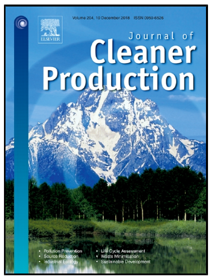
Accepted Manuscript



An Integrated MCDM Approach Considering Demands-Matching for Reverse Logistics

Han Wang, Zhigang Jiang, Hua Zhang, Yan Wang, Yihua Yang, Yi Li

PII:	S0959-6526(18)33147-0
DOI:	10.1016/j.jclepro.2018.10.131
Reference:	JCLP 14533
To appear in:	*Journal of Cleaner Production*
Received Date:	17 April 2018
Accepted Date:	10 October 2018

Please cite this article as: Han Wang, Zhigang Jiang, Hua Zhang, Yan Wang, Yihua Yang, Yi Li, An Integrated MCDM Approach Considering Demands-Matching for Reverse Logistics, *Journal of Cleaner Production* (2018), doi: 10.1016/j.jclepro.2018.10.131

An Integrated MCDM Approach Considering Demands-Matching for Reverse Logistics

Han Wang[a], ZhigangJiang[b*], Hua Zhang [b], Yan Wang[c], Yihua Yang[d], Yi Li [d]

[a]Hubei Key Laboratory of Mechanical Transmission and Manufacturing Engineering, Wuhan University of Science & Technology, Wuhan 430081, China
[b]Key Laboratory of Metallurgical Equipment and Control Technology, Wuhan University of Science & Technology, Wuhan 430081, China

[c]Department of Computing, Engineering and Mathematics, University of Brighton, Brighton, BN2 4GJ, United Kingdom
[d]Sevalo Construction Machinery Remanufacturing Co., Ltd , Wuhan 430040, China

Abstract
Reverse logistics (RL) has been regarded as a key driving force for remanufacturing. However, there are great uncertainties in terms of quality and quantity of used components for RL. There are also complexities in suppliers and operations. These make decision-making of RL very complex. In order to identify the best collection mode for used components, a demand-matching oriented Multiple Criteria Decision Making (MCDM) method is established. In this method, the damage level and remaining service life are firstly incorporated into the evaluation criteria of reuse modes, then a hybrid method (AHP-EW) that integrates Analytic Hierarchy Process (AHP) and Entropy Weight (EW) method is applied to derive criteria weights and the grey Multi-Attributive Border Approximation Area Comparison (MABAC) is adopted to rank the collection modes. Finally, sensitivity analysis is implemented to test the stability of the proposed method, and a demands-matching method is proposed to validate and evaluate the feasibility of the optimal alternative. The collection of used pressurizers is taken as case study to validate the applicability of the proposed model. The results showed the effectiveness of the proposed method in MCDM of RL.

Keywords: Reverse logistics; Multiple Criteria Decision Making; Demands matching; Damage level; Remaining service life

1. Introduction

Reverse logistics (RL) is recognized as a means to deal with the end-of-life (EOL) products in an environmental and friendly manner and has attracted an increasing amount of attentions in recent years (Zhalechian et al., 2016; Govindan et al., 2017a; Rajeev et al., 2017; Govindan et al., 2018a). In RL, the environmental impact, resource utilization, and business profits of used components/products are largely dependent on the collection modes (i.e., Third Party Take-back (TPT), Manufacturing Take-back (MT), and Retailer Take-back (RT)). Improper decision-making of collection mode may increase environmental burden, resource consumption, and reduce profits (Saha et al., 2016). Current decision-making of collection mode researches can be summarized in three main issues: establishing evaluation criteria system, deriving the weights of criteria, and decision-making based on rank of collection modes. As a significant strategy to save energy consumption and reduce carbon emission in industrial systems, it has been widely applied to many fields, especially in manufacturing and remanufacturing fields (Entezaminia et al., 2017; Wang et al., 2018).

The ever-increasing of EOL products and the strict environmental policies contribute to the development of remanufacturing including industrial, government, and research communities. As a means of eco-friendly and energy-efficient production, remanufacturing, a serious of process (e.g., disassembly, clean, inspect, reconditioning, and reassembly) to return EOL products/components to "like new or better than new" functional status, has attracted growing attention worldwide (Lee et al., 2017; Paterson et al., 2017; Zlamparet et al., 2017; Lu et al., 2018; Jin et al., 2018). Correspondingly, the increasing demands of customers' satisfaction, the maximum benefits for collection companies, and the minimum impact for environment put forward higher demands to the demands match between collection companies and used components in RL. The demands matching degree is one of the most important features to reflect the matching degree between collection companies' capacity as well as capability and used components. The condition characteristics of used components is the prerequisite of determining demands matching because the condition characteristics like damage level and remaining service life will directly determine the treatment methods and process routes, which finally impacts the companies' profits, environmental impact, and resource utilization (Jiang et al., 2016; Wang et al., 2017). This paper establishes an evaluation criteria system including condition characteristics of used components, which could be adopted to the decision-making of collection modes for used components.

The process of collection modes evaluation is the fundamental basis for decision-making of collection mode for used components, but various evaluation criteria, characteristics of criteria, and condition gap between the collection companies and used components make it a challenging problem. For instance, when considering the treatments means of used components, some criteria like damage level, remaining service life, energy consumption, and cost must be taken into consideration. Therefore, a multi-criteria decision-making (MCDM) method becomes the best choice to deal with this problem (Tian et al., 2018). The process of MCDM is consisted of four main steps: (1) alternatives generation, (2) establishment of evaluation criteria system, (3) determination of criteria weights, and (4) rank of alternatives (Senthil et al., 2018). Each criterion is relevant to an objective in a specific decision-making process, and normalization is normally used to transform different types of criteria into a same form (Ameri et al., 2018; Tsai et al., 2018). However, the qualitative criteria (e.g., performance degradation risk) and quantitative criteria (e.g., energy consumption) are common in decision-making of collection modes in RL, which thus there are many objective and subjective impacts/factors respectively. Analytic Hierarchy Process (AHP) and Entropy Weight (EW) are good ways to deal with these subjective and objective factors. To the best of our knowledge, few of literature has reported a hybrid method integrating AHP with EW to drive the weights of criteria for collection modes in RL. Once the weighted is determined, the rank of alternatives should be followed. The grey Multi-Attributive Border Approximation Area Comparison, an inclusive evaluation tool, has been viewed as an efficient decision support system for selection problems due to its consistent/stable solutions under the different conditions (Mardani et al., 2016; Zavadskas et al., 2016; Xue et al., 2016; Debnath et al., 2017). Sensitivity analysis is normally adopted to inspect the stability of the proposed MCDM method, while the matching between the evaluation object and alternatives from a practical perspective is rare. This may lead to that the final rank of alternatives is not suitable in real production. To this end, this paper presents a demands-matching oriented MCDM method to decide and inspect the collection mode for used components from a practical angle respectively. The novelties of this paper are: (1) Establishing quantification evaluation criteria of used components' condition. The quantified damage level and remaining service life are adopted to comprehensively evaluate the condition of used components; (2) Comprehensively considering the quantitative and qualitative criteria in evaluation criteria system. A hybrid method integrating AHP with EW is used to allocate the weights of criteria; (3) Introducing demands matching concept and establishing its mathematics. Considering the relationship between the capacity as well as capability of the collection companies and the condition of used components, demands matching is adopted to validate the feasibility of the collection modes rank obtained from the grey MABAC method, on the other hand, it is used to generate a feasible and rational collection mode from a practical perspective, which may give the future improvements suggestions for collection companies.

The layout of this research can be summarized: Section 2 provides a review of the relevant literature. The framework of this research and the evaluation criteria system are presented in Section 3. The method, i.e., a demand-matching based hybrid MCDM, is presented in Section 4. The verification of a case study with three collection modes, sensitivity analysis, and demands matching calculation are presented in Section 5. Finally, Section 6 provides the conclusions and future work.

2. Literature review

Decision-making of collection modes in reverse logistics is normally viewed as a typical MCDM problem, owing to the paucity of accurate and formal measurement criteria or programs. Approaches experts experience relevant to this area, mathematical models or simulations are used to the evaluation process of alternatives (Dehghanbaghi et al., 2016; Saha et al., 2016; Prakash et al., 2016; Mohammed et al., 2017; Shankar et al., 2018). In the literature, many previous researched have studied and presented various approaches/methods to implement the decision-making of used components, and the adopted impact criteria include environmental, risk, economical, and social aspects (Uygun et al., 2016; Ahmadi et al., 2017; Cai et al., 2018; Senthil et al., 2018). Many scholars as cases are shown in Table 1 to reflect the selection of evaluation criteria.

