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Component oriented remanufacturing decision-making for complex product using DEA and interval 2-tuple linguistic TOPSIS*

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Abstract

Remanufacturing has been attracting attentions of global manufacturers as an important sustainable development strategy. Component oriented remanufacturing decision-making for complex product involving two phases is proposed in this paper. The first phase is to decide which components to be remanufactured using DEA. To overcome the drawback of traditional DEA without weight constraints, an augmented DEA is applied to evaluate the efficiencies of the pre-selected components considering manufacturing characteristic, comparative cost advantage and general returned status. The second phase is to select an appropriate remanufacturing concept for each efficient component. Interval 2-tuple linguistic model is used in obtaining and collecting experts' evaluations. Besides subjective experts' weights, the objective weights of them are considered in the group decision-making process, which are determined by the precision degree of information experts have given. TOPSIS integrated with interval 2-tuple fuzzy linguistic representation model is proposed to rank alternative remanufacturing concepts. A new distance measuring method between two interval 2-tuple vectors is given out considering both the subjective and objective criteria weights. The objective criterion weight is determined by the discrete degree of the performances of all alternatives on this criterion. A case study is carried out to demonstrate the effectiveness of the developed remanufacturing decision-making approach for complex product.

Keywords: remanufacturing decision-making; data envelopment analysis; interval 2-tuple; concept selection; TOPSIS method

1. Introduction

Technological improvements can contribute to potential economy and society development to some extent, while sustainable production and consumption become the central issue of current international concern. In the real world practice, environmental protection and customized service development push the manufacturing companies to concern their products through the whole life cycle. Companies tend to extend their responsibilities to the product use and recycle phases, and they should develop strategies which can contribute to the efficient use of resources. One of the important strategies attracts manufacturers' attention is remanufacturing (or Reman) , which can be defined as a process to recover the discarded products back to

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'likenew' conditions and the warranty and quality are equivalent to those given by Original Equipment Manufacturer (OEM)[1]. The remanufacturing of products or components brings benefits to companies, customers and the environment. Products developed through remanufacturing incur 40–65% less cost and reduces energy needs by about 85% than those for new products [2]. In recent years, a growing number of OEMs such as Caterpillar, Kodak, Xerox and Delphi have exhibited increased interest in remanufacturing due to the potential for competitive gains, while improving their environmental performance ([3]; [4]).

Decision making is of great importance in product remanufacturing and there exists uncertainty in selecting optimal concept. Many researches have been made to propose decision models to solve this problem. Ullah et al. [5] proposed the optimal strategy to deal with decision making problems in machine tool remanufacturing. Karaulova and Bashkite [6] proposed an integrated method for evaluating the remanufacturability of the used industrial equipment. Goodall et al. [7] reviewed the state of art in tools and techniques used to evaluate remanufacturing feasibility. However, the existing approaches always deem the remanufacturable product as a whole and make remanufacturing strategies for the whole. Therefore, they are not suitable for dealing with complex product, which has so many components requiring independent decision-making, such as the large construction machinery. This paper pays attention to remanufacturing strategies making for companies which produce complex products. The complex product can hardly be remanufactured as a whole, and the research object should be a group of components. Some parts of the component can be renewed through cleaning, repairing, etc., and some invalid parts should be discarded and replaced. There exist two problems to be solved for remanufacturing strategies making aiming at complex product: selecting the feasible components which can be remanufactured and assessing the remanufacturing concepts for each selected component. The two problems are both multi-criteria decision making (MCDM) problems. However, they are different in the difficulty and complexity of the decision-making process.

Selecting the components to be carried on remanufacturing has to evaluate the critical components from the aspects such as manufacturing characteristics, manufacturing cost, remanufacturing cost and failure status. The goal is selecting the components with higher remanufacturing performance and lower recovering difficulty. The decision-making result is a group of feasible components. The evaluating criteria can be evaluated quantitatively by the experts from the design, manufacturing and service departments. DEA is a useful tool for performance assessment, which has been widely used in decision-making circumstances when more factors need to be considered. The efficiency assessed for each alternative component by DEA is the feasibility of implementing remanufacturing on it. The traditional DEA model has a shortcoming that the weights of input and output factors are determined in the optimizing process without restraint. The augmented DEA model with weight constraints can increase the distinguishing ability for decision-making units. For the selected components to be carried on remanufacturing activities, selecting an appropriate remanufacturing concept for each of them is critical for companies gaining benefits and ensuring customer satisfaction. Unreasonable concept selection may significantly decrease the remanufacturing performance and profitability. Concept evaluating criteria involve the environment protection, process difficulty, quality of the remanufactured components, etc. The related information lacks support of historical data and can hardly be assessed quantitatively. Therefore, this is a complex multi-criteria group decision making (MCGDM) problem with uncertain information.

The MCGDM problem of selecting remanufacturing concept is the critical research point in this paper. It is more rational for DMs to adopt imprecise linguistic terms to express their judgments. The commonly used means to deal with linguistic terms are the extension principle [8] which operates based on fuzzy numbers and the symbolic method [9] which computes based on the indexes of the linguistic terms. The results obtained by the above two methods do not exactly match any of the initial linguistic terms and require an approximation process to express the result in the initial expression domain. This produces the consequent loss of information and hence the lack of precision [10]. Herrera and Martínez [11] proposed the 2-tuple fuzzy linguistic representation model based on the concept of symbolic translation, which is composed by a linguistic term and a real number. This computational technique can compute with words without any loss of information. In recent studies, 2-tuple fuzzy linguistic representation model has been used in group MCDM problems successfully, e.g. material selection [12], product management [13] and computer network security systems evaluation [14]. In order to express individualized information fully for DMs, interval 2-tuple linguistic variable was defined by Lin et al. [15] to better express decision information by relaxing constraint of choosing from a given linguistic term set. For the information aggregating problem in group decision-making, the arithmetic weighted average is a popularly used operator because of its straightforwardness and convenience. However, how to determine the DM's weight has gained little attention of researchers. The common means is to assign weights to DMs subjectively according to their experiences and backgrounds. However, the DM with higher authority may not give judgment with higher precision degree. This paper will combine the subjective weight and the objective weight which is determined by the precision degree of information given by a DM, to assign a reasonable weight to him or her.

For remanufacturing concepts ranking problem, there does not exist a systematic decision-making approach based on interval 2-tuple linguistic variables. TOPSIS introduced by Hwang and Yoon [16] provides a well-structured analytical framework for alternatives ranking. Proposition a MCDM approach integrating the interval 2-tuple linguistic with TOPSIS is a reasonable and innovative attempt to solve component oriented concept selection in remanufacturing decision-making. A new distance measuring method between two interval 2-tuple vectors is given out considering both the subjective and objective criteria weights, and objective weight is determined by the discrete degree of all concepts' performances.

The rest of the paper is organized as follows. Section 2 presents a brief review of related works of this paper. In Section 3, the problem of component oriented remanufacturing decision-making for complex product is described, and selection of the feasible components using an augmented DEA is given out. The remanufacturing concept selection based on interval 2-tuple linguistic TOPSIS is presented in Section 4. In Section 5, the proposed approach is applied in a real world case of remanufacturing decision-making for hydraulic excavator in a Chinese company. Conclusions are then presented in the final section.

