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A Demands-Matching Multi-Criteria Decision-Making Method for Reverse Logistics

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Abstract

A demand matching oriented Multi-Criteria Decision-Making method is presented to identify the best collection mode for used components. In this method, the damage condition and remaining service life are incorporated into the evaluation criteria of reuse mode, then a hybrid method (AHP-EW) integrating Analytic Hierarchy Process (AHP) and Entropy Weight (EW) is used to derive the criteria weights and the grey Multi-Attributive Border Approximation Area Comparison (MABAC) is adopted to rank the collection modes. Finally, a sensitivity analysis is used to test the stability of the method and a demands-matching method is proposed to validate the feasibility of the optimal alternative. The method is validated using the collection of used pressurizers as case study. The results of which show the effectiveness of the proposed method.

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Keywords: Reverse Logistics; Multiple Criteria Decision Making; Demands matching; Damage condition; Remaining Service life

1. Introduction

Reverse logistics (RL) is regarded as a means to deal with the End-of-Life (EOL) products in an environmental and friendly manner [1] and has attracted an increasing amount of attentions [2]. In RL, used components are firstly collected from end-users and then undergo a series of EOL management operations, decisions were made in terms of collection options. Each of these options has different economic and environmental impacts. To make a sound decision, it is essential to develop a criteria index to make a comprehensive assessment of conditions of EOL products for decision making of the collection strategy.

Many studies on the evaluation criteria of RL were conducted focusing on environmental, economic, and social aspects. The characteristics of the RL were analyzed and a nonlinear integer programming model was proposed to determine the locations based on total cost [3]. A multi-echelon commodity facility location problem was tackled considering carbon emissions and procurement costs [4]. A fuzzy-set based multi-criteria decision-making model was proposed with criteria including cost, legislative factors, environment, and market [5]. The aforesaid literatures were focused on the environmental and economic criteria in decision-making for RL. Regrettably, studies that meaningfully considered the quality and risk are rare. The uncertain quality and the risk complicate the decision-making. There is a need to alleviate the uncertainties during the decision-making process. To this end, identifying the quality condition (e.g., remaining life and damage degree) and risk (e.g., demands and price) becomes a vital means to reduce the uncertainty in terms of quality and quantity [6, 7].

In addition to the determination of the evaluation criteria for decision-making of RL, it is necessary to assess the weights derivation of the criteria and provide the ranking of the decision-making options. To this end, a Multi-Criteria

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Decision-Making (MCDM) method could be employed. For instance, an ANP (Analytic Network Process) method was employed to quantify the stakeholders' decision-making in a survey combining stakeholders' behaviors [8]. The ANP method was employed to investigate the relative importance of RL service requirements and to select an appropriate Third-Party Logistics provider [9].

The aforesaid work provided valuable guidelines for decision making in RL. However, the effectiveness of these work may be impacted by subjective factors, such as scores by experts and evaluation by decision-makers, which may have an influence on the objectivity of the decision-making processes. To bridge the gap, objective information such as the statue information and the demands of the used components are incorporated into the evaluation criteria.

To summarize, an obstacle impeding the decision-making of RL strategy lies in a lack of objective methods that incorporate the objective information into decision-making process. The novelties of this paper are: (1) Reducing the uncertainties in terms of the quality and quantity of used products; (2) Incorporating the status information and the demands into the decision-making processes; and (3) Calculation of the demand matching level.

2. Framework of multi-criteria decision-making for RL

The proposed research framework of MCDM for RL is shown in Fig. 1.

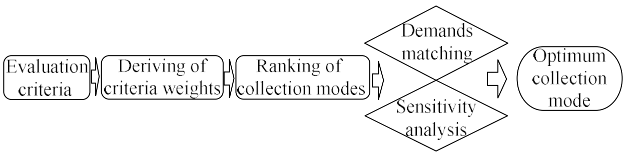

Fig. 1. Framework of multi-criteria decision-making for RL.

The MCDM in Fig. 1 includes five steps:

Step 1: Establishment of evaluation criteria. The evaluation criteria include status information of the used components (quality condition), impact on environment and people (sustainability), economic performance of the processing of EOL 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 factors and objective factors are considered simultaneously.

Step 3: Ranking of collection modes. 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 ranking, and the demand matching is to inspect suitability between collection modes and recyclers.

Step 5: Determination of the optimum collection mode. Through the proposed steps, the final optimum collection mode can be obtained, providing a decision-making reference for managers of manufacturing/remanufacturing companies.