Table 1 Literature on evaluation criteria in decision-making of used components

References	Evaluation criteria			
	Environmental	Risk	Economical	Social
Senthil et al. (2018)		✓		
Lintukangas et al. (2016)		✓	✓	
Zhao et al. (2016)		✓	✓	
Govindan et al. (2017b)	✓		✓	✓
Fathollahi-Fard et al. (2018)	✓		✓	
Kadambala et al. (2017)	✓		✓	✓
Banasik et al. (2017)	✓		✓	
Wu et al. (2016)	✓		✓	
Zarbakhshnia et al. (2018)	✓	✓	✓	✓
Govindan et al. (2016a)	✓	✓	✓	✓

The aforementioned literatures provide a guideline for the selection of evaluation criteria for collection in reverse logistics. However, few of them consider the basic physical condition (e.g., damage level and remaining service life) of used components. In detail, the damage level and remaining service life will determine the treatment means, remanufacturability, and remanufacturing process routes, which further influence other aspects, e.g., energy consumption and cost of treatment process (Wang et al., 2017; Kurilova-Palisaitiene et al., 2018). Therefore, the consideration of damage level and remaining service life in the evaluation process have a great significance on remanufacturing activities, operation optimization, and profits improvements of collection companies.

An overview of main decision-making of collection modes of used components in reverse logistics is presented briefly in this section. In general, the MCDM methods could be summarized into two types: 1) comprehensive decision-making methods. For instances, VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Gul et al., 2016), fuzzy AHP (Kubler et al., 2016), ELimination and Choice Expressing the REality (ELECTRE) (Govindan et al., 2016b), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) (R et al., 2017), Interval Type-2 Fuzzy Sets (IT2FSs) (Mousakhani et al., 2017), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Han et al., 2018), and Decision Making Trial and Evaluation Laboratory (DEMATEL) (Bouzon et al., 2018); 2) combinational decision-making methods. For example, Keshavarz et al. (2017) used the Evaluation based on Distance from Average Solution (EDAS) method and IT2FSs to evaluate the suppliers from environmental perspectives in supply chains. Sari. (2017) proposed a novel decision framework to evaluate green supply chain management practices, in which the Monte Carlo simulation, AHP, and VIKOR are developed under fuzzy environment. Senthil et al. (2018) proposed a hybrid MCDM integrating AHP, TOPSIS, and PROMETHEE for prioritizing the reverse logistics risk. Shaik et al. (2018) applied a hybrid multi-criteria method combining DEMATEL, fuzzy ANP, and AHP methods to assess the reverse logistics companies' performance, in which the performance attributes such as product lifecycle stages, strategies, processes, capabilities, and perspectives, and measures were considered. Govindan et al. (2018b) presented a hybrid method combing a variant of ELECTRE I accounting for the effect of reinforced preference, the revised Simos procedure, and Stochastic Multi-criteria Acceptability Analysis to select the most preferred service providers in reverse logistics.

The review of the previous researches illustrates that although there are many effective evaluation methods to deal with decision-making of collection modes for used components. Nevertheless, some aspects still be ignored, for instance, the quantified damage level and remaining service life of used components, which have a significant influence on the decision-making process of collection modes, is rarely considered in evaluation criteria system. The quantitative and qualitative criteria are common in evaluation criteria system, while the comprehensive derivation of weights for both quantitative and qualitative criteria is ignored. The gap between the collection companies' demands and the condition of used components determines the final decision-making of collection modes. The grey MABAC method is recognized to be an effective decision support tool to rank all kinds of alternatives. To this end, a demands-matching based MCDM method is proposed. The evaluation criteria system is established considering the quantified damage level and remaining service life. A hybrid method integrating AHP with EW is adopted to provide used components with a comprehensive condition evaluation from both quantitative and qualitative perspectives. The grey MABAC is applied to obtain the rank of collection modes. The demands matching degree is proposed to validate the feasibility of the rank obtained from grey MABAC method from a practical perspective.

3. Framework and evaluation criteria system of MCDM for RL

The proposed research framework of MCDM for RL is shown in Fig. 1. The proposed framework could assist analysts with respects to:

1) Understanding and determining the criteria for selecting collection modes;
2) Identifying the relative importance weights of criteria based on objective factors and subjective factors;
3) Ranking the alternatives and selecting the optimum collection mode on the basis of demands matching degree and sensitivity analysis.

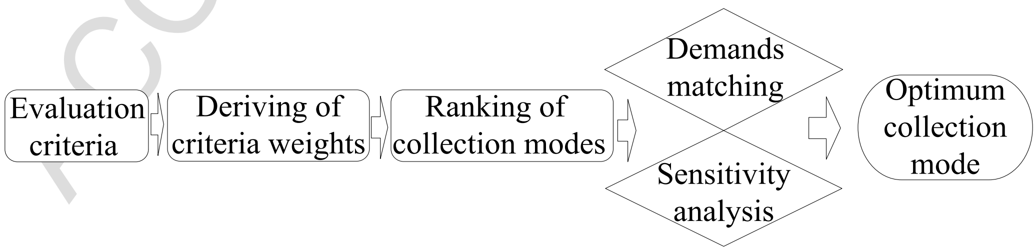


Fig. 1. Framework of multi-criteria decision-making for RL

The multi-criteria decision-making in Fig. 1 includes five steps:

Step 1: Establishment of evaluation criteria. The evaluation criteria include status information of the used components (quality), impacts on environment and people (sustainability), economic performance of processing used components (cost and profit), and uncertainties in terms of market and performance (risk).

Step 2: Deriving of the criteria weights. This step is to determine the relative importance weights of criteria using a hybrid AHP-EW method. In this method, the subjective and objective factors are considered simultaneously.

Step 3: Ranking of collection modes. The collection modes include Third Party Take-back (TPT), Manufacturer Take-back (MT), and Retailer Take-back (RT). This step is to rank the alternatives for collection using a grey MABAC method, which is based on the demands of used components.

Step 4: Sensitivity analysis and demands matching. The sensitivity analysis is to test the stability of the proposed rank of collection modes, and the demand matching is proposed to inspect suitability between collection modes and recyclers, whilst validate the effectiveness and the applicability of the proposed MCDM method.

Step 5: Determination of the optimum collection mode. Through the proposed steps, the final optimum collection mode can be obtained, which provides a guide for managers of manufacturing/remanufacturing companies to make a decision for collection mode selection of used components.

3.1 Evaluation criteria system of decision-making for RL

The selection of criteria is significant for the evaluation process and it has been acknowledged with a wide-ranging literature in introduction. This paper is focused on four types of factors including quality (B1), sustainability (B2), economy (B3), and risk (B4). There are three collection modes including Third Party Take-Back (TPT) in which used components with rich varieties and large volume are collected by third party companies, Manufacturing Take-Back (MT) in which original manufacturers are engaged in the collection of used parts with less varieties and large volume), and Retailer Take-Back (RT) in which the used components with less varieties and small volume are collected by retailers. The details are shown in Fig. 2.

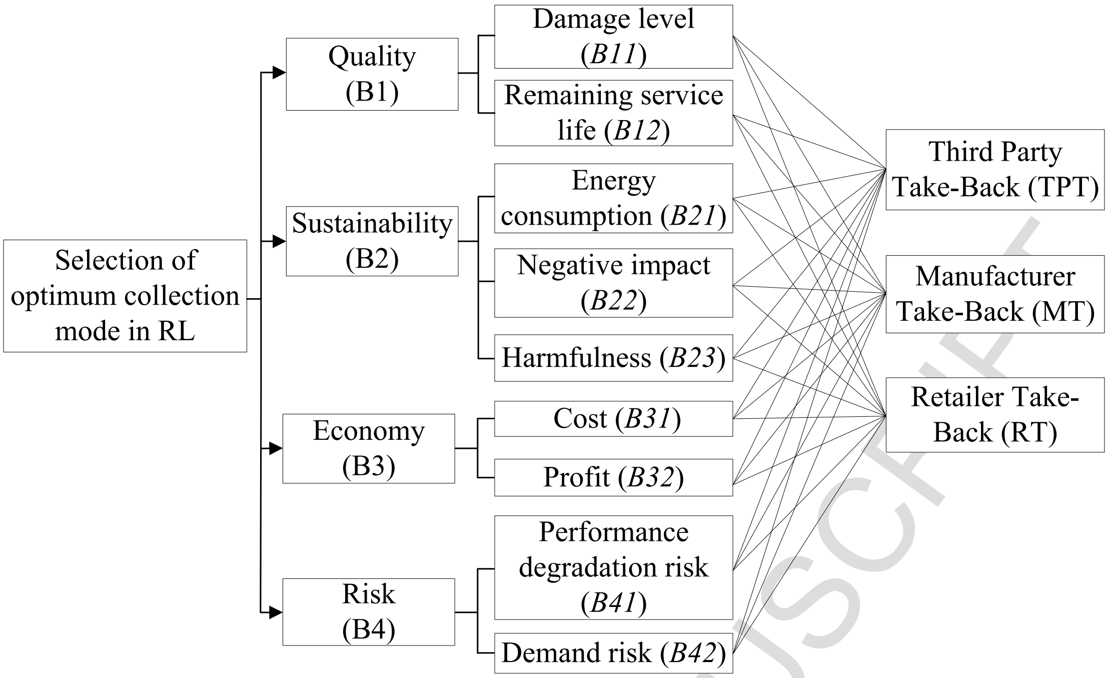


Fig. 2. Evaluation criteria of decision-making for reverse logistics

The nine criteria were established to evaluate the RL for decision makers and the detail definitions of the evaluation criteria are shown in Table 2.