2. Literature review

The United States and Europe consider remanufacturing as a consolidated activity that brings great benefits to the economy of these countries [17]. Developing remanufacturing activities or service is an important and necessary direction for manufacturing companies especially which produce complex and high value products. The existing researches mainly focus on three aspects: (1) analyzing the motives and advantages of remanufacturing; (2) applying this strategy in a specific industry from the technical perspective; (3) developing a decision-making model to select remanufacturing technology or concept.

Lebreton and Tuma [18] investigated to what extent remanufacturing activities could be extended and applied an OEM-centered decision model in order to analyze potential future scenarios. Seitz [19] examined whether the 'classic' motives for product recovery were applicable to automotive remanufacturing. Rathore et al. [20] investigated the opportunity of establishing remanufacturing as a formal activity and answered the fundamental questions of whether remanufactured products would be accepted by Indian consumers. Subramoniam et al. [21] developed the Reman Decision-Making Framework (RDMF) for OE supplier companies based on the following factors: strategic product planning, design for remanufacturing, plant location, production systems, physical distribution, and cooperation among remanufacturing stakeholders. AHP was employed to further validate the RDMF framework and to prioritize the strategic decision-making factors [22]. Jiang et al. [23] developed a MCDM model based on AHP for selecting remanufacturing technology considering technology portfolios.

The existing researches have not decomposed and analyzed the detailed remanufacturing decision-making process especially for companies which provide complex products and attempt to implement remanufacturing service. The remanufacturing decision-making problem for complex mechanical product can be decomposed into two sub-problems: evaluating the remanufacturing feasibility of the components and selecting the appropriate remanufacturing concept for each feasible component.

2.1. Problems on evaluating the remanufacturing feasibility of component

Selecting several feasible components to be remanufactured is a MCDM problem. DEA developed by Charnes et al. [24] is a commonly used MCDM method to measure and analyze the relative efficiencies of comparable decision-making units (DMUs) with multiple inputs and outputs. It has been used in ranking alternatives ([25]; [26]) and performance assessment in terms of efficiencies of DMUs ([27]; [28]). Dotoli and Falagario [29] proposed an approach integrating DEA, TOPSIS and linear programming to select supplier which had three phases, and DEA was used to evaluate the efficiency of each supplier in the first phase in order to select several suppliers for TOPSIS evaluation.

The traditional DEA model has a shortcoming that the weights of input and output factors are determined in the optimizing process without restraint. Dotoli et al. [30] proposed an extension of the DEA model called DEA-P in supplier selection, which provided the weights of the input and output factors directly in percentages and exhibited the same computational complexity with the traditional DEA. Kuo and Lin [31] applied ANP in considering the interdependency among factors to release the constraint of DEA that the users cannot set up factor weight preferences. Wu and Blackhurst [32] introduced weight constraints in DEA to reduce the possibility of having inappropriate input and output factor weights and applied this model to evaluate suppliers. The augmented DEA model considering weight constraints has enhanced discriminatory power and higher computational efficiency over basic DEA models, which can be applied to evaluate and select a group of efficient components to be considered in remanufacturing service development.

2.2. Problems on selecting remanufacturing concept for each feasible component

Remanufacturing concept selection is a typical MCGDM problem. The first difficult issue involved in the MCGDM is how to capture and integrate uncertain information existing in the decision-making process. Fuzzy set theory has been used in decision-making process for a long time due to its ability to deal with information involving vague and subjective characteristics of human nature. The use of linguistic information implies to operate with processes of computing with words (CWW). Rodríguez and Martínez [33] focused on and analyzed the symbolic linguistic computing models widely used in linguistic decision making. Many researchers ([34]; [35]) have successfully applied fuzzy theory to deal with uncertain linguistic information in concept evaluation. For using fuzzy set theory, linguistic evaluation information is expressed in triangle or trapezoidal fuzzy numbers, and the integrated fuzzy numbers by group decision-making can hardly match any of the initial linguistic terms. The 2-tuple fuzzy linguistic representation model was proposed to solve this problem, which can compute with words without any loss of information. Since it was proposed by Herrera and Martínez [11], this model has been researched and applied in MCDM problems popularly. The reasons of its wide usage are its accuracy, its usefulness for improving linguistic solving processes in different applications, its interpretability, its ease managing of complex frameworks in which linguistic information is included and so forth [36].

The common 2-tuple linguistic variables are always given by DMs from a given linguistic term set. DMs may find the cardinality of the term set is too small to fully express their professional judgments on some attributes or so big that the evaluations on some other attributes are out of their ability [37]. The interval-valued 2-tuple linguistic representation model can tolerate experts to select different numbers of linguistic terms to express their judgments. Zhang [37] put forward the interval-valued 2-tuple linguistic representation model based on the definition of Lin et al. [15], which can be regarded as a standardized interval 2-tuple linguistic model. By using interval 2-tuple linguistic representation model, decision information can be not only fully expressed but also be unified easily [38]. Therefore, the interval 2-tuple linguistic representation model is more flexible and accurate to deal with linguistic terms in group MCDM problems.

For the group decision-making problems, Herrera and Martínez [11] extended different classical aggregation operators to deal with the 2-tuple linguistic model. Generally, these operators aggregate all DMs' judgments based on the pre-determined DMs' weights considering their backgrounds. These static weights have certain subjectivity. Zhang [38] determined the DM's weight according to the precision degree of interval 2-tuple linguistic information he or she given. The subjective weight and objective weight reflected by the precision degree of given information being both taken into consideration in determining the DM's weight for group decision-making is a reasonable and efficient strategy.

The second difficult issue involved in the remanufacturing concept selection is how to rank the alternative concepts efficiently according to the group decision-making information. This issue is a typical MCDM problem. AHP developed by Saaty [39] is a commonly used MCDM method. Although the AHP method offers many advantages for concept evaluation, it can be a time-consuming process with the increase of the number of evaluation criteria and design alternatives. Furthermore, the consistency in the pair-wise comparisons must be controlled at a high-level because a low consistency may make AHP analysis meaningless. This strict requirement may force DMs to adjust their judgments iteratively and the objectivity of judgments may be distorted [40]. TOPSIS introduced by Hwang and Yoon [16] is another popular MCDM method. The framework of TOPSIS is to find the positive ideal solution (PIS) and the negative ideal solution (NIS) in the n-dimensional space, and determine the preferred alternative according to the relative closeness degree to the PIS. TOPSIS integrated with linguistic information treating approach is applied widely to solve decision making problems in management. Fuzzy TOPSIS has been used in evaluating service quality in service quality management [41], prioritizing failure modes for risk management [42] and ranking suppliers in supply chain management [43]. TOPSIS integrated with vague set has been used in supplier evaluation [44] and product design concept evaluation [45].

Integrating TOPSIS with interval 2-tuple linguistic model is an interesting and challenging attempt. The challenging point is how to calculate the distance between two interval 2-tuple vectors. Liu et al. [12] defined the distance between two interval 2-tuples based on the linear compensation. However, this definition can be improved by considering the definition of Euclidean distance to be much more appropriate and understandable. Another problem in the interval 2-tuple linguistic TOPSIS approach requiring to be solved is how to determine reasonable criteria weights. The perspective of solving this problem is similar to that of solving the DMs' weights determination problem in group decision-making. Therefore, criterion weight should be obtained by considering both subjective weight and objective weight. The objective weight of a criterion can be determined according to the discrete degree of the evaluations of all alternatives on this criterion.

3. Evaluating remanufacturing efficiencies of critical components using an augmented DEA

The complex product is composed of various components. The critical components have the possibility to catch the experts' interests in developing remanufacturing service or activities due to higher manufacturing cost and higher influence to overall performance, and then several components are selected to be remanufactured from them. This paper proposes a two-phase remanufacturing decision-making approach for complex products. The framework of the component oriented approach is shown in Fig.1.

