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Benchmarking of product recovery alternatives in reverse logistics

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Abstract

Purpose – Selection of best product recovery alternative in reverse logistics (RL) has gained great attention in supply chain community. The purpose of this paper is to provide a robust group decision-making tool to select the best product recovery alternative.

Design/methodology/approach – In this paper, fuzzy values, assigned to various criteria and alternatives by a number of decision makers, are converted into crisp values and then aggregated scores are evaluated. After obtaining experts' scores, objective and subjective weights of the criteria have been calculated using variance method and analytic hierarchy process, respectively. Then integrated weights of criteria are evaluated using different proportions of the two weights. The superiority and inferiority ranking (SIR) method is then employed to achieve the final ranking of alternatives. An example is presented to demonstrate the methodology.

Findings – The proposed methodology provides decision makers a systematic, flexible and realistic approach to effectively rank the product recovery alternatives in RL. The alternatives can easily be benchmarked and best recovery strategy can be obtained. The sensitivity analysis carried out by changing different proportion of objective and subjective weights reveals that best ranking alternative never changes and proves the robustness of the methodology. The present benchmarking framework can also be used by decision makers to simplify any problem which encounters multi-attribute decision making and multiple decision makers.

Research limitations/implications – The proposed methodology should be tested in different situations having varied operational and environmental conditions dealing with different products. A real case study from an industrial set up can help to assess the behavior of the proposed methodology. The presented methodology however can deal with such multi-disciplinary and multi-criteria issues in a simple and structured manner and ease the managers to select the best alternative.

Originality/value – A novel approach for decision making taking into account both objective and subjective weights for criteria has been proposed to rank the best recovery alternatives in RL. The proposed methodology uses SIR method to prioritize the alternatives. As RL alternative selection is an important issue and involves both technical and managerial criteria as well as multiple decision makers, the proposed robust methodology can provide guidelines for the practicing managers.

Keywords Analytical hierarchy process, Multi-attribute decision making, Product recovery, Reverse logistics, Integrated weight, Superiority and inferiority ranking method

Paper type Research paper

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1. Introduction

In a traditional supply chain, the logistic network starts with producers to the end customers through wholesalers and retailers. With the technological advancements and rapid changes in market demand, diverse range of product enters the market with reduced life cycle. This may lead to an open loop system causing resource shortage and environmental disaster. Besides environmental and social factors, the economic benefit associated with product take-back through recycling is forcing the manufacturers to develop a closed loop supply chain network with product exchange and recovery at its end-of-life. Products can also be returned for reasons such as customer dissatisfaction and warranty (Rogers and Tibben-Lembke, 1999; Tibben-Lembke, 2002). Reverse logistics (RL) aim at the backward flow of materials from customer to the supplier with the goals of maximizing value from the returned item or minimizing the total cost incurred. Such products can be sorted for reuse, remanufacture, recycle and disposal. Reuse of used products by some value addition is not a new concept. Industries are using remanufacturing for expensive products such as turbines used in airplane and electricity generation systems. In these cases, recovery of used products is economically more attractive than disposal (Koh *et al.*, 2002).

Proper planning and implementing RL could bring profit, customer satisfaction and a socio-economic benefit to the organization. Managing returned goods have created a need to develop framework and methods for addressing issues such as economic viability, logistics, disassembly, recycling and remanufacturing for an ever increasing number of products produced and discarded (Ilgin and Gupta, 2010). Collecting and recovering products is the key issue for the practitioners. For any manufacturing firm trying to set up a product take-back policy, a sound recovery strategy is a major concern for comprehending both the return flow of products as well as recovery and recycling activities. The concept of product recovery management introduced by Thierry *et al.* (1995) enlists five product recovery options such as repair, refurbishing, remanufacturing, cannibalization and recycling. Ilgin and Gupta (2010) state product recovery is an essential step in the broad area of sustainable development and emphasize reducing waste in supply chains. In order to manage solid wastes which are otherwise dumped, the process of recapturing the value of products and materials by means of various re-operations is defined as product recovery (Gungor and Gupta, 1999).