Table 2 Evaluation criteria and the corresponding definitions

Criteria No.	Criteria	Definitions
B11	Damage level	Damage degree of fault features (e.g., wear, deformation, and corrosion) of the used components.
B12	Remaining service life	Remaining usable time after the components has serviced for a period of time.
B21	Energy consumption	Energy consumption during the transportation and processing.
B22	Negative impact	Environmental impact of transportation from location of usage points on collection points, which is related to the distance between usage point and collection point.
B23	Harmfulness	Threats to the people in workplaces during the remanufacturing process.
B31	Cost	Cost during remanufacturing processing and transportation process.
B32	Profit	Return from the collection of used components.
B41	Performance degradation	The phenomenon that the used component fails to work due to certain processing demands.
B42	Demand risk	Demand uncertainty due to the variable market price of remanufactured components.

3.2 Mathematical modelling of criteria

3.2.1 Quality

The quality of used components can be reflected through the damage level and remaining service life.

(1) Damage level *B11*

Each used component may have one or more types of fault features and its damage level may be varied. In accordance with Li et al. (2013) and Wang et al. (2017), the quantified damage level can be obtained, in which the machine tool spindle is taken as the example and it can be divided into three evaluation score intervals. The damage level of used components is evaluated based upon the volumetric damage amount of the fault features and the score intervals are shown in Table 3.

Table 3 Damage level of fault features based on Li et al. (2013) and Wang et al. (2017)

Fault features	Volumetric damage amount intervals	Damage score intervals
Wear	$0<x<1.0mm^3$	[0, 3.3)
	$1.0\ mm^3 \leq x<2.0\ mm^3$	[3.3, 6.6)
	$x \geq 2.0mm^3$	[6.6, 10]
Crack	$0<y<0.6mm^3$	[0, 3.3)
	$0.6 \leq y<1.2mm^3$	[3.3, 6.6)
	$y \geq 1.2mm^3$	[6.6, 10]
Wear-corrosion	$0<z<1.0mm^3$	[0, 3.3)
	$1.0mm^3 \leq z<2.0mm^3$	[3.3, 6.6)
	$z \geq 2.0\ mm^3$	[6.6, 10]
Deformation	$0<w \leq 0.01L$	[0, 3.3)
	$0.01L<w \leq 0.02L$	[3.3, 6.6)
	$w>0.02L$	[6.6, 10]

Note: L represents the length of the axis-type components

(2) Remaining service life *B12*

The remaining service life of used components relates to the expected residual service time after being utilized for a period of time. In accordance with Zhang et al. (2013), the remaining service life for each used component can be identified using a Weibull distribution for mechanical component:

$$R_L = \theta_i \Gamma(\frac{\lambda_i + 1}{\lambda_i}) \tag{1}$$

$$\Gamma(x) = \int_0^{\infty} \nu^{x-1} \exp(-\nu) d\nu \tag{2}$$

where R_L represents the remaining life of the used component; θ_i and λ_i represent the scale parameter and shape parameter of the Weibull distribution respectively.

These two parameters can be obtained using least-squares method on the basis failure data and sensor data of the used components (Zhang et al., 2013); ν represents an intermediate variable.

Similarly, the remaining service life of used components can be evaluated according to remaining life score intervals. The three score intervals are according to the maximum and minimum of the remaining life.

3.2.2 Sustainability

The sustainability of RL can be revealed as the negative impacts (e.g., environmental impacts) brought by the collection points and energy consumption during the transportation and remanufacturing processing.

(1) Energy consumption *B21*

$$E = \sum_{i=1}^{p} e_i \cdot t_i + \sum_{j=1}^{s} E_T \cdot S_j \tag{3}$$

where E represents the total energy consumption during transportation and processing; e_i and t_i represent the unit remanufacturing processing energy consumption per hour and the mean remanufacturing processing time for the i^{th} component respectively; p represents the total number of used components; E_T represents the unit transportation energy consumption per kilometer; S_j represents the transportation distance for the j^{th} transportation route; s represents the total number of transportation routes.

(2) Negative impacts of the distance from usage points to collection points *B22*

Negative impacts mean the environmental pollution caused by the emission of transportation vehicle from usage points to collection points. According to He et al. (2007), it can be shown as follow:

$$F = \sum_{j} \left(S_j\right)^{\theta} \tag{4}$$

where F represents the negative impact brought by collection point and it is related to the distance from usage point to collection point; S_j represents the distance from collection point to usage point; θ represents the negative impact degree parameter related to distance, the range of which is [0.5, 1] and the value is related to the scale of collection points.

(3) Harmfulness of the remanufacturing process *B23*

In accordance with Golinska et al. (2018), the harmfulness remanufacturing process is regarded as a social performance indicator and it denotes the threats to the people in workplaces, which is shown as follow.

$$W = \sum_{k=1}^{N} \left(300D + 10S + M \right) \times L_k \tag{5}$$

where W represents the harmfulness of the remanufacturing process; D, S, and M represent the number of threats to the k^{th} workplace with a large risk, a medium risk, and a small risk respectively; N and L_k represent the number of work stands performing task and the number of people to the k^{th} workplace respectively, which is subjected to the impact of hazards (D, S, and M).

3.2.3 Economy

The economy of RL is mainly related to the cost and profit, and the two criteria are shown as follow.

(1) Cost *B31*

The cost for RL is composed of the remanufacturing processing cost and transportation cost.

$$C = \sum_{i=1}^{p} c_i \cdot t_i + \sum_{j=1}^{s} C_T \cdot S_j \tag{6}$$

where C represents the total cost during remanufacturing processing and transportation; c_i represents the unit remanufacturing processing cost per hour for the i^{th} component (RMB/h); C_T represents the unit transportation cost per kilometer (RMB/km).

(2) Profit *B32*

The profit may be different due to the collection mode, recycle distance, and collection demand etc. In accordance with Yao et al. (2004), the profit for three collection modes can be expressed as follow:

A. Profit of Third Party Take-Back (TPT)

$$P_1 = \frac{K\left(\phi - \beta c_m\right)^2}{2\beta\left[4K - \beta\left(\chi - t\right)\left(t - S\right)\right]} \tag{7}$$

B. Profit of Retailer Take-Back (RT)

$$P_2 = \frac{K(\phi - \beta c_m)^2}{2\beta[8K - \beta(\chi - S)(t - S)]} \tag{8}$$

C. Profit of Manufacturer Take-Back (MT)

$$P_3 = \frac{K(\phi - \beta c_m)^2}{\beta[8K - \beta(\chi - S)^2]} \tag{9}$$

where c_m represents the unit cost of virgin products made from raw materials; χ represents the saving cost due to the collection of used components and it equals to the difference between the cost of virgin product and the remanufacturing cost of the same type used product; S represents the unit collection cost; t represents the transfer price when a manufacturer pays for a third party or retailer; ϕ and β represent the positive parameters related to the variance of the product price respectively; K represents a parameter related to collection rate.

3.2.4 Risk

The risk includes the performance degradation risk and the demand risk of used components. The performance degradation may happen when the returned used components are not dealt with timely. With time going by, this leads to the performance degradation and increase the uncertainty of used components' quality finally. For instance, if the collected gear boxes are not dealt with for a long time, then the surface of these component will be rusting. Thus, the performance of gear boxes will degrade and the quality will be more uncertain.

(1) Performance degradation risk *B41*

The performance degradation is regarded as an important performance indicator of used components, which is greatly influenced by the environment condition. However, it is hard to quantify the performance degradation value. The expert scoring method is adopted, in which the comment set include {very good, good, normal, bad, and very bad} and the corresponding values are {10, 8, 6, 4, 2}.

(2) Demand risk *B42*

The demand risk of remanufactured components is primarily influenced by market price. According to Hua. (2006), the demand risk of remanufactured components can be shown as:

$$f(\zeta_i) = D_{p_i}(p_i) = E(p_i - \overline{p_i})^2 \tag{10}$$

where $f(\zeta_i)$ represents the demand risk of the i^{th} type remanufactured component under a fluctuated market price; ζ_i represents the price variable for the i^{th} type remanufactured component; p_i and $\overline{p}_i$ represent price of the i^{th} type remanufactured component and the mean price of the remanufactured component respectively.