3.1. Determining the evaluation factors in the augmented DEA

In DEA model, the efficiency of a DMU is defined as the ratio between the sum of weighted outputs values and the sum of weighted inputs values. Since higher efficiency is expected for a DMU, the measures of the-larger-the-better type are used as output measures while the measures of the-smaller-the-better type are used as input measures [46]. DMUs are ranked in terms of their efficiencies. The principle of determining the evaluation factors in the augmented DEA is selecting factors influencing remanufacturing efficiency and easy to be measured at the same time. The technical and economic factors are typical points of great importance .The technical feasibility of component remanufacturing can be analyzed based on the physical structure and the returned status. The economic feasibility can be analyzed from comparison between manufacturing cost and remanufacturing cost. Manufacturing characteristic, comparative cost advantage and general status of the returned components are assumed as the three key factors used to judge a component whether to be remanufactured or not in this paper. Manufacturing characteristic is assessed from four aspects which are disassembly index, test index, replace index and restore index.

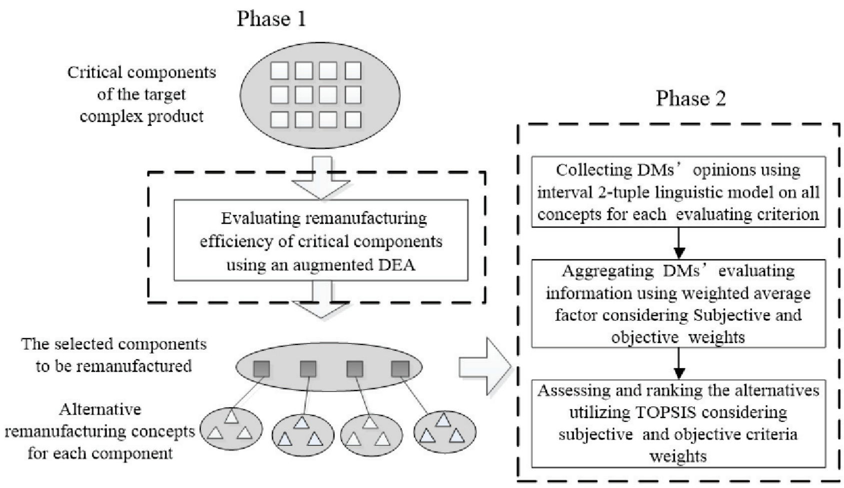

Fig. 1. Problem formulation of remanufacturing decision-making.

Disassembly index defined as μ_D reflects the disassembling efficiency of a component composed of many parts. The higher the disassembly index is, the better the component's remanufacturing efficiency is.

$$\mu_D = \textit{the number of parts which can be disassembled} \times \frac{1}{\textit{averaged disaseembly time}} \quad (1)$$

Test index defined as μ_T reflects the testing efficiency of a component. The higher the test index is, the better the component's remanufacturing efficiency is.

$$\mu_T = \textit{the number of parts which can be tested} \times \frac{1}{\textit{averaged test time}} \quad (2)$$

Replace index defined as μ_R reflects the replaceable ability and assembling efficiency of a component. The higher the replace index is, the better the component's remanufacturing efficiency is.

$$\mu_R = \textit{the number of parts which can be replaced} \times \frac{1}{\textit{averaged assembly time}} \quad (3)$$

Restore index defined as μ_{Rc} reflects the restored performance of a component. The higher the restore index is, the better the component's remanufacturing efficiency is.

$$\mu_{Rc} = \textit{the number of parts which can be restored} \times \frac{1}{\textit{averaged restore time}} \quad (4)$$

The four aspects are all benefit index. They can be evaluated by experienced experts quantitatively according to the standards of their specialized fields. The integrated evaluation of the four aspects can be obtained by the simple arithmetic average factor, and it should be normalized first to be deemed as an output value of the augmented DEA model.

Comparative cost advantage defined as c is evaluated based on the manufacturing cost and remanufacturing cost.

$$c = \frac{\textit{manufacturing cost - remanufacturing cost}}{\textit{manufacturing cost}} \quad (5)$$

Manufacturing cost can be obtained quantitatively from the manufacturing department. It has much higher necessity to conduct remanufacturing activity for the component with higher manufacturing cost. Remanufacturing cost can be estimated quantitatively according to the experiences of remanufacturing experts and existing remanufacturing information from other companies. It has much higher necessity to conduct remanufacturing activity for the component with lower remanufacturing cost. Comparative cost advantage is a benefit index and it is an output factor of the augmented DEA model.

General returned status reflects the possible status of the retrieved component, and it can determine the remanufacturing difficulty to some extent. The general returned status of a component depends on the main failure modes (FMs) which can lead to the component scrap, and it can be analyzed by evaluating the integrated severity evaluation of several main FMs. The severity of a FM is evaluated quantitatively by the experts from the pre-given severity rating scale. The quantity of FMs evaluated is also determined previously by the experts. The higher the severity value is, the higher the component's remanufacturing difficulty is. Therefore, the general returned status is a cost index and its normalized value is an input value in the augmented DEA model.

3.2. The augmented DEA model

In DEA, suppose n DMUs (i.e. n components) need to be evaluated in terms of m inputs and s outputs. In this paper, m=2 and s=1. Let x_{ij} (i = 1,2,...,m) and y_{rj} (r = 1,2,...,s) be the input and output values of DMU_j (j= 1,2,...,n). The efficiency of DMU_j is defined by

$$E_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_r x_{rj}}, \ j = 1,2,\cdots,n \tag{6}$$

where v_i (i = 1,2,...,m) and u_r (r = 1,2,...,s) are weighting factors for the m inputs and s outputs.

The objective of the DEA efficiency evaluation model is to find a set of v_i and u_r to maximize the efficiency of an observed DMU, while assuring the efficiencies of the other DMUs are not larger than one. The original DEA model developed by Charnes et al. [24] uses a fractional non-linear programming model to maximize the efficiency of an observed DMU. By using the transformation developed by Charnes and Cooper [47], a linear programming (LP) model which is equivalent to the fractional programming model can be obtained. The LP DEA models are classified into two categories: the output maximization LP model and the input minimization LP model.

The output maximization LP model with virtual standards and weight constraints for the DMU_0 (the DMU under evaluation) is described as follows:

$$Max \ E_0 = \sum_{r=1}^{s} u_r y_{r0} \tag{7}$$

$$s.t. \begin{cases} \sum_{i=1}^{m} v_i x_{i0} = 1 \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, j = 1,2,\cdots,n \\ \sum_{r=1}^{s} u_r y_r^* - \sum_{i=1}^{m} v_i x_i^* \le 0 \\ \frac{u_g}{u_k} \le \frac{Distance(u_k)}{Distance(u_g)}, \quad g,k = 1,2,\cdots,s \\ \frac{v_g}{v_k} \le \frac{Distance(v_k)}{Distance(v_g)}, \quad g,k = 1,2,\cdots,m \\ \frac{u_g}{v_k} \le \frac{Distance(v_k)}{Distance(u_g)}, \quad g = 1,2,\cdots,s, \ k = 1,2,\cdots,m \end{cases}$$

where y_r^* is the maximum value of the output factor u_r in the component base, $y_r^* = \max_{j=1}^{n} y_{rj}$; x_i^* is the maximum value of the output factor v_i in the component base, $x_i^* = \max_{j=1}^{n} x_{ij}$; $Distance(u_k)$ is the difference of maximum value and minimum value of u_k.

$$Distance(u_k) = \max_{k=1}^{s} u_k - \min_{k=1}^{s} u_k \ ,$$
$$Distance(v_k) = \max_{k=1}^{m} v_k - \min_{k=1}^{m} v_k \ . \tag{8}$$

The efficiency values of all components obtained by the augmented DEA model are used to classify the components into two categories. The efficient category goes on to be analyzed to select a remanufacturing concept for each component in it.

