drivers (as shown in Fig. 8 and Fig. 9), among all 14 first-level indicators, remanufacturing cost, environmental benefit, electrical energy consumption, and resource utilization are the most important factors affecting remanufacturing ecological performance. Furthermore, the impact of factors related to service level and social responsibility on REP is not clear from the results of grey relation analysis. This is mainly due to the interaction between various indicators. In this study, the identified key REP key drivers with an order from most important to least important are: energy saving rate (reflecting the attitude towards energy sustainability), remanufacturing process cost (reflecting the production inputs of remanufacturing) and rate of remanufacturing for EOL products (reflecting utilization of waste resources).

Based on the above analysis, the following feasible implications are proposed on improving the REP. Firstly, the remanufacturing process cost is mainly reflected in the investment in technology and labor power. So, the ability to repair EOL products should be improved to increase economic benefits. Secondly, remanufacturing enterprises need to strive to increase the efficiency of resource utilization. This means they need to expand output without increasing investment. The best way is to optimize the process and implement lean production. Thirdly, considering that the rate of remanufacturing for EOL products determines the REP to a certain extent, it is imperative to strengthen the detection of EOL products. Detailed detection makes it easier to determine the degree of damage to the EOL products, which helps to develop a reasonable repair solution and ultimately enhance the remanufacturing rate.

Our results are encouraging in the evaluation and improvement of remanufacturing ecological performance. Our work provides a valuable reference for the research and practice of remanufacturing ecological performance management. It should be noted that there are still some limitations in this study. Firstly, in the performance evaluation process, it is difficult to quantify the expected performance value. Secondly, due to the limited amount of data, it is impossible to verify the proposed method in more depth. These will be improved in further research.

7 Conclusion

Evaluation on remanufacturing ecological performance is of great significance for realizing the economic and environmental benefits of enterprises and promoting the sustainable development of the entire remanufacturing industry. In this study, a data-driven model for evaluating remanufacturing ecological performance is established. Different from the traditional qualitative evaluation, improved DEA method is used to realize the quantitative analysis of ecological performance in this model. R Clustering technique is used to select indicators to avoid subjective results generated by researchers randomly selecting indicators. Finally, combined with the evaluation results, the key drivers impacting the remanufacturing ecological performance are identified by Grey Relational Analysis.

The feasibility of the proposed method in meeting the objectives of this research is clearly illustrated by the remanufacturing ecological performance evaluation of hydraulic cylinder and boom cylinders. In addition, energy-saving rate, remanufacturing process cost and rate of remanufacturing for EOL products are identified as key drivers impacting the remanufacturing ecological performance. So as to improve remanufacturing ecological performance, optimizing production technology, implementing lean remanufacturing and raising public acceptability over remanufacturing products are effective measures.

The main contribution of this study is proposing a data-driven method for evaluating the REP. Overall, the insights gained from this study provide a solid basis for further research. This study nevertheless has several limitations. Some of the indicator data is replaced by other indicators due to the inadequacy of the relevant data, it may have an uncertain effect on the results. Owing to the small number of samples, the generalizability of the findings is constrained. Future studies should use as much data as possible to overcome these problems. And such as big data technology should be utilized to increase the objectivity and universality of the results and enhance the accuracy of the analysis for REP.

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References

[1] Hassani S, Saidur R, Mekhilef S, et al. Environmental and exergy benefit of nanofluid-based hybrid

PV/T systems[J]. Energy Conversion and Management, 2016, 123: 431-444.

[2] Dash A, Agrawal S, Gairola S, et al. Optimization and Performance Characteristics of Building Integrated Photovoltaic Thermal (BIPVT) System in Cold Climatic Conditions[J]. Asian Journal of Water, Environment and Pollution, 2018, 15(3): 63-72.

[3] Jia S, Yuan Q, Cai W, et al. Establishing prediction models for feeding power and material drilling power to support sustainable machining[J]. The International Journal of Advanced Manufacturing Technology, 2019, 100(9-12): 2243-2253.

[4] Singh S, Agrawal S. Parameter identification of the glazed photovoltaic thermal system using Genetic Algorithm–Fuzzy System (GA–FS) approach and its comparative study[J]. Energy Conversion and Management, 2015, 105: 763-771.

[5] Cai W, Lai K, Liu C, et al. Promoting sustainability of manufacturing industry through the lean energy-saving and emission-reduction strategy[J]. Science of The Total Environment, 2019, 665: 23-32.

[6] Liu L, Jia Y, Lin Y, et al. Performance evaluation of a novel solar photovoltaic–thermal collector with dual channel using microencapsulated phase change slurry as cooling fluid[J]. Energy Conversion and Management, 2017, 145: 30-40.

[7] Peng S, Li T, Zhao J, et al. Petri net-based scheduling strategy and energy modeling for the cylinder block remanufacturing under uncertainty[J]. Robotics and Computer-Integrated Manufacturing, 2019, 58: 208-219.