4. Methods

In order to accomplish the aforementioned aims, a novel MCDM method is presented. In this method, an AHP-EW method is developed to classify the criteria. Then a grey MABAC method considering demands of the collection modes/companies is proposed to identify the optimum collection mode. Finally, a sensitivity analysis is implemented to test the stability of the grey MABAC method; a demands-matching degree is introduced to validate the effectiveness and the applicability of the optimal alternative and the proposed MCDM method.

4.1 Integration of AHP and EW for deriving criteria weights

The aim of this hybrid method is to investigate the major relationship between criteria and the details are shown as follow.

Step 1: Standardization of criteria data. This step is to obtain the dimensionless criteria and it is assumed that there are ***m*** collection modes and ***n*** evaluation criteria. The value of the evaluation criteria is derived from the status condition of used components and practical operation condition of collection companies. The initial criteria matrix can be shown as follow:

$$X = \left(x_{ij}\right)_{m\times n} \quad i = 1,2,\ldots,m; j = 1,2,\ldots,n \tag{11}$$

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{12}$$

Therefore, the standardized evaluation matrix can be obtained:

$$Y = \left(y_{ij}\right)_{m\times n} \tag{13}$$

Step 2: Determination of criteria weights. This step considers two methods i.e., AHP and EW methods to determine the weight of each criterion w'_j and $w"_j$, in which the calculation process of EW is shown in Fig. 3.

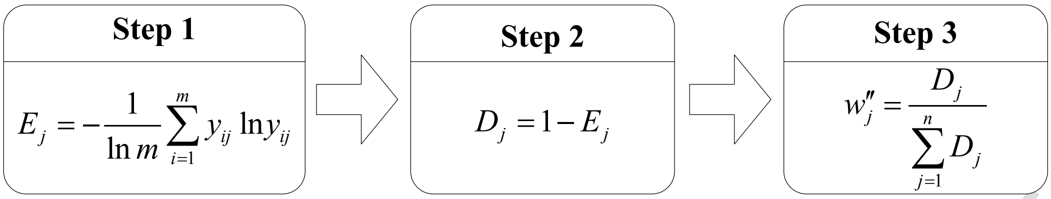


Fig. 3. Calculation process of Entropy Weight

Step 3: Determination of comprehensive weights. A weight partition coefficient α is used to obtain a comprehensive weight which integrates the weights obtained from AHP method with weights obtained from EW method. The comprehensive weight can be expressed as:

$$w_j = \alpha w_j' + (1-\alpha) w_j'' \quad 0 \le \alpha \le 1 \tag{14}$$

4.2 Grey MABAC based on demands for decision-making of collection modes

Once the weight coefficients of evaluation criteria have been obtained, the rank of alternatives of the collection modes can be implemented through the grey MABAC method based on demands. According to Debnath et al. (2017), the process of implementing this method consists of the following steps:

Step 1: Formation of the initial decision-matrices (X) based on demands. Consider RL problems with ***m*** collection modes alternatives $(R_i, i = 1, 2, ..., m)$, which are evaluated based on ***n*** evaluation criteria $(B_j, j = 1, 2, ..., n)$. Consider $Y = [\Theta y_{ij}]_{m \times n}$ is a decision matrix based on the demands of collection companies:

$$Y = [\Theta y_{ij}]_{m \times n} = \begin{bmatrix} [\underline{y}_{11}, \overline{y}_{11}] & [\underline{y}_{12}, \overline{y}_{12}] & \cdots & [\underline{y}_{1n}, \overline{y}_{1n}] \\ [\underline{y}_{21}, \overline{y}_{21}] & [\underline{y}_{22}, \overline{y}_{22}] & \cdots & [\underline{y}_{2n}, \overline{y}_{2n}] \\ \vdots & \vdots & \vdots & \vdots \\ [\underline{y}_{m1}, \overline{y}_{m1}] & [\underline{y}_{m2}, y_{m2}] & \cdots & [\underline{y}_{mn}, \overline{y}_{mn}] \end{bmatrix}_{m \times n} \tag{15}$$

where Θy_{ij} represents the evaluation grade of R_i in terms of the criteria B_j; $\underline{y}_{ij}$ and $\overline{y}_{ij}$ represent the lower and upper limit (i.e., grey correlation border) of the i^{th} criterion of j^{th} collection mode respectively; ***m*** and ***n*** represent the amount of collection modes and the total number of criteria respectively.

Step 2: Normalization of grey decision-making matrix. The aim of this step is to obtain the dimensionless criteria, which includes benefit type and cost type criteria.

A. Benefit type criteria

$$\Theta z_{ij} = \left[\underline{z}_{ij}, \overline{z}_{ij}\right] = \left[\frac{\underline{y}_{ij}}{y_j^{\max}}, \frac{\overline{y}_{ij}}{y_j^{\max}}\right] \tag{16}$$

B. Cost type criteria

$$\Theta z_{ij} = \left[\underline{z}_{ij}, \overline{z}_{ij}\right] = \left[\frac{y_j^{\min}}{\overline{y}_{ij}}, \frac{y_j^{\min}}{\underline{y}_{ij}}\right] \tag{17}$$

where $y_j^{\min} = \min\limits_{1 \le i \le m}\left(\underline{y}_{ij}\right)$ and $y_j^{\max} = \max\limits_{1 \le i \le m}\left(\overline{y}_{ij}\right)$. Therefore, the normalized decision matrix can be obtained:

$$Z = \left[\Theta z_{ij}\right]_{m \times n} = \begin{bmatrix} \left[\underline{z}_{11}, \overline{z}_{11}\right] & \left[\underline{z}_{21}, \overline{z}_{21}\right] & \cdots & \left[\underline{z}_{1n}, \overline{z}_{1n}\right] \\ \left[\underline{z}_{11}, \overline{z}_{11}\right] & \left[\underline{z}_{22}, \overline{z}_{22}\right] & \cdots & \left[\underline{z}_{2n}, \overline{z}_{2n}\right] \\ \vdots & \vdots & \vdots & \vdots \\ \left[\underline{z}_{m1}, \overline{z}_{m1}\right] & \left[\underline{z}_{m2}, \overline{z}_{m2}\right] & \cdots & \left[\underline{z}_{mn}, \overline{z}_{mn}\right] \end{bmatrix}_{m \times n} \tag{18}$$

Step 3: Calculation of grey decision-making matrix (F). The evaluation indicators of the weighted matrix (F) can be calculated based on the following equations:

$$\Theta f_{ij} = \left[\underline{f}_{ij}, \overline{f}_{ij}\right] = \omega_j \times \Theta z_{ij} = \left[\omega_j \cdot \underline{z}_{ij}, \omega_j \cdot \overline{z}_{ij}\right] \tag{19}$$

where Θz_{ij} represents the criterion of the normalized matrix (Z) and ω_j represents the weight coefficient of criterion j. The weighted matrix (F) can be expressed as follow:

$$F = \left[\Theta f_{ij}\right]_{m \times n} = \begin{bmatrix} \left[\underline{f}_{11}, \overline{f}_{11}\right] & \left[\underline{f}_{12}, \overline{f}_{12}\right] & \cdots & \left[\underline{f}_{1n}, \overline{f}_{1n}\right] \\ \left[\underline{f}_{11}, \overline{f}_{11}\right] & \left[\underline{f}_{22}, \overline{f}_{22}\right] & \cdots & \left[\underline{f}_{2n}, \overline{f}_{2n}\right] \\ \vdots & \vdots & \vdots & \vdots \\ \left[\underline{f}_{m1}, \overline{f}_{m1}\right] & \left[\underline{f}_{m2}, \overline{f}_{m2}\right] & \cdots & \left[\underline{f}_{mn}, \overline{f}_{mn}\right] \end{bmatrix}_{m \times n} \tag{20}$$

Step 4: Determination of grey border approximation area matrix (U). The grey border approximation area for each criterion can be obtained based on the equation as follow:

$$\Theta u_j = \left[\underline{u}_j, \overline{u}_j\right] = \left[\left(\prod_{i=1}^{m} \underline{f}_{ij}\right)^{1/m}, \left(\prod_{i=1}^{m} \overline{f}_{ij}\right)^{1/m}\right] \tag{21}$$

where $\left[\underline{f}_{ij}, \bar{f}_{ij}\right]$ represents the elements of the weighted matrix (F) and $\boldsymbol{m}$ represents the total number of collection modes. Once the value of Θu_j for each criterion function is obtained, a border approximation area vector (i.e., $u = \left(\Theta u_1, \Theta u_1, ..., \Theta u_n\right)_{1\times n}$) can be formed. The grey border approximation area matrix (U) can then be constructed, which is shown as below:

$$U = \begin{bmatrix} [\underline{u}_1, \bar{u}_1] & [\underline{u}_2, \bar{u}_2] & \cdots & [\underline{u}_n, \bar{u}_n] \\ [\underline{u}_1, \bar{u}_1] & [\underline{u}_2, \bar{u}_2] & \cdots & [\underline{u}_n, \bar{u}_n] \\ \vdots & \vdots & \vdots & \vdots \\ [\underline{u}_1, \bar{u}_1] & [\underline{u}_2, \bar{u}_{12}] & \cdots & [\underline{u}_n, \bar{u}_n] \end{bmatrix} \tag{22}$$