The selection of best suitable product recovery alternative becomes a multi-criteria, multi-disciplinary problem involving both technical and managerial criteria (time/cost, legislative factor, quality and environmental impact) as well as multiple decision makers (Wadhwa *et al.*, 2009). There is always a need for some logical mathematical tool to help decision makers when a large number of selection attributes are involved. Recently, a good number of multi-attribute decision making (MADM) techniques and their applications have been proposed with their own merits and demerits. Designing a decision-making model requires quantitative and qualitative evaluation based on criteria such as cost/time, legislative factors, environmental impact, quality, market, etc. Performance must be considered on the basis of these criteria to determine a suitable reverse manufacturing option depending on the expert opinion in this domain. Wadhwa *et al.* (2009) have proposed a value adding MADM approach using fuzzy technique for order preference by similarity to ideal solution (Fuzzy TOPSIS) method for the product recovery alternative selection. Mahapatara *et al.* (2013) have proposed a novel multi-criteria approach considering both the objective and subjective weights of alternates. An effort is made in the method to find the objective weight using variance method and subjective weights using analytic hierarchy process (AHP) method and finally TOPSIS method is applied to rank the alternatives. TOPSIS method measures the distance of individual alternative with ideal solution. It does not consider the comparative evaluation of set of criteria.

One of the most preferred approaches is AHP which has been developed by Saaty (1980). AHP decomposes a decision-making problem into a system of hierarchies of attributes and alternatives. However, AHP is not suitable to solve constrained multi-objective problems and causes rank reversal during decision making (Rao, 2007). TOPSIS introduced by Hwang and Yoon (1981) is based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal solution. Positive ideal solution is a solution that maximizes the benefit criteria and minimizes non-benefit criteria whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Wang and Elhag, 2006). VIKOR (in Serbian: Vlse Kriterijumska Optimizacija I Kompromisno Resenje) method suggested by Opricovic and Tzeng and ELECTRE (Elimination and Choice Translating Reality) method by Roy uses the concept of outranking relationship. But the procedure is rather lengthy (Rao *et al.*, 2011). Superiority and Inferiority (SIR) method by Xu (2001) integrates both the outranking approach and the concept of TOPSIS. One of the main features of the method is that it can deal with cardinal as well as non-cardinal data. In present work, the SIR method has been applied considering both the objective and subjective weight of the criteria and uses superiority and inferiority scores comparing criteria values of set of alternatives. It offers decision makers to select different generalized criteria which represents attitude toward preference structure and its intensity making the method more flexible. The approach presented can systematically analyze expert judgments on decision criteria and alternatives in rationalizing the ranking process.

2. Literature review

A large number of RL practices have been reported in a wide range of studies. For instance, case studies and implementation of RL in electronic industry of China (Lau and Wang, 2009), consumer electronic industry in USA (Janse *et al.*, 2010), bottling and packaging firms in Europe (Gonzalez-Torre *et al.*, 2004) and publishing industry of China (Wu and Cheng, 2006) are few examples. RL is the process of planning, implementing and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal (Hawks, 2006). De Brito *et al.* (2005) have analyzed activities involved in RL to emphasize reverse flow of products initiated by organizations. RL is capable of preventing environmental pollution by reducing the environmental burden of end-of-life products at its source (Toffel, 2003). Managing the product return increases the customer's satisfaction level and retention (Senthil *et al.*, 2014). Companies that use RL as an opportunity for enhanced business will prosper by maintaining customer support and the ultimate issue for profitability (Krumwiede and Sheu, 2002). Sharma *et al.* (2011) also suggest that the awareness of RL could bring economic benefits by recovery of the returned product for use. Sheu (2008) explains that collection process and recovery process must exist at various stages in the reverse channel.

De Brito and Dekker (2002) proposed four main reverse logistic processes. First, there is collection which refers to bringing the products from the customer to a point of recovery. Second, facility for combined inspection, selection and sorting process must exist.