[8] Ding Z, Jiang Z, Zhang H, et al. An integrated decision-making method for selecting machine tool guideways considering remanufacturability[J]. International Journal of Computer Integrated Manufacturing, 2018,DOI：10.1080/0951192X.2018.1550680.

[9] Wang H, Jiang Z, Zhang H, et al. An integrated MCDM approach considering demands-matching for reverse logistics[J]. Journal of Cleaner Production, 2019, 208: 199-210.

[10] Cai W, Liu C, Lai K, et al. Energy performance certification in mechanical manufacturing industry: A review and analysis[J]. Energy Conversion and Management, 2019, 186: 415-432.

[11] Jiang Z, Jiang Y, Wang Y, et al. A hybrid approach of rough set and case-based reasoning to remanufacturing process planning [J]. Journal of Intelligent Manufacturing, 2019, 30(1): 19-32.

[12] Deng Q, Liu X, Liao H. Identifying critical factors in the eco-efficiency of remanufacturing based on the fuzzy DEMATEL method[J]. Sustainability, 2015, 7(11): 15527-15547.

[13] Jia S, Yuan Q, Cai W, et al. Energy modeling method of machine-operator system for sustainable machining[J]. Energy conversion and management, 2018, 172: 265-276.

[14] Schraven M, Heyer S, Rütthard N. Remanufacturing and reuse of production equipment at an automotive OEM[M]//Sustainable manufacturing. Springer, Berlin, Heidelberg, 2012: 125-130.

[15] Sabharwal S, Garg S. Determining cost effectiveness index of remanufacturing: A graph theoretic approach[J]. International Journal of Production Economics, 2013, 144(2):521-532.

[16] Sang Fan, Li Enzhong, Zheng Handong, Peijing Shi, Prediction of Remanufacturing Cost Combination of Heavy-Duty Engine Based on State, Surface Engineering and Remanufacturing. 2017, (3): 18-22.

[17] Sundin E, Lee H M. In what way is remanufacturing good for the environment?[M]//design for innovative value towards a sustainable society. Springer, Dordrecht, 2012: 552-557.

[18] Mao Guopin, Zhu Youwei, Wu Cha. A Study on the Environmental Influence Comparison Between Engine Manufacturing and Remanufacturing[J]. Automobile Engineering, 2009, 31(6):565-568.

[19] Xu Bowen. The Resource and Environment benefits Evaluation Model On the Recycling and Remanufacturing System of End-of-life Construction Machinery Products[D]. Hunan University, 2016.

[20] Liu Z, Jiang Q, Li T, et al. Environmental benefits of remanufacturing: A case study of cylinder heads remanufactured through laser cladding[J]. Journal of Cleaner Production, 2016, 133: 1027-1033.

[21] Goldey C L, Kuester E U, Mummert R, et al. Lifecycle assessment of the environmental benefits of remanufactured telecommunications product within a “green” supply chain[C]// IEEE International Symposium on Sustainable Systems & Technology. IEEE, 2010.

[22] Yang S S, Ngiam H Y, Ong S K, et al. The impact of automotive product remanufacturing on environmental performance[J]. Procedia CIRP, 2015, 29: 774-779.

[23] Quariguasi-Frota-Neto J, Bloemhof J. An analysis of the Eco-Efficiency of remanufactured personal computers and mobile phones [J]. Production and Operations Management, 2012, 21(1): 101-114.

[24] Golinska P, Kuebler F. The method for assessment of the sustainability maturity in remanufacturing companies[J]. Procedia Cirp, 2014, 15: 201-206.

[25] Liao H, Deng Q, Wang Y, et al. An environmental benefits and costs assessment model for remanufacturing process under quality uncertainty[J]. Journal of Cleaner Production, 2018, 178:45-58.

[26] Shi Yunxia. The Environment and Economic Benefit Evaluation Models for Remanufacturing Under Quality Uncertain[D]. Hunan University, 2018.

[27] Van Loon P, Van Wassenhove L N. Assessing the economic and environmental impact of remanufacturing: a decision support tool for OEM suppliers[J]. International Journal of Production Research, 2017:1-13.

[28] Diaz R, Marsillac E. Evaluating strategic remanufacturing supply chain decisions[J]. International

Journal of Production Research, 2017, 55(9): 2522-2539.

[29] Graham I, Goodall P, Peng Y, et al. Performance measurement and KPIs for remanufacturing[J]. Journal of Remanufacturing, 2015, 5(1): 10.

[30] Deng Q, Liu X, Liao H. Identifying critical factors in the eco-efficiency of remanufacturing based on the fuzzy DEMATEL method[J]. Sustainability, 2015, 7(11): 15527-15547.

[31] Liu Xiahui. Identifying Critical Factors in the Eco-Efficiency of Remanufacturing Based on the Fuzzy DANP Method[D]. Hunan University, 2016.

[32] Singh S, Agrawal S. Efficiency maximization and performance evaluation of hybrid dual channel semitransparent photovoltaic thermal module using fuzzyfied genetic algorithm[J]. Energy conversion and management, 2016, 122: 449-461.