Step 5: Calculation of preference criteria matrix (L). According to the Euclidean distance between the grey numbers Θf_{ij} and Θu_j, the preference criterion matrix of collection modes can be calculated, which is shown as follow:

$$L = F - U = \left[l_{ij}\right]_{m\times n} = \begin{bmatrix} d\left(\Theta f_{11}, \Theta u_1\right) & d\left(\Theta f_{12}, \Theta u_2\right) & \cdots & d\left(\Theta f_{1n}, \Theta u_n\right) \\ d\left(\Theta f_{21}, \Theta u_1\right) & d\left(\Theta f_{22}, \Theta u_2\right) & \cdots & d\left(\Theta f_{2n}, \Theta u_n\right) \\ \vdots & \vdots & \vdots & \vdots \\ d\left(\Theta f_{m1}, \Theta u_1\right) & d\left(\Theta f_{m2}, \Theta u_2\right) & \cdots & d\left(\Theta f_{mn}, \Theta u_n\right) \end{bmatrix}_{m\times n} \tag{23}$$

The preference criteria consist of benefit type and cost type criteria, which are shown as follow:

A. Benefit type criteria

$$l_{ij} = \begin{cases} d\left(\Theta f_{ij}, \Theta u_j\right) & if \quad \Theta f_{ij} > \Theta u_j \\ -d\left(\Theta f_{ij}, \Theta u_j\right) & if \quad \Theta f_{ij} < \Theta u_j \end{cases} \tag{24}$$

B. Cost type criteria

$$l_{ij} = \begin{cases} -d\left(\Theta f_{ij}, \Theta u_j\right) & if \quad \Theta f_{ij} > \Theta u_j \\ d\left(\Theta f_{ij}, \Theta u_j\right) & if \quad \Theta f_{ij} < \Theta u_j \end{cases} \tag{25}$$

Step 6: Rank of collection modes. The ranking process of alternatives can be accomplished through the add operation of the elements' distance in Eq. (23), which is shown as follow:

$$RR(R_i) = \sum_{j=1}^{n} q_{ij} = \sum_{j=1}^{n} d(\Theta f_{ij}, \Theta u_j); \qquad i = 1,2,\dots,m \tag{26}$$

5. Case study

There are three collection modes/companies: TPT, MT, and RT that are engaged in collecting used pressurizers, a key part of construction machinery. During the service, the pressurizers are damaged and worn under high pressure and high frequent impacts. These three collection companies wish to collect the used pressurizers according to their demands and the status information of used pressurizers. The data of this case study was collected in Wuhan Qianlima Construction Machinery Co., Ltd and its industry partners of this proposed research. The demands of the three companies/modes are shown in Table 4.

Table 4 Demands of three companies for collecting used pressurizers

Criteria	*B11*	*B12*	*B21*	*B22*	*B23*	*B31*	*B32*	*B41*	*B42*
TPT	medium	low	medium	low	medium	low	high	medium	Low
MT	low	high	medium	medium	high	medium	medium	low	Medium
RT	low	high	low	high	medium	medium	high	low	High

A score interval is set to quantify the demands of three companies. The “low”, “medium”, and “high” are corresponding to score intervals [1, 3], [4, 6] and [7, 9] respectively.

5.1 Deriving relative importance weights using hybrid AHP-EW method

With the help of the remanufacturing production, basic condition information of the three collection companies, reverse logistics information, and various reports of remanufacturing workshop, the criteria’s value of the used pressurizers can be obtained. Once the above criteria’s value has been determined, the scores of these evaluation criteria (see Table 4) can be obtained through nominalization operation based on the mathematic models in Section 2.2. The rank of each criterion can be obtained according to the aggregated scores of evaluation criterion (Table 5).

Table 5 Scores of evaluation criteria

Criteria	*B11*	*B12*	*B21*	*B22*	*B23*	*B31*	*B32*	*B41*	*B42*
TPT	3.86	1.28	8.60	3.24	3.20	8.25	4.50	4.00	5.98
MT	3.86	1.28	3.19	3.38	5.43	3.42	0.63	4.00	5.98
RT	3.86	1.28	0.25	3.47	1.28	0.59	5.76	4.00	5.98

Table 6 Aggregate scores of evaluate criteria

Criteria	*B11*	*B12*	*B21*	*B22*	*B23*	*B31*	*B32*	*B41*	*B42*
Aggregate score	3.86	1.28	4.01	3.36	3.30	4.09	3.63	4.00	5.98
Rank	5	9	3	7	8	2	6	4	1

In accordance with the scores in Table 5 and the hybrid method in Section 3.1, the criteria weighing can be obtained as follow:

$$w_j^{'} = (0.1152, 0.0382, 0.1197, 0.1003, 0.1219, 0.1083, 0.0986, 0.1193, 0.1785) \quad (27)$$

$$w_j^{''} = (0.0010, 0.0010, 0.4103, 0.0003, 0.3186, 0.2233, 0.0436, 0.0010, 0.0010) \quad (28)$$

The equations (27) and (28) are obtained using AHP method and EW method respectively. Meanwhile, the weight partition coefficient α is set as 0.5 and the normalized comprehensive weight is shown in Eq. (29).

$$w_j = (0.0581, 0.0196, 0.2650, 0.0503, 0.2203, 0.1658, 0.0711, 0.0602, 0.0896) \quad (29)$$

5.2 Evaluation of alternatives of collection using grey MABAC method

According to grey MABAC methods in Section 3.2, the value of the evaluation matrix can be obtained in Eq. (30) and the rank results are shown in Table 7.

$$RR(R_i) = [-0.6829, -0.3849, -0.8262]^T, \quad i = 1,2,3 \quad (30)$$

Table 7 Closeness coefficients and rankings of collection modes

Collection modes	$RR(R_i)$	Rank
TPT	-0.6829	2
MT	-0.3849	1
RT	-0.8262	3

On the basis of the values in Table 7, the initial collection modes can be ranked as MT >TPT>RT.

5.3 Sensitivity analysis and demanding matching analysis

5.3.1 Sensitivity analysis

In order to test the stability of grey MABAC method, a large amount of sensitivity analyses is conducted. According to Moghassem et al. (2013), the modified weights of criterion can be obtained as follow:

$$w_j^N = (1 \pm \beta) w_j^O \quad (31)$$

where β represents changing rate of the original weight w_j^O; w_j^N represents new weight of evaluation criteria.

Table 8 Eight scenarios of criteria weights

Criteria	Original	1	2	3	4	5	6	7	8
B11	0.0581	0.0531	0.0611	0.0681	0.0631	0.0511	0.0481	0.0589	0.0541
B12	0.0196	0.0246	0.0166	0.0096	0.0146	0.0266	0.0296	0.0188	0.0236
B21	0.2650	0.2680	0.2600	0.2690	0.2950	0.2750	0.2700	0.2150	0.2655
B22	0.0503	0.0473	0.0553	0.0463	0.0203	0.0403	0.0453	0.1003	0.0498
B23	0.2203	0.2253	0.2233	0.2503	0.2103	0.2303	0.2703	0.2273	0.2603
B31	0.1658	0.1608	0.1628	0.1358	0.1758	0.1558	0.1158	0.1558	0.1258
B32	0.0711	0.0701	0.0711	0.0731	0.0811	0.0711	0.0211	0.0771	0.0711
B41	0.0602	0.0612	0.0652	0.0602	0.0502	0.0702	0.0602	0.0542	0.0632
B42	0.0896	0.0896	0.0846	0.0876	0.0896	0.0796	0.1396	0.0896	0.0866

On the basis of data in Table 8 and the proposed method in Section 3.2, the results of eight scenarios can be obtained, which are shown in Table 9 and Fig. 4.