4. Selecting remanufacturing concept based on interval 2-tuple linguistic TOPSIS

For the selected components to be remanufactured, experts are called together to design alternative remanufacturing concepts or strategies from the process perspective. The second MCGDM phase is carried out to evaluate the alternative remanufacturing concepts for each selected component. The significant problems in this phase are constructing the evaluation index, acquiring the interval 2-tuple evaluation information and applying TOPSIS to rank the alternative concepts.

For a specific component, designing a remanufacturing concept has to consider the part cleaning technology, part testing technology, etc., and has to decide whether a part to be replaced by a new one or to be restored. The evaluation index to measure a concept involves the following five aspects: environment protection (i.e., the amount of pollution emissions), remanufacturing cost including equipment cost, labor cost and resource consumption (energy and material), process difficulty represented by process time and technical requirements, quality of remanufactured component involving the reliability and work efficiency, and required service level involving training and maintenance. For a component lacking data on remanufacturing activities, the above criteria are hard to be evaluated quantitatively. Linguistic variables are preferred in this circumstance. The interval 2-tuple linguistic representation model is used to facilitate DMs to express diversified opinions.

4.1. Interval 2-tuple linguistic variables

Let $S=\{s_i : i = 0,1,2,\cdots,g\}$ be a finite and totally ordered discrete linguistic term set, where s_i represents a possible value for a linguistic variable, and it must have the following characteristics [48]:

- The set is ordered: $s_i \ge s_j$ if $i \ge j$.
- There is the negation operator: neg (s_i) = s_j such that $j=g-i$.
- Max operator: max $(s_i, s_j) = s_i$ if $s_i \ge s_j$.
- Min operator: min $(s_i, s_j) = s_i$ if $s_i \le s_j$.

Definition 1 [11]: *Let β be a value representing the result of an aggregation of the indices of a set of labels assessed in linguistic term set S, i.e., the result of a symbolic aggregation operation $\beta \in [0,g]$, being g+1 the cardinality of S. Let $i = round(\beta)$ and $\alpha = \beta - i$ be two values such that $i \in [0,g]$ and $\alpha \in [-0.5,0.5)$, then α is called a symbolic translation.*

The linguistic representation model 2-tuple (s_i,α_i), $s_i \in S$, $\alpha_i \in [-0.5,0.5)$ is developed from the above concept.

- s_i represents the linguistic label center of the information;
- α_i is a numerical value expressing the value of the translation from the original result β to the closest index label, i ,in the linguistic term set S, i.e., the symbolic translation.

Definition 2 [11]: *Let $S = \{s_0, s_1, \cdots, s_g\}$ be a linguistic term set and $\beta \in [0,g]$ to be a value representing the result of a symbolic aggregation, then the 2-tuple that expresses the equivalent information to β is obtained with the function Δ.*

$$\Delta : [0,g] \rightarrow S \times [0.5,-0.5) \tag{9}$$

$$\Delta(\beta) = (s_i,\alpha_i)\text{, with } \begin{cases} s_i, & i = round(\beta) \\ \alpha_i = \beta - i, & \alpha_i \in [-0.5,0.5) \end{cases}$$

where $round(\cdot)$ is the usual round operation, s_i has the closest index label to β and α_i is the value of the symbolic translation.

Contrarily, let $S = \{s_0, s_1, \cdots, s_g\}$ be a linguistic term set and (s_i,α_i) be a 2-tuple. There is always a Δ^{-1} function:

$$\Delta^{-1}:\ S \times [0.5,-0.5) \rightarrow [0,g] \tag{10}$$

$$\Delta^{-1}(s_i,\alpha_i) = i + \alpha_i = \beta$$

The original linguistic evaluation variable can be converted into a linguistic 2-tuple by adding a value zero as symbolic translation: $s_i \in S \Rightarrow (s_i, 0)$.

To ensure the DMs can fully express their opinions from a finite linguistic term set, the interval-valued 2-tuple linguistic representation model is used under multi-granular linguistic context. DMs can select one linguistic variable from the given set or give an interval set from one linguistic variable to another due to the uncertainty of decision-making. A single linguistic variable can also be transformed into an interval from.

Definition 3 [37]: *Suppose $S = \{s_0, s_1, \cdots, s_g\}$ be an ordered linguistic term set. An interval 2-tuple is composed of two linguistic terms and two crisp numbers, denoted by $((s_i,\alpha_i),(s_j,\alpha_j))$, where $i \le j$ and $\alpha_i \le \alpha_j$ if $i = j$, $s_i(s_j)$ and $\alpha_i(\alpha_j)$ represent the linguistic label of the predefined linguistic term set S and symbolic translation, respectively. The interval 2-tuple expresses the equivalent information as an interval value $\Delta[\beta_i,\beta_j](\beta_i,\beta_j \in [0,1], \beta_i \le \beta_j)$, which is derived by the following function:*

$$\Delta[\beta_i,\beta_j] = ((s_i,\alpha_i),(s_j,\alpha_j))\text{, with}$$

$$\begin{cases} s_i, & i = round(\beta_i * g) \\ s_j, & j = round(\beta_j * g) \\ \alpha_i = \beta_i - i/g, & \alpha_i = [-0.5/g, 0.5/g) \\ \alpha_j = \beta_j - j/g, & \alpha_j = [-0.5/g, 0.5/g) \end{cases} \tag{11}$$

Conversely, there is always a Δ^{-1} function such that an interval 2-tuple can be converted into an interval value $[\beta_i,\beta_j](\beta_i,\beta_j \in [0,1], \beta_i \le \beta_j)$ as follows:

$$\Delta^{-1}((s_i,\alpha_i),(s_j,\alpha_j)) = [i/g + \alpha_i, j/g + \alpha_j] = [\beta_i,\beta_j] \tag{12}$$

The negation operator over an interval 2-tuple is defined as follows

$$Neg((s_i,\alpha_i),(s_j,\alpha_j)) = \Delta([1-\Delta^{-1}(s_j,\alpha_j),1-\Delta^{-1}(s_i,\alpha_i)]) \quad (13)$$

4.2. Dynamic group decision-making with interval 2-tuple linguistic information

Given that A_i ($i=1,\cdots,m$) represents the i th remanufacturing concept for an efficient component, C_j ($j=1,\cdots,n$) represents the j th evaluation criterion. A group of DMs $\{d_k | 1\le k\le h\}$ are selected to give their judgments on each criterion of all alternative concepts. Suppose $S=\{s_0,s_1,\ldots,s_g\}$ is a pre-given linguistic variable set for supporting DMs to give their judgments. p_{ij}^k $(k=1,\cdots,h)$ represents the judgment of d_k on C_j of A_i , which takes the form of interval linguistic variable $[s_a,s_b]$, $0\le a\le b\le g$.