2.1. Criteria of decision-making for RL

The selection of criteria is significant for 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 condition (B1), sustainability (B2), economy (B3), and risk (B4). There are three collection modes including Third Party Take-Back (TPT) (collection companies that focus on collecting used components with rich varieties and large volume), Manufacturer Take-Back (MT) (collection companies that are engaged in the collection of used parts with less varieties and large volume), and Retailer Take-Back (RT) (collection companies that collect the used components with less varieties and small volume), in which the details are shown in Fig. 2.

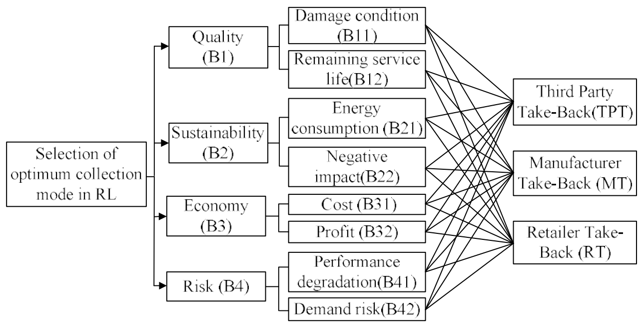

Fig. 2. Evaluation criteria of decision-making for RL.

The eight criteria were established to evaluate the RL for decision makers and the detail definitions of the evaluation criteria are shown in Table 1.

Table 1. Evaluation criteria and its definition.

Criteria No.	Criteria	Definition
B11	Damage condition	The damage level of fault features (e.g., wear, deformation and corrosion) of the used components.
B12	Remaining service life	The remaining usable time after the components has serviced for a period of time.
B21	Energy consumption	The energy consumption during the transportation and processing.
B22	Negative impact brought by collection point	The impact from location of the collection points on usage points, and it is related to the distance between the collection point and usage point.
B31	Cost	Cost during remanufacturing processing and transportation process.
B32	Profit	The recovered value from used components through remanufacturing.
B41	Performance degradation	The phenomenon that the old machine fails to work due to certain processing demands for new products.
B42	Demand risk	The demand uncertainty due to the variable price of used components.

2.2. Mathematic modeling of criteria

2.2.1 Quality condition

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

(1) Damage level

The damage level of each used component may vary. In accordance with the references [10] and [11], the quantified damage condition can be obtained.

(2) Remaining service life

The remaining service life of the used component relates to the expected residual service time after being utilized for a period of time. According to the method in reference [12], the remaining service life for each used component (mechanical component) can be identified.

2.2.2 Sustainability

The sustainability of the reverse logistics can be revealed as the negative impacts brought by collection points and energy consumption during the transportation and remanufacturing processing.

(1) Energy consumption

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

where E is the total energy consumption during the transportation and processing (kJ); e_i and t_i are the unit remanufacturing processing energy consumption (kJ/min) and mean remanufacturing processing time (min) for the i^{th} component; p represents the total number of used components; E_T is the unit transportation energy consumption per kilometre (kJ/km), S_j is the transportation distance for the j^{th} transportation route (km), S is the total transportation route.

(2) Negative impact brought by collection point

The negative impact should be considered since the collection process of used components will deteriorate the environment of usage points. According to the equations in reference [13], the negative impact can be obtained.

2.2.3 Economy

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

(1) Cost

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

$$C = \sum_{i=1}^{p} c_i \cdot t_i + \sum_{j=1}^{s} C_T \cdot S_j \tag{2}$$

where C is the total cost during the remanufacturing processing and transportation (RMB) c_i is the unit remanufacturing processing cost per hour for the i^{th} type component (RMB/h); C_T is the unit transportation cost per kilometre (RMB/km); S_j represents the distance from collection point to consumption area (km).

(2) Profit

The profit may be different due to the collection mode, recycle distance and collection demand etc. In accordance with the equations of reference [14], the profit for three recyclers/collection companies can be obtained.

2.2.4 Risk

The risk includes the performance degradation and demand risk. The performance degradation may happen when the return used parts/machines are not dealt with timely. With time going by, this leads to the performance degradation and increase the uncertainty of used components' quality finally.

(1) Performance degradation

The performance degradation is greatly influenced by the environment condition. According to the reference [15], the performance degradation can be obtained.

(2) Demand risk

The demand risk of the used components is primarily influenced by the price. The demand risk of the components can be obtained according to the reference [16].

3. 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 is proposed to identify the optimum collection mode. Finally, a demand matching degree is introduced to validate the feasibility of the optimal alternative.