Table 9 Collection modes rank of eight scenarios based on

Collection Modes	Original	1	2	3	4	5	6	7	8
	RRi (Rank)	RRi (Rank)	RRi (Rank)	RRi (Rank)	RRi (Rank)	RRi (Rank)	RRi (Rank)	RRi (Rank)	RRi (Rank)
TPT	-0.6829 (2)	-0.1520 (2)	-0.1687 (2)	-0.1260 (1)	-0.1389 (2)	-0.1808 (3)	-0.4111 (3)	-0.0723 (2)	-0.1209 (3)
MT	-0.3849 (1)	0.1279 (1)	0.1475 (1)	-0.2156 (2)	0.1453 (1)	0.1320 (1)	0.1015 (1)	-0.0237 (1)	0.3397 (1)
RT	-0.8262 (3)	-0.1862 (3)	-0.2026 (3)	-0.4949 (3)	-0.2231 (3)	-0.1422 (2)	-0.2172 (2)	-0.2397 (3)	0.0591 (2)

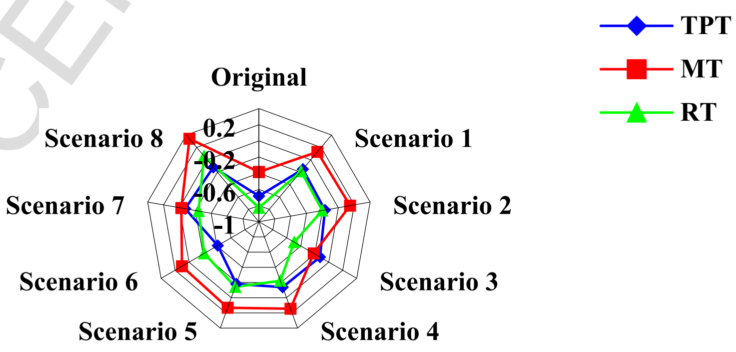


Fig. 4. Results of sensitivity analysis

The sensitivity analysis is to test the stability of the proposed grey MABAC method, which has benefit of reliability in decision-making process. Small changes were made on criteria, which have little impacts on the ranking of collection modes. The ranking sequence (MT>TPT>RT) accounts for the large percentage among the eight scenarios and only Scenarios 3, 5, 6, and 8 are different from others. This is due to that the difference value of the maximum and minimum among the Scenarios 3, 5, 6, and 8 are larger than that for other scenarios, whilst the values of the criteria for the three scenarios are smoothly changed. Among the four different scenarios, Scenarios 5, 6, and 8 keep the same top status of MT, while Scenario 3 is reversed (see Table 9). This may due to that the weight of *B12* in Scenario 3 is much smaller than other scenarios, leading to the larger difference when conducting Euclidean distance calculation.

The rank is still to be consistent unless large difference of the maximum and minimum values or among criteria for one scenario. The test of the stability or robustness shows the effectiveness in rank sequence (see column 5 of Table 9). MT and TPT enjoy the top rank in most scenarios, and the MT can be selected as the optimal collection mode since RT and TPT always follow the MT (see Fig. 4).

5.3.2 Demands matching

The demands of collection companies/modes reflect the capabilities and conditions of handling used components. The higher matching level between the collection company's capabilities and the condition of the used components will lead to the higher profit and efficiency for the company. In order quantify the level, the demand match degree is firstly introduced including the following two steps:

Step 1: Quantification of demands matching

$$DM_{ij} = \frac{|DS_{i\max} - DS_{i\min}|}{|CS_{ij} - DS_{i\min}|}, j = 1,2,\ldots,n, i = 1,2,\ldots,m \qquad (32)$$

where DM_{ij} represents the quantified demands matching; $DS_{i\max}$ and $DS_{i\min}$ represent the upper boundary and lower boundary of demand score for the i^{th} collection mode respectively, which are derived on the maximum and minimum scores in Table 4 respectively. The larger of the quantified demands matching, the better of the collection mode is; CS_j represents the condition scores of evaluation criteria of used component (see Table 5).

Step 2: Metric of demands match

$$MD_i = \frac{N_i}{n}, i = 1,2,\ldots,m \qquad (33)$$

where MD_i represents the demands match degree; N_i represents the numbers of satisfied criteria, we could set that if $0.5 \le DM_{ij} \le 1$ (see Fig. 5), then $N_i = 1$, otherwise $N_i = 0$.

In accordance with Eq. (33), the quantified value of demands matching level for three collection modes can be shown as follow:

Table 10 Quantified value of demands matching degree for three collection modes

Collection modes	*B11*	*B12*	*B21*	*B22*	*B23*	*B31*	*B32*	*B41*	*B42*
TPT	0.36	0.04	**0.95**	0.28	0.27	**0.91**	0.44	0.37	**0.62**
MT	**0.65**	0.21	**0.53**	**0.56**	**0.91**	**0.57**	0.11	**0.67**	**1.00**
RT	**0.65**	0.21	0.04	**0.58**	0.21	0.10	**0.96**	**0.67**	**1.00**

On the basis of Eq. (33) and values in Table 10, the demands matching degree and its distribution can be obtained in Table 11 and Fig. 5 respectively.

Table 11 Rank of demands matching degree

Collection modes	DM_j	Rank
TPT	1/3	3
MT	7/9	1
RT	5/9	2

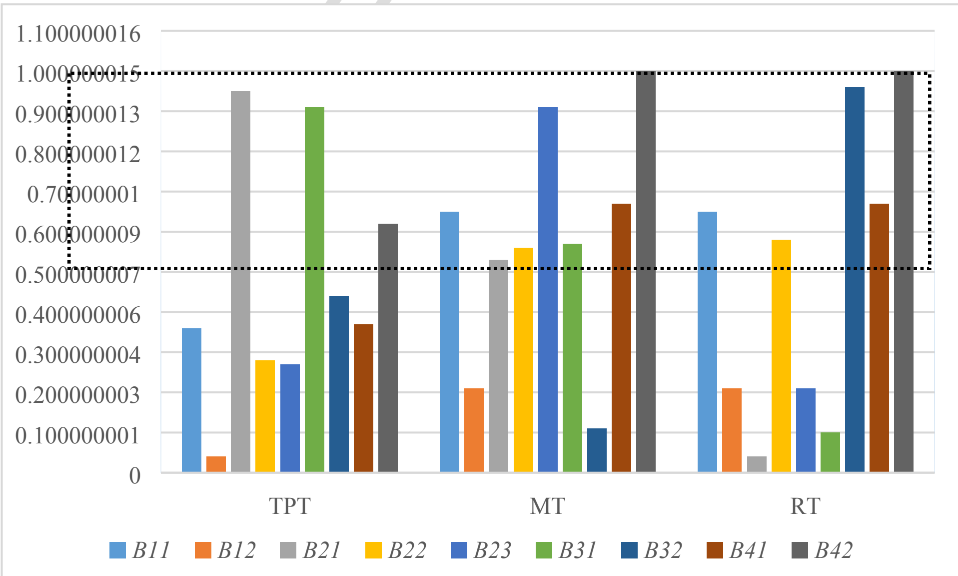


Fig. 5. Distribution of demands matching degree for three collection modes

Therefore, the MT has a top demand matching degree for RL followed by TPT and RT (Table 11). Among the three collection modes, MT has more satisfied criteria (i.e., demands match degree is between 0.5 and 1.0, and the satisfied area is marked with dotted box), followed by RT and TPT (Fig. 5).

Sensitivity analysis in Section 4.3.1 and the calculation of demands matching degree in Section 4.3.2 have jointly validated that MT is the best collection mode for used pressurizers. The former demonstrates the stability and of the proposed grey MABAC method, and the latter validates the effectiveness and applicability of the proposed MCDM method. The integration of sensitive analysis and the calculation of demands matching degree may be a meaningful and robust method to select the optimal collection mode for used components.

5.4 Results and discussion

The weight of each evaluation criterion was obtained through the AHP-EW method, in which the AHP method and EW method are used to determine the weights of some qualitative criteria and alleviate the subjective impacts of AHP respectively. Table 5 represents the scores of evaluation criteria for three collection modes that were obtained using Eqs. (1)-(10). Based on these scores, the weighs of each criterion can be obtained through AHP-EW method (see Eq. (29)). Accordingly, these weights of evaluation criteria are applied to obtain the rank of collection modes in grey MABAC through Euclidean distance. Table 7 presents the rank results of the three collection modes and were obtained on the basis of Eqs. (15)-(26) and Table 4. Tables 8 and 9 illustrate the eight different scenarios and the corresponding rank respectively. The generation of scenarios is according to the method in Eq. (31). Fig. 4 compares the three collection modes among the eight scenarios, and these scenarios show that the MT is the ideal collection mode for used pressurizers. The demands matching is firstly proposed to match the capacity and the capability of the company with condition of used parts as shown in Eqs. (32)-(33). Tables 10 and 11 display the quantified scores of demands matching degree and its rank respectively. The results denote that MT has a stable demands match degree for night criteria, which may due to the medium degree of components' evaluation criteria scores (see Table 4) and the medium demands for criteria of MT in comparison with TPT and RT (Fig. 5). The setting of standard range of quantified demands matching (DM_{ij}) may have influence on the final rank of collection modes, which could be decided by the managers according to the company condition. The results of demands matching recommend that the MT is superior to the RT and TPT collection modes especially in Harmfulness (*B23*) and except for Profit (*B32*). This validates the effectiveness of the proposed multi-criteria decision-making method from the perspective of practical demand-condition matching between the company and used components rather than criteria evaluation.