The interval linguistic evaluation information $(([s_a,s_b])_{ij}^k)_{m\times n}$ was transformed into interval 2-tuple linguistic information $(((s_a,0),(s_b,0))_{ij}^k)_{m\times n}$. The next work is to integrate the evaluation information of all DMs' into a collective matrix and to select an ideal concept. The dynamic group decision-making approach involves the following two steps:

Step 1. Determine the DM's subjective weight and objective weight.

Step 2. Integrate the DMs' evaluations using the weighted averaging operator.

The subjective DMs' weight reflects his or her experience and background, which is given in advance. Suppose sw_k represent the subjective weight of d_k , where $0\le sw_k\le 1$, $\sum_{k=1}^{h} sw_k=1$. The objective weight of a certain DM varies from one criterion to another in the decision matrix, and it reflects the precision degree of his or her evaluation comparing with those of other DMs' on the same criterion.

Take the computation of objective weight of d_k on the criterion C_j for A_i evaluation as an example, which is defined as dw_k^{ij} .

Let $((s_{ija}^1,\alpha_{ija}^1),(s_{ijb}^1,\alpha_{ijb}^1))$, $((s_{ija}^2,\alpha_{ija}^2),(s_{ijb}^2,\alpha_{ijb}^2))$,…, $((s_{ija}^k,\alpha_{ija}^k),(s_{ijb}^k,\alpha_{ijb}^k))$,…, $((s_{ija}^h,\alpha_{ija}^h),(s_{ijb}^h,\alpha_{ijb}^h))$ be the interval 2-tuple linguistic information given by all the DMs, where $1\le k\le h$, $\alpha_{ija}^k | 1\le k\le h=0$, $\alpha_{ijb}^k | 1\le k\le h=0$. The degree of precision of $((s_{ija}^k,\alpha_{ija}^k),(s_{ijb}^k,\alpha_{ijb}^k))$ is formulated as follows.

$$DP((s_{ija}^k,\alpha_{ija}^k),(s_{ijb}^k,\alpha_{ijb}^k)) = 1-\frac{[\Delta^{-1}(s_{ijb}^k,\alpha_{ijb}^k)-\Delta^{-1}(s_{ija}^k,\alpha_{ija}^k)]/g+1/g}{1+1/g} \quad (14)$$

For the interval 2-tuple linguistic information ((s_0, 0),(s_g,0)), which is the extreme case, the degree of precision of this information is zero. This result indicates that the extreme evaluation information is invalid.

The objective weight dw_k^{ij} of d_k is calculated as:

$$dw_k^{ij}=\frac{DP((s_{ija}^k,\alpha_{ija}^k),(s_{ijb}^k,\alpha_{ijb}^k))}{\sum_{k=1}^{h} DP((s_{ija}^k,\alpha_{ija}^k),(s_{ijb}^k,\alpha_{ijb}^k))} \quad (15)$$

The final weight w_k^{ij} of d_k can be determined by combing the subjective weight sw_k and the objective weight dw_k^{ij} .

$$w_k^{ij}=\alpha_1\cdot sw_k+\alpha_2\cdot dw_k^{ij},\ 0\le\alpha_1,\alpha_2\le 1,\ \alpha_1+\alpha_2=1 \quad (16)$$

where α_1 and α_2 explains the attention degree to the professional background and information precision, respectively.

The collective evaluation matrix $E=((s_{ija},\alpha_{ija}),(s_{ijb},\alpha_{ijb}))_{m\times n}$ can be obtained according to the subjective and objective DMs' weights.

$$((s_{ija},\alpha_{ija}),(s_{ijb},\alpha_{ijb})) = \Delta\left[\sum_{k=1}^{h} w_{ij}^k\cdot\Delta^{-1}(s_{ija}^k,\alpha_{ija}^k),\sum_{k=1}^{h} w_{ij}^k\cdot\Delta^{-1}(s_{ijb}^k,\alpha_{ijb}^k)\right] \quad (17)$$

4.3. Interval 2-tuple linguistic TOPSIS

TOPSIS integrated with interval 2-tuple linguistic evaluation is proposed to select a proper remanufacturing concept for each feasible component. The process of interval 2-tuple linguistic TOPSIS involves the following steps.

Step 1. Identify the *PIS* and the *NIS* from the collective concept evaluation matrix E ($i=1,\cdots,m$, $j=1,\cdots,n$).

$$\text{PIS}=\left\{[(s_{ja}^+,\alpha_{ja}^+),(s_{jb}^+,\alpha_{jb}^+)]\right\}= \begin{cases}[\max_i(s_{ija},\alpha_{ija}),\ \max_i(s_{ijb},\alpha_{ijb})] & \textit{for benefit criterion}\\ [\min_i(s_{ija},\alpha_{ija}),\ \min_i(s_{ijb},\alpha_{ijb})] & \textit{for cost criterion}\end{cases} \quad (18)$$

NIS= $\left\{[(s_{ja}^{-},\alpha_{ja}^{-}),(s_{jb}^{-},\alpha_{jb}^{-})]\right\}=$

$$\begin{cases}[\min_i(s_{ija},\alpha_{ija}),\ \min_i(s_{ijb},\alpha_{ijb})] & \textit{for benefit criterion}\\ [\max_i(s_{ija},\alpha_{ija}),\ \max_i(s_{ijb},\alpha_{ijb})] & \textit{for cost criterion}\end{cases} \quad (19)$$

Step 2. Compute the relative closeness degree between the performance of A_i defined as P_i and the *PIS* in the matrix *M*.

P_i is represents by $\{\tilde{p}_{i1},\tilde{p}_{i1},\cdots,\tilde{p}_{ij},\cdots,\tilde{p}_{in}\}$,where $\tilde{p}_{ij}=[(s_{ija},\alpha_{ija}),(s_{ijb},\alpha_{ijb})]$.

The definition of the distance between two interval 2-tuples $\tilde{p}_{ij}$ and $\tilde{p}_j^{+}$ is given as follows.

$$d(\tilde{p}_{ij},\tilde{p}_j^{+})=\Delta\{[\frac{1}{2}[((\Delta^{-1}(s_{ija},\alpha_{ija})-\Delta^{-1}(s_{ja}^{+},\alpha_{ja}^{+}))^2 +(\Delta^{-1}(s_{ijb},\alpha_{ijb})-\Delta^{-1}(s_{jb}^{+},\alpha_{jb}^{+}))^2]]^{1/2}\} \quad (20)$$

The distance between one concept and *PIS* or *NIS* is measured according to the criteria weights. The subjective criteria weights $\{sw_j, j=1,\cdots,n\}$ are pre-determined by DMs according to their professional assessments. From the objective perspective, the discrete degree of all concepts on each criterion also influences the criterion weight. The larger the difference among all concepts on one criterion is, the higher the weight of this criterion is, and vice versa.

The discrete degree $dis(C_j)$ is measured by calculating the summarized distance between each evaluation and the central value.

$$dis(C_j)=\sum_{i=1}^{m}\Delta\{[\frac{1}{2}[((\Delta^{-1}(s_{ija},\alpha_{ija})-\Delta^{-1}(\bar{s}_{ja},\bar{\alpha}_{ja}))^2 +(\Delta^{-1}(s_{ijb},\alpha_{ijb})-\Delta^{-1}(\bar{s}_{jb},\bar{\alpha}_{jb}))^2]]^{1/2}\} \quad (21)$$

where $\Delta^{-1}(\bar{s}_{ja},\bar{\alpha}_{ja})$ is the averaged value of $\Delta^{-1}(s_{ija},\alpha_{ija})$ ($1\le i\le m$), $\Delta^{-1}(\bar{s}_{jb},\bar{\alpha}_{jb})$ is the averaged value of $\Delta^{-1}(s_{ijb},\alpha_{ijb})$ ($1\le i\le m$).