3.1. AHP-EW for deriving the criteria weights

This hybrid method aims to investigate the relationship between criteria and the details are shown as follow.

Step 1: Standardization for indicator data. It is assumed that there are ***m*** collection modes and ***n*** evaluation indicators. The value of the evaluation indicators is derived from the status condition of the used components and practical operation condition of companies. The initial indicator matrix can be shown as follow:

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad i = 1, 2, ..., m; j = 1, 2, ..., n \tag{3}$$

Step 2: Determination of the indicators' weights. This step considers two methods i.e., AHP and EW methods to determine the weight of each indicator w_j^l and w_j^r respectively.

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

$$w_j = \alpha w'_j + (1-\alpha) w''_j \quad 0 \le \alpha \le 1 \tag{4}$$

3.2. Grey MABAC for collection modes decision making

Once the weight coefficients of evaluation indicators have been obtained, the ranking of alternatives of the collection modes can be implemented through the grey MABAC method based on demands. According to [17], the process of implementing this method consists of the following steps:

Step 1: Formation of the initial decision matrices based on demands. Consider the reverse logistics problems with $\boldsymbol{m}$ collection modes alternatives $(R_i, i = 1,2,...,m)$, which are evaluated based on the $\boldsymbol{n}$ 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 the collection points:

$$Y = [\Theta y_{ij}]_{m\times n} = \begin{bmatrix} [\underline{y}_{11}, \overline{y}_{11}] & [\underline{y}_{12}, \overline{y}_{12}] & \cdots & [\underline{y}_{1n}, \overline{y}_{1n}] \\ [\underline{y}_{21}, \overline{y}_{21}] & [\underline{y}_{22}, \overline{y}_{22}] & \cdots & [y_{2n}, \overline{y}_{2n}] \\ \vdots & \vdots & \vdots & \vdots \\ [\underline{y}_{m1}, \overline{y}_{m1}] & [\underline{y}_{m2}, y_{m2}] & \cdots & [\underline{y}_{mn}, \overline{y}_{mn}] \end{bmatrix}_{m\times n} \tag{5}$$

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

Step 2: Normalization of the grey decision-making matrix. The aim of this step is to obtain the dimensionless criteria. There exist two types of criteria, i.e., benefit and cost types.

A. Benefit type criteria

$$\Theta z_{ij} = [\underline{z}_{ij}, \overline{z}_{ij}] = \left[\frac{\underline{y}_{ij}}{y_j^{\max}}, \frac{\overline{y}_{ij}}{y_j^{\max}}\right] \tag{6}$$

B. Cost type criteria

$$\Theta z_{ij} = [\underline{z}_{ij}, \overline{z}_{ij}] = \left[\frac{y_j^{\min}}{\overline{y}_{ij}}, \frac{y_j^{\min}}{\underline{y}_{ij}}\right] \tag{7}$$

where $y_j^{\min} = \min\limits_{1\le i\le m}(\underline{y}_{ij})$ and $y_j^{\max} = \max\limits_{1\le i\le m}(\overline{y}_{ij})$.

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

$$\Theta f_{ij} = [\underline{f}_{ij}, \overline{f}_{ij}] = \omega_j \times \Theta z_{ij} = [\omega_j \cdot \underline{z}_{ij}, \omega_j \cdot \overline{z}_{ij}] \tag{8}$$

where Θz_{ij} is the indicator of the normalized matrix and ω_j is the weight coefficients of the criterion j. The weighted matrix can be expressed as follow:

Step 4: Determination of the grey border approximation area matrix. The grey border approximation area for each criterion can be obtained according to the equation as follow:

$$\Theta u_j = [\underline{u}_j, \overline{u}_j] = \left[\left(\prod_{i=1}^{m} \underline{f}_{ij}\right)^{1/m}, \left(\prod_{i=1}^{m} \overline{f}_{ij}\right)^{1/m}\right] \tag{9}$$

where $[\underline{f}_{ij}, \overline{f}_{ij}]$ are the elements of the weighted matrix and $\boldsymbol{m}$ is the total number of collection modes. Once the value of Θu_j for each criterion function is obtained, a border approximation area vector can be formed.

Step 5: Calculation of the preference indicators matrix. According to the Euclidean distance between the grey numbers Θf_{ij} and Θu_j, the preference indicator matrix of the collection modes for the matrix elements can be obtained.