According to the results above, it can be concluded that the collection mode MT is the optimal collection mode for pressurizers with the best performance of reverse logistics practices (see Figs. 4 and 5). In accordance with Table 6, the aggregated scores for evaluation criteria Demand risk (*B42*), Cost (*B31*), and Energy consumption (*B21*) are 5.98, 4.09, and 4.01 respectively, which rank as *B42*> *B31*> *B21*> other criteria; while Harmfulness (*B23*) and Remaining service life (*B12*) are 3.30 and 1.28 respectively, which rank *B12* < *B31* < other criteria. Therefore, it can be found that Demand risk (*B42*), Cost (*B31*), and Energy consumption (*B21*) are the top three factors of importance of reverse logistics, while Harmfulness (*B23*) and Remaining service life (*B12*) are the least prioritized factors, the analysis of the top three factors is made as follow.

Demand risk: In real-world collection operation, the companies have to consider the its situation in terms of the capacity and capability for dealing with used components. Because the demands matching degree between the company and the used components will determine the company how to process these components and how many they can process. In detail, if the condition of used components in terms of quantity and damage level is matched greatly with the company, then this company will make a maximum profit. Each company has its stable processing capacity and capability, and thus is influenced easily by the demands of remanufactured components, which is directly associated with the market price. This may be a little different from the viewpoints from Zarbakhshnia et al. (2018) who viewed that the financial and operational risk had minimal impacts on the decision-making of third-party reverse logistics providers. This may due to the fact that these risks are focused on the markets/customers or companies separately while do not consider the connection between the markets and companies.

Cost: The cost of operation is widely recognized as a determining factor that influence the final decision-making of collection modes (Zarbakhshnia et al., 2018; Shaik et al., 2018). This research considers the remanufacturing processing cost and transportation cost, which are associated with the quality of remanufactured components and the transportation routes respectively. The remanufacturing cost is mainly consisted of machine cost, tool cost, and labor cost, while the labor cost accounts for the largest percent due to the labor-intensive characteristics of remanufacturing (Wang et al., 2017). Mihi et al. (2014) found that the reverse logistics activities and its type affect the cost, and it is important to select he most feasible portfolios of reverse logistics activities. On the one hand, the cost will affect the collection company to decide whether to collect, how many to collect, and how to process. On the other hand, the processing methods driven by cost lead to varied quality of remanufactured components, which will impact the acceptability of the markets/customers. The research interestingly shows that the determination of the accurate adopted information in terms of quantities and prices before acquisition has a strong effect on recovery of used products (Jiao et al. (2018); Liu et al. (2016)).

Energy consumption: Although the reverse logistics is viewed as an important link of environmental sustainability through collecting useful materials, used products/components, and disposing of waste, many issues like energy consumption during the transportation and remanufacturing processing in workshop should be considered. The different transportation ways, routes, and remanufacturing method may cause varied energy consumption. On the basis of this, Bazan et al. (2016) recommended and presented the modeling of energy consumption during production with a simplified form. The research shows that the incorporation of energy consumption can make reverse logistics more sustainable, and more representative of the real-world intricacy and sophistication.

6. Conclusion and future work

A demands-matching orientated MCDM method is established for RL, including weights derivation, rank of collection modes, sensitivity analysis, and quantification of demands matching degree. An AHP-EW method is used to derive criteria weights, in which the damage level and remaining life are incorporated into evaluation criteria. Then a grey MABAC is applied to rank collection modes. Finally, a sensitivity analysis is implemented to test the stability of proposed method, and the quantification of demands matching is proposed to evaluate the feasibility of the optimal collection modes. The used pressurizers are taken as the example to validate the effectiveness and the applicability of the proposed methods.

This research adopts a novel hierarchical MCDM method, which considers the demands of collection companies and the condition of used components for optimal strategy. The demands of collection companies reveal the abilities of handling RL. The closer between demands of the company and the conditions of used components, the higher profit and efficiency for the company is. Without demands matching, the collection modes from the MCDM may not achieve the maximum profit as well we efficiency and the minimum environmental impact for collection companies. In detail, the high demands matching of the collection company for the same types of used pressurizer can improve the utilization efficiency of resource and equipment of the company. This will contribute to collection company more profitable and efficient for RL.

The proposed method can be adopted to determine the best collection modes of used components/products for collection companies. This paper is limited to weighing of each indicator while ignore the interdependence of them. The utilization of advanced information techniques, such as big data, cloud computing, and artificial intelligent will make the method more efficient and customized. Future work can be focused on: 1) the integration of intelligent techniques so as to construct an intelligent decision-making system for collection companies; 2) studying the effect of interdependence of criteria upon the final decision-making using ANP method.

Acknowledgments

The work described in this paper was supported by the National Natural Science Foundation of China (51675388, 51605347), Wuhan University of Science and Technology graduate student short-term abroad (Habitat) training special funds (024/24000203). These financial contributions are gratefully acknowledged.

References

Ahmadi, H.B., Kusi-Sarpong, S., Rezaei, J., 2017. Assessing the social sustainability of supply chains using Best Worst Method. Resources Conservation and Recycling 126, 99-106.

Ameri, A.A., Pourghasemi, H.R., Cerda, A., 2018. Erodibility prioritization of sub-watersheds using morphometric parameters analysis and its mapping: A comparison among TOPSIS, VIKOR, SAW, and CF multi-criteria decision making models. Sci. Total Environ. 613, 1385-1400.

Bazan, E., Jaber, M.Y., Zanoni, S., 2016. A review of mathematical inventory models for reverse logistics and the future of its modeling: An environmental perspective. Applied Mathematical Modelling 40, 4151-4178.

Bouzon, M., Govindan, K., Rodriguez, C.M.T., 2018. Evaluating barriers for reverse logistics implementation under a multiple stakeholders' perspective analysis using grey decision making approach. Resources, Conservation and Recycling 128, 315-335.

Banasik, A., Kanellopoulos, A., Claassen, G.D.H., Bloemhof-Ruwaard, J.M., van der Vorst, J.G.A.J., 2017. Closing loops in agricultural supply chains using multi-objective optimization: A case study of an industrial mushroom supply chain. International Journal of Production Economics 183, 409-420.

Cai, W., Liu, C., Zhang, C., Ma, M., Rao, W., Li, W., He, K., Gao, M., 2018. Developing the ecological compensation criterion of industrial solid waste based on emergy for sustainable development. Energy 157, 940-948.

Debnath, A., Roy, J., Kar, S., Zavadskas, E., Antucheviciene, J., 2017. A Hybrid MCDM Approach for Strategic Project Portfolio Selection of Agro By-Products. Sustainability 9, 1302.

Dehghanbaghi, M., Hosseininasab, H., Sadeghieh, A., 2016. A hybrid approach to support recovery strategies (A case study). Journal of Cleaner Production 113, 717-729.

Entezaminia, A., Heidari, M., Rahmani, D., 2017. Robust aggregate production planning in a green supply chain under uncertainty considering reverse logistics: a case study. The International Journal of Advanced Manufacturing Technology 90, 1507-1528.

Fathollahi-Fard, A.M., Hajiaghaei-Keshteli, M., 2018. A stochastic multi-objective model for a closed-loop supply chain with environmental considerations. Applied Soft Computing 69, 232-249.

Govindan, K., Soleimani, H., 2017a. A review of reverse logistics and closed-loop supply chains: a Journal of Cleaner Production focus. Journal of Cleaner Production 142, 371-384.

Govindan, K., Darbari, J.D., Agarwal, V., Jha, P.C., 2017b. Fuzzy multi-objective approach for optimal selection of suppliers and transportation decisions in an eco-efficient closed loop supply chain network. Journal of Cleaner Production 165, 1598-1619.

Govindan, K., Bouzon, M., 2018a. From a literature review to a multi-perspective framework for reverse logistics barriers and drivers. Journal of Cleaner Production 187, 318-337.

Govindan, K., Kadziński, M., Ehling, R., Miebs, G., 2018b. Selection of a sustainable third-party reverse logistics provider based on the robustness analysis of an outranking graph kernel conducted with ELECTRE I and SMAA. Omega. In Press. https://doi.org/10.1016/j.omega.2018.05.007

Golinska-Dawson, P., Kosacka, M., Werner-Lewandowska, K., 2018. Sustainability Indicators System for Remanufacturing, in: Golinska-Dawson, P., Kübler, F. (Eds.), Sustainability in Remanufacturing Operations. Springer International Publishing, Cham, pp. 93-110.

Govindan, K., Muduli, K., Devika, K., Barve, A., 2016a. Investigation of the influential strength of factors on adoption of green supply chain management practices: An Indian mining scenario. Resources, Conservation and Recycling 107, 185-194.

Govindan, K., Jepsen, M.B., 2016b. ELECTRE: A comprehensive literature review on methodologies and applications. European Journal of Operational Research 250, 1-29.

Gul, M., Celik, E., Aydin, N., Taskin Gumus, A., Guneri, A.F., 2016. A state of the art literature review of VIKOR and its fuzzy extensions on applications. Applied Soft Computing 46, 60-89.

Han, H., Trimi, S., 2018. A fuzzy TOPSIS method for performance evaluation of reverse logistics in social commerce platforms. Expert Systems with Applications 103, 133-145.