The objective weight of criterion dw_j is determined by normalizing $dis(C_j)$. Let $dis(C_j)$ be represented as (D_j,α_j) in the form of 2-tuple linguistic model and w_j is the final dynamic weight of the j th evaluation criterion.

$$dw_j=\frac{\Delta^{-1}(D_j,\alpha_j)}{\sum_{j=1}^{n}\Delta^{-1}(D_j,\alpha_j)} \quad (22)$$

$$w_j=\beta_1\cdot sw_j+\beta_2\cdot dw_j,\ 0\le\beta_1,\beta_2\le 1,\ \beta_1+\beta_2=1 \quad (23)$$

where β_1 and β_2 explains the attention degree to the subjective aspect and objective aspect, respectively.

$$D(P_i,PIS)=\sum_{j=1}^{n}w_j\cdot d(\tilde{p}_{ij},\tilde{p}_j^{+}) \quad (24)$$

$$D(P_i,NIS)=\sum_{j=1}^{n}w_j\cdot d(\tilde{p}_{ij},\tilde{p}_j^{-}) \quad (25)$$

Let $D(P_i,PIS)$ and $D(P_i,NIS)$ be represented as (P_i,α_i) and (N_i,α_i) in the form of 2-tuple linguistic model, respectively. The relative closeness degree between P_i and the *PIS* is defined as

$$R_i=\Delta\left[\frac{\theta_1\Delta^{-1}(P_i,\alpha_i)}{\theta_1\Delta^{-1}(P_i,\alpha_i)+\theta_2\Delta^{-1}(N_i,\alpha_i)}\right],0\le\theta_1,\theta_2\le 1\,. \quad (26)$$

where θ_1 , θ_2 explains the attention degree to the PIS and the NIS respectively.

Finally, alternatives are ranked according to C_i in ascending order. The alternative which has a small C_i will have a higher position in the order. Generally, C_i ranked first is the ideal concept to select.

5. Case study

Company H is one of the famous companies manufacturing construction machinery in China, which provides complex mechanical products and related service to domestic customers such as excavator, bulldozer, crane and so forth. Sustainability and innovation are its future developing strategy. The world-class companies in this field have devoted a lot of efforts to remanufacturing business. With the promotion of this trend, company H begins to make remanufacturing strategies to improve its market competiveness. Component oriented remanufacturing decision-making of the hydraulic excavator produced in this company is presented as a real-world example to demonstrate the application of the proposed approach. The relevant information comes from a collaborative project with this company.

5.1. Selecting the efficient components to be remanufactured

Experts from the design department and after-sale department are called together to decide the key components of hydraulic excavator. 12 components are selected to be analyzed by the proposed augmented DEA. These components are air cylinder head assembly, cooling water pump, injector assembly, compressor, brake assembly, control device, short engine, hydraulic oil cylinder, track assembly, hydraulic valve, hydraulic pump and turbocharger assembly, which are defined as M_1, M_2, …, M_{12}, respectively. They are analyzed from the following three factors: manufacturing characteristic, comparative cost advantage and general returned status. The evaluation data of the three factors are shown in Table 1. The illustration of how to obtain the related data is given as follows.

Factor 1. The manufacturing characteristic is evaluated by averaging the four aspects, which are the disassembly index μ_D, the test index μ_T, the replace index μ_R and the restore index μ_{Rc}. These aspects are assessed by experienced experts quantitatively using Eq. (1-4), respectively.

Factor 2. The comparative cost advantage is assessed by balancing the manufacturing cost and remanufacturing cost using Eq. (5). The cost data are estimated by experts from the work experience and industry data.

Factor 3. The general status of the returned component is assessed by synthesizing the severity evaluation of several main FMs. The number of FMs evaluated is determined as three in this case. The severity of FM is evaluated in numerical scales. The parameter scales used in severity evaluation are: remote (1), low (2/3), moderate (4/5/6), high (7/8), and very high (9).

All the evaluation data of components on each factor is normalized in order to implement the augmented DEA by using Eq. (7-8). The final evaluation result is that four components are selected to be taken into the second decision-making phase. The four components are air cylinder head assembly (M_1), cooling water pump (M_2), injector assembly (M_3) and hydraulic oil cylinder (M_8).

5.2. Determining the evaluation information in interval 2-tuple TOPSIS

The Engineers from the manufacturing department give alternative remanufacturing concepts for the components M_1, M_2, M_3 and M_8. Taking concept evaluation on M_1 as an example in this case, six remanufacturing concepts are given out by manufacturing engineers. The alternative concepts A_1, A_2, ...and A_6 for M_1 are the evaluation objects in the second decision-making phase. The evaluation criteria are given by senior experts including environmental protection level (C_1), remanufacturing cost (C_2), process difficulty (C_3), quality (C_4) and required service level (C_5). The importance weights of them are: 0.162, 0.186, 0.309, 0.244 and 0.099, respectively. $C_1$and C_4 are the benefit criterion, and C_2, C_3 and C_5 are the cost criterion.

There are ten DMs from manufacturing, design, R&D and after-sale department participating in the remanufacturing concept evaluation. The objective weights of the ten DMs are pre-determined as 0.125, 0.109, 0.084, 0.131, 0.064, 0.209, 0.093, 0.075, 0.069 and 0.041, respectively.

All DMs give their judgments on each alternative concept aiming at the five evaluation criteria. A totally ordered discrete linguistic term set S_1 is pre-given to express evaluation on C_1 and C_4. Another pre-given set S_2 is used to express evaluation on C_2 , C_3 and C_5.

S_1= $\{ s_0$ =extremely poor; s_1 =very poor; s_2 =poor; s_3 =slightly poor; s_4 =fair; s_5 =slightly good; s_6 =good; s_7 =very good; s_8 = extremely good$\}$.

Table 1. The evaluation data of the 12 key components for the augmented DEA.

		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}
Manufacturing characteristic	Disassembly index	0.93	0.92	0.98	0.88	0.90	0.85	0.78	0.95	0.87	0.89	0.84	0.84
	Test index	0.82	0.85	0.95	0.75	0.86	0.72	0.79	0.91	0.81	0.81	0.78	0.79
	Replace index	0.98	0.94	0.88	0.86	0.92	0.82	0.85	0.95	0.78	0.77	0.81	0.81
	Restore index	0.81	0.79	0.92	0.82	0.67	0.71	0.68	0.85	0.93	0.71	0.68	0.72
Economy index	Manufacturing cost($)	1190	560	820	1080	470	165	4500	320	120	140	3500	3800
	Remanufacturing cost($)	750	320	480	820	290	110	2500	170	80	85	2800	3000
	c	0.370	0.429	0.415	0.241	0.383	0.333	0.444	0.469	0.333	0.393	0.200	0.211
General status of returned components	Severity of FM_1	4	3	2	6	8	5	7	4	4	6	7	5
	Severity of FM_2	6	5	4	4	8	6	6	2	6	6	6	8
	Severity of FM_3	3	4	5	3	7	7	4	3	6	7	8	9

S_2= { s_0 =extremely low; s_1 =very low; s_2 =low; s_3 =slightly low; s_4 =fair; s_5 =slightly high; s_6 = high; s_7 =very high; s_8 = extremely high}.