Step 6: Ranking the collection modes alternatives. The ranking process of alternatives can be accomplished through calculating the sum of the elements in distance matrix, which is shown as below:

$$RR(R_i) = \sum_{j=1}^{n} q_{ij} = \sum_{j=1}^{n} d(\Theta f_{ij}, \Theta u_j); \quad i = 1,2,...,m \tag{10}$$

4. Case study

Consider three collection modes/companies: TPT, MT, and RT that are engaged in collecting used pressurizers, a key part of automobiles. During the service, pressurizers are damaged and worn under high pressure and high frequent impact. These three collection companies wish to recycle the used pressurizers according to their demands and the status information of used pressurizer. The data of this case study came from real data from industry partners of this proposed research, in which the demands are shown in Table 2.

Table 2. Demands of the three companies for collecting used pressurizers.

	B11	B12	B21	B22	B31	B32	B41	B42
TPT	**M**	**L**	**M**	**L**	**L**	**H**	**M**	**L**
MT	**L**	**H**	**M**	**M**	**M**	**M**	**L**	**M**
RT	**L**	**H**	**L**	**H**	**M**	**H**	**L**	**H**

Note: "**H**" means high; "**M**" means medium; "**L**" means low

4.1. Deriving the relative importance weights

The damage condition and the remaining service life information of the used pressurizer can be obtained through the mathematic equations and methods in Section 2.2.1. In accordance with the value in Table 3, the energy consumption and negative impact can also be obtained. According to Table 4, the cost and profit can be determined.

Table 3. Values of energy consumption and negative impact.

Parameters	e_1	e_2	e_3	t_1	t_2	E_T
Value	390	348	372	18	19.5	3045.2
Parameters	t_3	C_T	S_1	S_2	S_3	
Value	15	2.64	10	7.5	6.5	

Table 4. Values related to the equations of cost and profit.

Parameters	π	t	c_m	k	s	β	ϕ
Value	20	20	30	200	10	2	100

On the basis of aforementioned values of the parameters, the score of each criterion can be determined in Table 5.

Table 5. Scores of the evaluation criteria.

Criteria	B11	B12	B21	B22	B31	B32	B41	B42
TPT	3.86	1.28	8.60	3.24	8.25	4.50	4.71	5.98
MT	3.86	1.28	3.19	3.38	3.42	0.63	4.71	5.98
RT	3.86	1.28	0.25	3.47	0.59	5.76	4.71	5.98

According to the scores in Table 5 and the hybrid method in Section 3.1, the criteria weighting can be obtained. Then the weight partition coefficient α is set as 0.5 and the normalized comprehensive weight is w_j = (0.1277, 0.1244, 0.0940, 0.1560, 0.1310, 0.1189, 0.1165, 0.1335).

4.2. Evaluation of alternatives of collection

According to the grey MABAC method in Section 3.2, the evaluation matrix value can be obtained, which are shown in Table 6. Based on the data in Table 7 and the method in Section 3.2, the results of eight scenarios can be obtained, which are shown in Table 8 and Fig. 3.

Table 6. Closeness coefficients and rankings of collection modes.

Collection modes	$RR(R_i)$	Ranking
TPT	-0.0228	3
MT	-0.0009	1
RT	-0.0014	2

On the basis of the values in Table 6, the initial collection modes can be ranked as MT>RT>TPT.

Table 7. Eight scenarios of criteria weights.

Scenarios	Original	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
B11	0.1277	0.1276	0.1226	0.1208	0.1310	0.1409	0.0932	0.1711	0.0586
B12	0.1244	0.1225	0.1274	0.1292	0.1190	0.1158	0.1568	0.0789	0.1915
B21	0.0940	0.1065	0.1330	0.1686	0.1832	0.0812	0.1028	0.0757	0.1436
B22	0.1560	0.1436	0.1170	0.0815	0.0669	0.1688	0.1472	0.1743	0.1065
B31	0.1310	0.0586	0.1156	0.1064	0.1582	0.0811	0.0996	0.1565	0.1837
B32	0.1189	0.1914	0.1344	0.1436	0.0918	0.1689	0.1504	0.0935	0.0663
B41	0.1165	0.1058	0.0817	0.1350	0.1558	0.1258	0.1158	0.1808	0.0734
B42	0.1335	0.1440	0.1683	0.1149	0.0971	0.1175	0.1342	0.0692	0.1764

Table 8. Ranking of collection modes for eight scenarios of criteria weights.