He, B., Yang, C., Yang, J., 2007. A multi-objective optimization model of reverse logistics for solid wastes. Industrial Engineering and Management 17, 76-79.

Hua, C.C., 2006. Probability and risk models of demand for the price of commodity. Journal of Nanjing Normal University (Engineering and technology) 6, 70-74.

Jiao, Z., Ran, L., Zhang, Y., Li, Z., Zhang, W., 2018. Data-driven approaches to integrated closed-loop sustainable supply chain design under multi-uncertainties. Journal of Cleaner Production 185, 105-127.

Jin, H., Yih, Y., Sutherland, J.W., 2018. Modeling operation and inventory for rare earth permanent magnet recovery under supply and demand uncertainties. Journal of Manufacturing Systems 46, 59-66.

Jiang, Z., Zhou, T., Zhang, H., Wang, Y., Cao, H., Tian, G., 2016. Reliability and cost optimization for remanufacturing process planning. Journal of Cleaner Production 135, 1602-1610.

Kadambala, D.K., Subramanian, N., Tiwari, M.K., Abdulrahman, M., Liu, C., 2017. Closed loop supply chain networks: Designs for energy and time value efficiency. International Journal of Production Economics 183, 382-393.

Kurilova-Palisaitiene, J., Sundin, E., Poksinska, B., 2018. Remanufacturing challenges and possible lean improvements. Journal of Cleaner Production 172, 3225-3236.

Kubler, S., Robert, J., Derigent, W., Voisin, A., Le Traon, Y., 2016. A state-of the-art survey & testbed of fuzzy AHP (FAHP) applications. Expert Systems with

Applications 65, 398-422.

Keshavarz Ghorabaee, M., Amiri, M., Zavadskas, E.K., Turskis, Z., Antucheviciene, J., 2017. A new multi-criteria model based on interval type-2 fuzzy sets and EDAS method for supplier evaluation and order allocation with environmental considerations. Computers & Industrial Engineering 112, 156-174.

Liu, H., Lei, M., Deng, H., Keong Leong, G., Huang, T., 2016. A dual channel, quality-based price competition model for the WEEE recycling market with government subsidy. Omega 59, 290-302.

Li, C.B., Li, L.L., Cao, H.J., Wang, Q., 2013. Fuzzy learning system for uncertain remanufacturing process time of used components. Journal of Mechanical Engineering. 49, 137-146.

Lu, B., Yang, J., Ijomah, W., Wu, W., Zlamparet, G., 2018. Perspectives on reuse of WEEE in China: Lessons from the EU. Resources, Conservation and Recycling 135, 83-92.

Lee, C.-M., Woo, W.-S., Roh, Y.-H., 2017. Remanufacturing: Trends and issues. International Journal of Precision Engineering and Manufacturing-Green Technology 4, 113-125.

Lintukangas, K., Kähkönen, A.-K., Ritala, P., 2016. Supply risks as drivers of green supply management adoption. Journal of Cleaner Production 112, 1901-1909.

Mardani, A., Zavadskas, E.K., Govindan, K., 2016. VIKOR Technique: A Systematic Review of the State of the Art Literature on Methodologies and Applications. Sustainability 8, 37.

Mousakhani, S., Nazari-Shirkouhi, S., Bozorgi-Amiri, A., 2017. A novel interval type-2 fuzzy evaluation model based group decision analysis for green supplier selection problems: A case study of battery industry. Journal of Cleaner Production 168, 205-218.

Mohammed, F., Selim, S.Z., Hassan, A., Syed, M.N., 2017. Multi-period planning of closed-loop supply chain with carbon policies under uncertainty. Transport. Res. Part D-Transport. Environ. 51, 146-172.

Moghassem, A., 2013. Comparison among two analytical methods of multi-criteria decision making for appropriate spinning condition selection. World Applied Science Journal21, 784-794.

Mihi Ramírez, A., Morales, V.J.G., 2014. Improving organisational performance through reverse logistics. Journal of the Operational Research Society 65, 954-962.

Prakash, C., Barua, M.K., 2016. An analysis of integrated robust hybrid model for third-party reverse logistics partner selection under fuzzy environment. Resources Conservation and Recycling 108, 63-81.

Paterson, D.A.P., Ijomah, W.L., Windmill, J.F.C., 2017. End-of-life decision tool with emphasis on remanufacturing. Journal of Cleaner Production 148, 653-664.

Rajeev, A., Pati, R.K., Padhi, S.S., Govindan, K., 2017. Evolution of sustainability in supply chain management: A literature review. Journal of Cleaner Production 162, 299-314.

R, K., Ks, R., Saeid, A.B., 2017. A new extension to PROMETHEE under intuitionistic fuzzy environment for solving supplier selection problem with linguistic preferences. Applied Soft Computing 60, 564-576.

Senthil, S., Murugananthan, K., Ramesh, A., 2018. Analysis and prioritisation of risks in a reverse logistics network using hybrid multi-criteria decision making methods. Journal of Cleaner Production 179, 716-730.

Shaik, M.N., Abdul-Kader, W., 2018. A hybrid multiple criteria decision making approach for measuring comprehensive performance of reverse logistics enterprises. Computers & Industrial Engineering 123, 9-25.

Saha, S., Sarmah, S.P., Moon, I., 2016. Dual channel closed-loop supply chain coordination with a reward-driven remanufacturing policy. International Journal of Production Research 54, 1503-1517.

Shankar, R., Bhattacharyya, S., Choudhary, A., 2018. A decision model for a strategic closed-loop supply chain to reclaim End-of-Life Vehicles. International Journal of Production Economics 195, 273-286.

Sari, K., 2017. A novel multi-criteria decision framework for evaluating green supply chain management practices. Computers & Industrial Engineering 105, 338-347.

Tian, G., Zhang, H., Feng, Y., Wang, D., Peng, Y., Jia, H., 2018. Green decoration materials selection under interior environment characteristics: A grey-correlation based hybrid MCDM method. Renewable and Sustainable Energy Reviews 81, 682-692.

Tsai, S.-B., Yu, J., Ma, L., Luo, F., Zhou, J., Chen, Q., Xu, L., 2018. A study on solving the production process problems of the photovoltaic cell industry. Renewable and Sustainable Energy Reviews 82, 3546-3553.

Uygun, O., Dede, A., 2016. Performance evaluation of green supply chain management using integrated fuzzy multi-criteria decision making techniques. Computers & Industrial Engineering 102, 502-511.

Wu, C., Barnes, D., 2016. An integrated model for green partner selection and supply chain construction. Journal of Cleaner Production 112, 2114-2132.

Wang, H., Jiang, Z., Zhang, X., Wang, Y., Wang, Y., 2017. A fault feature characterization based method for remanufacturing process planning optimization. Journal of Cleaner Production 161, 708-719.

Wang, H., Jiang, Z., Wang, Y., Zhang, H., Wang, Y., 2018. A two-stage optimization method for energy-saving flexible job-shop scheduling based on energy dynamic characterization. Journal of Cleaner Production 188, 575-588.

Xue, Y.-X., You, J.-X., Lai, X.-D., Liu, H.-C., 2016. An interval-valued intuitionistic fuzzy MABAC approach for material selection with incomplete weight information. Applied Soft Computing 38, 703-713.

Yao, W.X., 2004. Comparison of different take-back models in reverse logistics. Management Science in China 17, 76-79.

Zavadskas, E., Mardani, A., Turskis, Z., Jusoh, A., Nor, K., 2016. Development of TOPSIS method to solve complicated decision-making problems: An overview on developments from 2000 to 2015. Int. J. Inf. Technol. Decis.

Mak. 15, 645-682.

Zhalechian, M., Tavakkoli-Moghaddam, R., Zahiri, B., Mohammadi, M., 2016. Sustainable design of a closed-loop location-routing-inventory supply chain network under mixed uncertainty. Transportation Research Part E: Logistics and Transportation Review 89, 182-214.

Zlamparet, G.I., Ijomah, W., Miao, Y., Awasthi, A.K., Zeng, X., Li, J., 2017. Remanufacturing strategies: A solution for WEEE problem. Journal of Cleaner Production 149, 126-136.

Zhang, X.G., Zhang, H., Jiang, Z.G., 2013. Remanufacturing scheme decision model and application based on remaining useful life estimation. Journal of Mechanical Engineering. 49, 51-57.

Zarbakhshnia, N., Soleimani, H., Ghaderi, H., 2018. Sustainable third-party reverse logistics provider evaluation and selection using fuzzy SWARA and developed fuzzy COPRAS in the presence of risk criteria. Applied Soft Computing 65, 307-319.

Zhao, X., Hwang, B.-G., Gao, Y., 2016. A fuzzy synthetic evaluation approach for risk assessment: a case of Singapore's green projects. Journal of Cleaner Production 115, 203-213.