[33] Song M L, Fisher R, Wang J L, et al. Environmental performance evaluation with big data: Theories and methods[J]. Annals of Operations Research, 2018, 270(1-2): 459-472.

[34] Bi G B, Song W, Zhou P, et al. Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model[J]. Energy Policy, 2014, 66: 537-546.

[35] Wang K, Yu S, Zhang W. China’s regional energy and environmental efficiency: A DEA window analysis based dynamic evaluation[J]. Mathematical and Computer Modelling, 2013, 58(5-6): 1117-1127.

[36] Chen C, Yan H. Network DEA model for supply chain performance evaluation[J]. European journal of operational research, 2011, 213(1): 147-155.

[37] Sarkis J, Cordeiro J J. Ecological modernization in the electrical utility industry: An application of a bads–goods DEA model of ecological and technical efficiency[J]. European Journal of Operational

Research, 2012, 219(2): 386-395.

[38] Cook W D, Du J, Zhu J. Units invariant DEA when weight restrictions are present: ecological performance of US electricity industry[J]. Annals of Operations Research, 2017, 255(1-2): 323-346.

[39] Lo Storto C. Ecological efficiency based ranking of cities: A combined DEA cross-efficiency and Shannon's entropy method[J]. Sustainability, 2016, 8(2): 124.

[40] Xiaoping Z, Yuanfang L, Wenjia W. Evaluation of urban resource and environmental efficiency in China based on the DEA model[J]. Journal of resources and ecology, 2014, 5(1): 11-20.

[41] Liu X, Chu J, Yin P, et al. DEA cross-efficiency evaluation considering undesirable output and ranking priority: a case study of eco-efficiency analysis of coal-fired power plants[J]. Journal of cleaner production, 2017, 142: 877-885.

[42] Chang Y T, Zhang N, Danao D, et al. Environmental efficiency analysis of transportation system in China: A non-radial DEA approach[J]. Energy policy, 2013, 58: 277-283.

[43] Yang L, Ouyang H, Fang K, et al. Evaluation of regional environmental efficiencies in China based on super-efficiency-DEA[J]. Ecological Indicators, 2015, 51: 13-19.

[44] Wang X, Li Z, Meng H, et al. Identification of key energy efficiency drivers through global city benchmarking: A data driven approach[J]. Applied energy, 2017, 190: 18-28.

[45] Peral J, Maté A, Marco M. Application of data mining techniques to identify relevant key performance indicators[J]. Computer Standards & Interfaces, 2017, 54: 76-85.

[46] Torregrossa D, Hansen J, Hernández-Sancho F, et al. A data-driven methodology to support pump performance analysis and energy efficiency optimization in Waste Water Treatment Plants[J]. Applied energy, 2017, 208: 1430-1440.

[47] Ehm F. A data-driven modeling approach for integrated disassembly planning and scheduling[J].

Journal of Remanufacturing, 2018: 1-19.

[48] Zhang Y, Ren S, Liu Y, et al. A framework for Big Data driven product lifecycle management[J]. Journal of Cleaner Production, 2017, 159: 229-240.

[49] Mashhadi A R, Behdad S. Optimal sorting policies in remanufacturing systems: Application of product life-cycle data in quality grading and end-of-use recovery[J]. Journal of Manufacturing Systems, 2017, 43: 15-24.

[50] Hu Y, Liu S, Lu H, et al. Remaining useful life assessment and its application in the decision for remanufacturing[J]. Procedia CIRP, 2014, 15: 212-217.

[51] Zhang Y, Liu S, Liu Y, et al. The ‘Internet of Things’ enabled real-time scheduling for remanufacturing of automobile engines[J]. Journal of cleaner production, 2018, 185: 562-575.

[52] Ovchinnikov A, Blass V, Raz G. Economic and environmental assessment of remanufacturing strategies for product+ service firms[J]. Production and Operations Management, 2014, 23(5): 744-761.

[53] YAN Zhi-xiong, ZHANG Ning, SONG Hong-fang, et. al. A grid performance assessment method based on DEA[J]. Power System Protection and Control, 2014, 42(7):67-72.

[54] Zhao Xiaoguang, Song Shijie, Guan Yuanyuan. Analysis of key Influencing Factors of Mining Subsidence with grey A grey correlation degree based analysis of the key factors influencing surface subsidence caused by mining[J]. Chinese Coal, 2010, 36(9):124-127.

[55] Liu Ming, Study on Corporate Environmental Performance Evaluation Based on Improved DEA[C]. 2nd International Conference on Education, Management and Social Science (ICEMSS 2014), 393-396.

[56] Pang Lei. Research on Enterprise Environment Performance Evaluation based on DEA[D]. Beijing University of Posts and Telecommunications, 2018.

[57] Qingyou Y , Xu W, Wanwang G . Evaluation on the Relative Effectiveness of Black Start Schemes Based on TRIS[J]. Electric Power, 2017, 50(3): 113-116.