Step 1: Acquire DMs' judgments on each criterion of all alternatives. DMs can give their judgments with different granularities of uncertainty according to personalized habit and background. The granularity of uncertainty is reflected by the width of the interval-formed linguistic judgment. The interval-formed linguistic judgment of decision maker d_1 given on alternative A_1 is shown in Table 2. All the DMs' interval 2-tuple linguistic evaluation information on A_1 is shown in Table 3.

Table 2. The interval-formed linguistic judgment of $d_1$given on A_1

d_1	C_1	C_2	C_3	C_4	C_5
A_1	$[s_2, s_4]$	$[s_5, s_7]$	$[s_3, s_5]$	$[s_6, s_7]$	$[s_3, s_4]$

Step 2: Aggregate all the DMs' judgments on each criterion of all alternatives to obtain the final decision matrix according to the DMs' subjective weights and the objective weights.

The objective weight of each DM varies from criterion to criterion for different alternatives, and it can be calculated by Eq. (14-15).The subjective weights of all DMs' and their various objective weights on A_1 is given in Table 4. The final weights of all DMs on each criterion of different alternatives can be obtained by averaging the subjective and objective weights using Eq. (16). In this case, α_1 and α_2 in Eq. (16) are assigned the same value 0.5. Fig.2 shows the distribution of all the DMs' subjective weights and final weights on different criteria. From this figure, it can be illustrated that DM d_3 has the highest subjective weight, but his or her final weight on all criteria are not much higher than the other

DMs' weights because of the information he or she given has much higher uncertainty degree. In the contrary, DM d_{10} has the lowest subjective weight, but his or her final weights on all criteria are not much lower than the other DMs' weights. The final weight of d_{10} on C_5 is even higher than the final weight of d_9. This is because that the information he or she given has much lower uncertainty degree.

The final decision matrix of all alternative concepts obtained by aggregating all the DMs' judgments is shown is Table 5. The information in this table are in the form of interval 2-tuples .The translated evaluation on A_1 in interval 2-tuple linguistic information is: $((s_3,-0.27), (s_5, -0.32)), ((s_5,-0.30), (s_6, 0.41)), ((s_4,-0.38), (s_5, 0.49)), ((s_5, 0.38), (s_7, -0.21)), ((s_3,-0.43), (s_4, 0.23))$. This form of information is convenient for experts to distinguish or compare the performances of all criteria. However, the first step to deal with the final decision matrix is calculating the distance between each alternative's evaluation information and the PIS/NIS, and the interval 2-tuple linguistic information should be transformed into the interval 2-tuples. Therefore, the final decision matrix as shown in Table 5 is given in the form of interval 2-tuples.

Step 3: Identify the *PIS* and *NIS* of the final decision

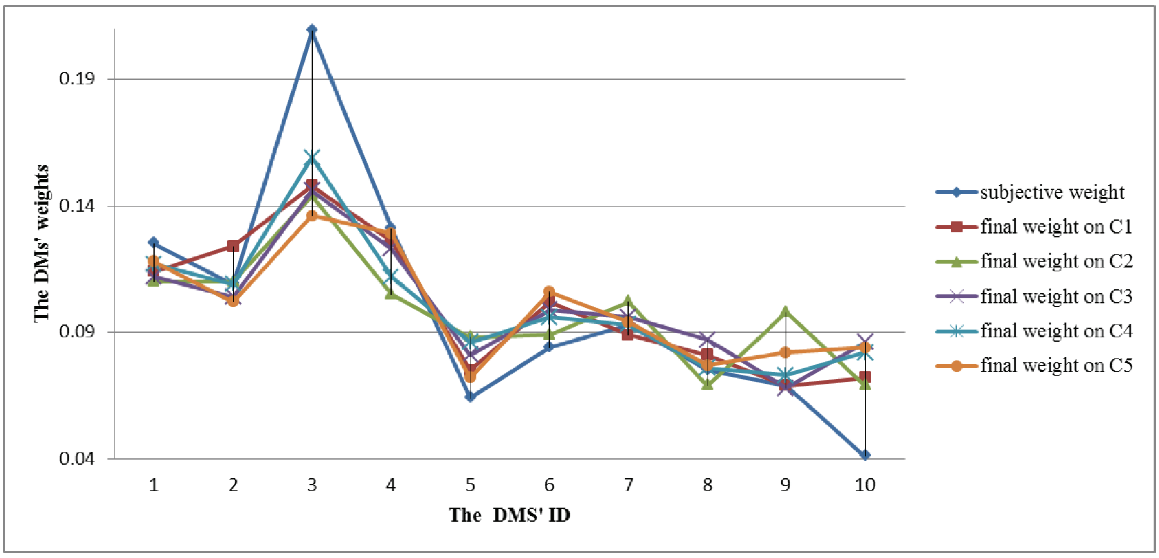

Fig. 2. The distribution of all the DMs' subjective weights and final weights on different criteria.

Table 3. All the DMs' interval 2-tuple linguistic evaluation information on A_1.

A_1	C_1	C_2	C_3	C_4	C_5
d_1	$((s_2,0),(s_4,0))$	$((s_5,0),(s_7,0))$	$((s_3,0),(s_5,0))$	$((s_6,0),(s_7,0))$	$((s_3,0),(s_4,0))$
d_2	$((s_2,0),(s_2,0))$	$((s_4,0),(s_5,0))$	$((s_4,0),(s_6,0))$	$((s_5,0),(s_6,0))$	$((s_3,0),(s_5,0))$
d_3	$((s_2,0),(s_5,0))$	$((s_4,0),(s_7,0))$	$((s_4,0),(s_7,0))$	$((s_6,0),(s_7,0))$	$((s_2,0),(s_6,0))$
d_4	$((s_3,0),(s_4,0))$	$((s_5,0),(s_8,0))$	$((s_3,0),(s_4,0))$	$((s_5,0),(s_7,0))$	$((s_4,0),(s_4,0))$
d_5	$((s_3,0),(s_6,0))$	$((s_5,0),(s_6,0))$	$((s_4,0),(s_6,0))$	$((s_5,0),(s_6,0))$	$((s_1,0),(s_4,0))$
d_6	$((s_4,0),(s_4,0))$	$((s_3,0),(s_5,0))$	$((s_4,0),(s_5,0))$	$((s_6,0),(s_7,0))$	$((s_2,0),(s_2,0))$
d_7	$((s_4,0),(s_7,0))$	$((s_6,0),(s_7,0))$	$((s_5,0),(s_7,0))$	$((s_5,0),(s_7,0))$	$((s_2,0),(s_4,0))$
d_8	$((s_2,0),(s_5,0))$	$((s_4,0),(s_8,0))$	$((s_2,0),(s_4,0))$	$((s_5,0),(s_8,0))$	$((s_2,0),(s_5,0))$
d_9	$((s_3,0),(s_7,0))$	$((s_6,0),(s_6,0))$	$((s_3,0),(s_7,0))$	$((s_4,0),(s_7,0))$	$((s_3,0),(s_5,0))$
d_{10}	$((s_3,0),(s_5,0))$	$((s_5,0),(s_5,0))$	$((s_4,0),(s_4,0))$	$((s_6,0),(s_6,0))$	$((s_3,0),(s_3,0))$

Table4. The subjective weights of all DMs' and their objective weights on A_1.

	sw_k	dw_k^{11} (C_1)	dw_k^{12} (C_2)	dw_k^{13} (C_3)	dw_k^{14} (C_4)	dw_k^{15} (C_5)
	0.125	0.102	0.098	0.098	0.108	0.111
d_2	0.109	0.136	0.115	0.098	0.108	0.095
d_3	0.209	0.085	0.082	0.082	0.108	0.063
d_4	0.131	0.119	0.082	0.115	0.092	0.127
d_5	0.064	0.085	0.114	0.098	0.108	0.079
d_6	0.084	0.136	0.098	0.115	0.108	0.127
d_7	0.093	0.085	0.115	0.098	0.092	0.095
d_8	0.075	0.085	0.066	0.098	0.077	0.079
d_9	0.069	0.068	0.131	0.066	0.077	0.095
d_{10}	0.041	0.102	0.098	0.131	0.123	0.127

matrix, and the results are listed in Table 5.