Third, facility for reprocessing and direct recovery is needed. Reprocessing includes the options such as repair, refurbishing, remanufacturing, retrieval, recycling and incineration. Direct recovery involves reuse, re-sale and redistribution. Redistribution is the process of bringing recovered goods to new users. The product recovery process varies from industry to industry in which the RL is applied. Srivastava (2008) classifies recovery processes into repair, refurbish, remanufacture and recycle activities. In Wadhwa *et al.* (2009), based on the level of quality and the degree of disassembly, the recovery processes are classified as repairing, refurbishing, remanufacturing, recycling and cannibalization processes. Kapetanopoulou and Tagaras (2011) have defined various product recovery activities as: first, repair involving the replacement or restoration of failed components in order to return the product to a functional condition; second, refurbishing meaning product reconditioning and possible upgrading without full disassembly; third, remanufacturing where the product is completely disassembled and some parts are machined so that the product returns to like-new condition; fourth, cannibalization referring to recovery of a restricted set of reusable parts from used products; and fifth, recycling meaning simply the reuse of materials from returned products without conserving the product identity. Srivastava and Srivastava (2006) mentioned that consumers expect to trade in an old product when they buy a new one and therefore different products may be returned at different stages of their life cycles and may go for remanufacturing, repair, reconfiguration and recycling as per the most appropriate deposition decision at their end-of-life. In Iakovou *et al.* (2009), the residual values, environmental burden, weight, quantity and ease of use disassembly of each component has been considered in the evaluation of end-of-life alternatives for a product. In deciding the right alternative, decision makers have to take into account a large number of criteria including technological, economic, political, legal and social factors (Mahapatara *et al.*, 2013). The selection of best suitable product recovery alternative becomes a complex multi-criteria, multi-disciplinary problem (Wadhwa *et al.*, 2009). In the presence of multiple criteria and number of decision makers, the selection of best possible one out of a large number of alternatives available becomes a MADM problem which always requires a simple and logical method to reach at most appropriate selection option. For solving MADM problem, methods like AHP, TOPSIS, VIKOR and ELECTRE are frequently used.

AHP is one of the most widely used MADM methods which can handle both quantitative and qualitative data. In the context of RL, Xiangru and Xin (2010) have used AHP for selection of third party RL providers. Barker and Zabinsky (2011) presents a multi-criteria decision-making model for conceptual decisions in RL network design using AHP. Vijayvargiya and Dey (2010) have used AHP for selection of best logistics provider. Lin and Shiue (2013) have presented an evaluation model using AHP to measure weights of several criteria to decide the collection strategy of RL of Taiwan photovoltaic industry. Senthil *et al.* (2014) presents a hybrid methodology based on AHP and TOPSIS for selection and evaluation of RL operating channels. Xiangru and Xin (2010) have used AHP for selection of third party RL providers. Ravi (2012) used combination of AHP and TOPSIS methods for determining most appropriate third party RL provider. Yuksel (2009) used AHP as a decision-making tool for selection of center location for e-waste collection. Though AHP is advantageous in many aspects, the problem of uncertainty becomes a bottleneck for it because the core of AHP is the preference matrix consisting of pair-wise comparison which involves some subjective and uncertain factors (Wu, 2007). Wadhwa *et al.* (2009)

have applied fuzzy TOPSIS method to select reverse manufacturing alternative. However, only objective weights for importance of criteria and alternatives are considered by them (Mahapatara *et al.*, 2013). In some studies, researchers have used AHP method to determine subjective weights of importance of criteria while applying TOPSIS method for ranking of alternatives. Mahmoodzadeh *et al.* (2007) have implemented a method for the selection of projects based on TOPSIS using fuzzy AHP for the calculation of weights of the criteria. Onüt and Soner (2008) have used AHP for the calculation of the weights and applied fuzzy TOPSIS method for the selection of locations of waste disposal. Torfi and Rashidi (2011) have applied the same framework to select project managers for construction companies. Percin (2009) has applied the modified Delphi method, AHP and TOPSIS methodology in the decision of 3PL provider selection in a Turkish automotive supplier company.