Scenarios	Original	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8
	RRi(Rank)	RRi(Rank)	RRi(Rank)	RRi(Rank)	RRi(Rank)	RRi(Rank)	RRi(Rank)	RRi(Rank)	RRi(Rank)
TPT	-0.0228(3)	-0.0244(3)	-0.0182(3)	-0.0108(3)	-0.0117(2)	-0.0184(1)	-0.0239(3)	-0.0172(3)	-0.0387(3)
MT	-0.0009(1)	-0.0010(1)	-0.0029(2)	-0.0014(1)	-0.0017(1)	-0.0206(3)	0.0014(1)	-0.0071(1)	0.0076(1)
RT	-0.0014(2)	-0.0014(2)	-0.0018(1)	-0.0098(2)	-0.0138(3)	-0.0187(2)	-0.0004(2)	-0.0072(2)	0.0012(2)

4.3. Sensitivity analysis and demanding matching analysis

4.3.1 Sensitivity analysis

In order to test the robustness of the weighting method and the ranking modes, a sensitivity analysis is conducted. According to the reference in [18], the modified weights of the criteria can be obtained.

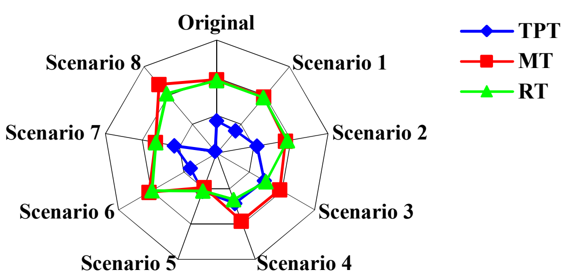

Fig. 3. Results of sensitivity analysis.

The sensitivity analysis is to test the stability of the proposed method, which has the 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>RT>TPT) accounts for the large percentage among the eight scenarios and only Scenarios 2, 4, and 5 are different from others. This is due to that the difference of the maximum and minimum among these three scenarios are larger than other scenarios, whilst the criteria values for three scenarios are smoothly changed.

The ranking is still to be consistent except the large difference of the maximum and minimum values among criteria for one scenario. Otherwise, the test of the robustness shows the effectiveness in ranking sequence (see Table 8). MT and RT enjoy the top ranking in most scenarios, and the MT can be selected as the optimal collection mode since RT and TPT always follow the MT (see Fig. 3).

4.3.2 Demands matching

The demands of the collection companies reflect the capabilities and conditions of handling the 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, a demand match degree is proposed and it can be defined as follow:

Step 1: Quantification of the demands matching level

$$DM_j = \frac{|DS_{j\max} - DS_{j\min}|}{|CS_j - DS_{j\min}|}, j = 1, 2, ..., n \tag{11}$$

where DM_j represents the quantified demands matching; $DS_{j\max}$ and $DS_{j\min}$ represent the maximum and minimum demand score for the j^{th} criteria respectively; CS_j represents the condition score of the used component.

Step 2: Metric of demands match

$$MD_i = \frac{N_i}{n}, i = 1, 2, ..., m \tag{12}$$

where MD_i is the demands match degree; N_i represents the numbers of the satisfied criteria, we set that if $DM_j \geq 1$, then $N_i = 1$, otherwise $N_i = 0$.

In accordance with Eq. (12), the quantified value of demands matching level for the three collection modes can be shown as follow:

Table 9. Quantified value of demands matching degree

Collection modes	B11	B12	B21	B22	B31	B32	B41	B42
TPT	**14.29**	**7.14**	0.43	0.89	0.28	0.80	**2.82**	0.40
MT	0.70	0.35	**2.47**	**3.23**	**3.45**	0.59	0.54	**1.01**
RT	0.70	0.35	**2.67**	0.57	0.59	0.31	0.54	**1.96**

According to Eq. (12) and Table 9, the demands matching degree can be obtained and the demands degree rank is MT>TPT>RT. The MT has a top demand matching degree for remanufacturing RL followed by TPT and RT. The results validate the applicability of the proposed MCDM method.

According to the sensitivity analysis in Section 4.3.1 and the calculation of demands matching in Section 4.3.2, the best collection mode for used pressurizer is MT. In sum, the two procedures may be meaningful to evaluate the collection modes for used components.

5. Conclusions and future work

This research presents a novel hierarchical MCDM method, which considers the demands of the collection companies and the conditions of used components for optimal RL strategy. Without demands matching, the collection modes from MCDM may not achieve the maximum profit and efficiency for collection companies. Future work can be focused on the integration of intelligent techniques so as to construct an intelligent decision-making system for collection companies.

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