Step 4: Determine the final criteria weights by combining the pre-determined subjective weights and objective weights.

The objective weight of one criterion is calculated according to the discrete degree of all the alternatives' evaluations on this criterion using Eq. (21-22). The calculation of final criterion weight is carried out using Eq. (23). In this case, β_1 and β_2 in Eq. (23) are assigned the same value 0.5. The subjective weight, objective weight and final weight of all the criteria are given out in Table 6.

Table5. The final decision matrix of all alternative concepts aiming at M_1

M_1	C_1	C_2	C_3	C_4	C_5
A_1	Δ [2.73,4.68]	Δ [4.70,6.41]	Δ [3.62,5.49]	Δ [5.38,6.79]	Δ [2.57,4.23]
A_2	Δ [2.04,3.98]	Δ [5.47,7.36]	Δ [3.21,5.23]	Δ [4.23,6.18]	Δ [5.62,7.98]
A_3	Δ [4.19,6.24]	Δ [3.11,4.99]	Δ [2.17,4.34]	Δ [5.85,8.07]	Δ [2.38,5.19]
A_4	Δ [3.85,6.01]	Δ [2.77,4.39]	Δ [2.76,4.58]	Δ [5.47,7.43]	Δ [6.13,8.75]
A_5	Δ [1.87,3.49]	Δ [5.89,7.29]	Δ [2.89,4.51]	Δ [2.45,4.67]	Δ [4.17,6.64]
A_6	Δ [3.28,5.59]	Δ [3.76,5.81]	Δ [2.67,4.12]	Δ [6.17,7.92]	Δ [1.63,3.87]
PIS	Δ [4.19,6.24]	Δ [2.77,4.39]	Δ [2.17,4.12]	Δ [6.17,8.07]	Δ [1.63,3.87]
NIS	Δ [1.87,3.49]	Δ [5.89,7.36]	Δ [3.62,5.49]	Δ [2.45,4.67]	Δ [6.13,8.75]

Table 6. Three different weights of all criteria on M_1

M_1	C_1	C_2	C_3	C_4	C_5
The subjective weight	0.162	0.186	0.309	0.244	0.099
The objective weight	0.175	0.208	0.083	0.206	0.328
The integrated weight	0.169	0.197	0.196	0.225	0.214

Step 5: Calculate the closeness degree between each alternative and the *PIS*, *NIS* with the final criteria weights using Eq. (24-25). The result is shown in Table 7.

- In the circumstance of subjective weights, C_4 is the worst concept. However, the relative close degree of C_4 in the circumstance of objective weights is much higher, and its ranking position rises obviously in the circumstance of integrated weights. The change of ranking position for C_4 is the largest of those for all concepts. In the circumstance of integrated weights, C_3 is the worst concept and it has much lower relative close degree with the *PIS* in the other two circumstances.

Table7. The closeness degree between each alternative and the PIS, NIS

M_1	A_1	A_2	A_3	A_4	A_5	A_6
$D(P_i,PIS)$	Δ (1.86)	Δ (3.45)	Δ (0.576)	Δ (1.85)	Δ (3.55)	Δ (0.662)
$D(P_i,NIS)$	Δ (2.59)	Δ (0.988)	Δ (3.88)	Δ (2.56)	Δ (0.869)	Δ (3.81)
R_i	Δ (0.418)	Δ (0.777)	Δ (0.129)	Δ (0.42)	Δ (0.803)	Δ (0.148)

Step 6: Calculate the relative closeness degree between each alternative and the *PIS* using Eq. (26), where θ_1 , θ_2 are assigned the same value 0.5.

The result is shown in Table 7. C_5 is the ideal concept for M_1. Furthermore, the results in three different circumstances: evaluation with the subjective criteria weights, evaluation with the objective criteria weights and evaluation with the integrated criteria weights, are contrasted intuitively in Fig.3.

- In the circumstance of subjective weights, C_5 ranks first and C_2 ranks second. In the circumstance of integrated weights, C_5 also ranks first, but the distance between it and C_2 is shortened. This change is brought by the gap existing among the objective criteria weights.

  Therefore, C_3 is worse than C_4 from the comprehensive perspective.

Therefore, the ranking result in the circumstance of integrated criteria weights has higher rationality and effectiveness than the circumstance considering the subjective criteria weights exclusively.

6. Conclusions

Manufacturing companies are striving to implement sustainable development strategies and obtain a larger share of the market to enhance competitiveness and profitability. Remanufacturing is an important strategy which can benefit manufacturers and customers,

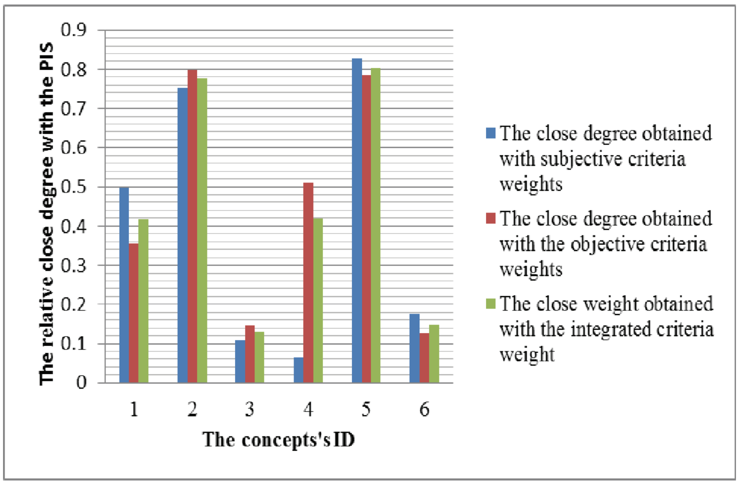

Fig. 3. The comparative relative close degrees of all concepts with three different criteria weights.

especially for complex product with higher manufacturing cost. Systematic remanufacturing decision-making research for complex product is rare in literature research. In this paper, a component oriented remanufacturing decision-making for complex product is proposed for manufacturers to select feasible components to be remanufactured and evaluate remanufacturing concepts for each of them.

The major characteristics of this research are summarized as follows.

- An augmented DEA is proposed to evaluate efficiencies of pre-selected components. Three factors are considered: Manufacturing characteristic, comparative cost advantage and general returned status.
- TOPSIS integrated with interval 2-tuple linguistic is proposed to select remanufacturing concept for efficient components. The DMs' subjective weights and objective weights are both considered in deriving the collective judgments. The objective weights are determined by the precision degrees of information given by DMs. The related close degree between each alternative and PIS/NIS is calculated by considering subjective and objective criteria weights. The objective criterion weight is determined by the discrete degree of all alternative's performances on this criterion.

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