Mahapatara *et al.* (2013) have used integrated weights taking into consideration different proportion of objective as well as subjective weights of the criteria. In this work, variance approach has been applied for evaluating objective weight considering number of decision makers and AHP method for subjective weight determination. Moreover, linguistic variables (expressed in fuzzy membership function) used to extract data from the experts to account for uncertainty is converted to crisp problem while finding ranking of alternatives applying TOPSIS method. Superiority and inferiority ranking (SIR) method represents a general MADM approach because it uses new type of information extracted from original decision matrix instead of using the decision matrix directly (Xu, 2001). The method gives a concept of superiority and inferiority matrix (*S*- and *I*-matrix) via generalized criteria proposed by Brans *et al.* (1986); thus describing the intensity of superiority and inferiority of alternatives. Tam *et al.* (2004) have mentioned that SIR method draws together the strengths of most multi-criteria decision-making models in handling non-quantifiable, cardinal and/or ordinal data and allows imprecise information by introducing concepts of indifference and preference of each criterion. SIR method is applied by Marzouk (2008) for ranking model for contractor selection and Chan *et al.* (2011) for selection of solar energy for green building. Marzouk *et al.* (2013) have used the method for evolution of most suitable offer for procurement of equipment installed in a facility. Tam and Tong (2008) have applied the method for locating large scale harbor front project. Wang *et al.* (2009) have used SIR method for gray stochastic multi-criteria decision making.

3. Proposed methodology

Selection of reverse manufacturing alternatives is a MADM problem with qualitative and quantitative factors. Normally in an MADM approach, the best alternative is chosen from a set of n alternatives $\{R_1, R_2, \ldots, R_n\}$ where the performance of the alternatives are judged on the basis of a set of m attributes (criteria) $\{C_1, C_2, \ldots, C_m\}$ by a group of k decision makers (*DMs*) $\{DM_1, DM_2, \ldots, DM_k\}$. The weights for the attributes are given as $\{w_1, w_2, \ldots, w_m\}$. The decision makers evaluate each alternative under a criterion and provide a rating value of x_{ij} where $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$. The decision matrix can be given by Table I.

The methodology proposed in this paper for selection of favorable reverse manufacturing alternative consists of four major computational steps as mentioned below. The method uses fuzzy rating scales using triangular membership functions for extracting rating values for alternatives in linguistic terms. The linguistic attribute values are converted into crisp scores. The method uses integrated weights for assigning attribute weights composed of objective and subjective weights. By varying proportion of objective and subjective weights, a large number of decision-making scenarios can be generated.

3.1 Identification of alternatives and selection attributes

Select reverse manufacturing alternatives available and various criteria/attributes that influence the alternatives. The attributes are basically of two types namely beneficial and non-beneficial. For beneficial attributes, higher values (maximization) and for non-beneficial, lower values (minimization) are preferred.

3.2 Assigning rating values to alternatives under various selection attributes

After identification of the attributes for the selection of alternatives, rating values for each alternative under various attributes are assigned. Both quantitative and qualitative values can be assigned by the decision makers. However, at the decision level, it is not always possible to perform quantitative evaluation of the entire criteria. Therefore, linguistic values are used by the experts to provide the rating values to the alternatives under various attributes. To convert the qualitative terms into quantitative values, a conversion scale based on the works of Chen (1985) is used. This approximation converts linguistics terms into corresponding crisp values. A seven-point scale is chosen for the representation. Table II, proposed by Rao *et al.* (2011), presents the seven-point fuzzy scale for rating values using triangular fuzzy numbers and corresponding crisp representation to the help users to assign rating values. The fuzzy numbers used are shown in Figure 1.

	Attributes				
Alternatives	C_1 (w_1)	C_2 (w_2)	–	–	C_m (w_m)
R_1	x_{11}	x_{12}	–	–	x_{1m}
R_2	x_{21}	x_{22}	–	–	x_{2m}
–	–	–	–	–	–
–	–	–	–	–	–
R_n	x_{n1}	x_{n2}	–	–	x_{nm}

Table I. Decision table

Linguistic rating	Fuzzy number	Right score	Left score	Crisp score
Very poor (VP)	M_1 (0,0,0)	0	1	0
Medium poor (MP)	M_2 (0,0.1,0.2)	0.1818	0.9091	0.1364
Medium fair (MF)	M_3 (0.2,0.3,0.4)	0.3636	0.7273	0.3182
Fair (F)	M_4 (0.4,0.5,0.6)	0.5455	0.5455	0.5
Medium good (MG)	M_5 (0.6,0.7,0.8)	0.7273	0.3636	0.6818
Good (G)	M_6 (0.8,0.9,1)	0.9091	0.1818	0.8636
Very good (VG)	M_7 (1,1,1)	1	0	1

Table II. Fuzzy and crisp values for attribute rating

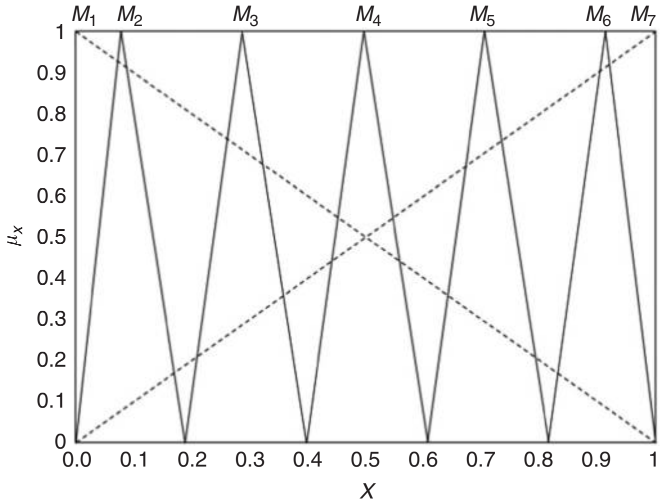

Figure 1.
Membership function of fuzzy numbers

The method uses a fuzzy scoring approach. The crisp score of fuzzy number M is obtained as follows (Chen, 1985):

$$\mu_{\max}(x) = \begin{cases} x, 0 \leqslant x \leqslant 1 \\ 0, \text{otherwise} \end{cases} \tag{1}$$

$$\mu_{\min}(x) = \begin{cases} 1-x, \ 0 \leqslant x \leqslant 1 \\ 0, \text{otherwise} \end{cases} \tag{2}$$

The fuzzy max and fuzzy min of fuzzy numbers are defined in a manner such that absolute locations of fuzzy numbers can be automatically incorporated in the comparison cases. The left score of each fuzzy number M_i is defined as:

$$\mu_L(M_i) = \operatorname*{Sup}_x \left[\mu_{\min}(x) \wedge \mu_{M_i}(x)\right] \tag{3}$$

The $\mu_L(M_i)$ score is a unique, crisp, real number in (0, 1). It is the maximum membership value of the intersection of fuzzy number M_i and the fuzzy min. The right score is obtained in a as:

$$\mu_R(M_i) = \operatorname*{Sup}_x \left[\mu_{\max}(x) \wedge \mu_{Mi}(x)\right] \tag{4}$$

Again $\mu_R(M_i)$ is a crisp number (0, 1). Given the left and right scores, the total crisp score of a fuzzy number M_i is defined as:

$$\mu_T(M_i) \ = \left[\mu_R(M_i)+1- \ \mu_L(M_i)\right]/2 \tag{5}$$

These ratings may be given by a single or a group of decision maker. Yue (2011) states that MADM problems can provide reliable results if analysis of multiple experts is taken into account instead of the analysis of a single expert. To prepare a decision table with aggregate rating values (x_{ij}), the assigned ratings given by decision makers to alternative i for the attribute j are then averaged. After determining the aggregate values, a normalized value matrix of attributes (x^*_{ij}) is prepared in which the values can be normalized for different alternatives using following equations:

$$x^*_{ij} = \left[x_{ij}/\left(x_{ij}\right)_{\max}\right] \text{ for beneficial attributes} \tag{6}$$

$$x^*_{ij} = \left[\left(x_{ij}\right)_{\min}/x_{ij}\right] \text{ for non beneficial attributes} \tag{7}$$

where x_{ij} is the attribute value of alternative i under attribute j.

3.3 Determination of weights of importance of the identified attributes

The weight of relative importance of the attributes is computed for the selection of alternatives available. The computation of weights proposed in earlier studies considers objective weights only neglecting the preference of the experts (Chan and Tong, 2007; Maniya *et al.*, 2010; Jahan *et al.*, 2010a, b). The proposed methodology uses integration of both objective weights and subjective preferences of the attributes. The objective weights can be computed using the data available in the normalized decision matrix prepared in previous step. The subjective preferences can be evaluated through pair-wise comparison of the alternatives.

3.3.1 Computation of objective weights of importance of the attributes. For determination of objective weights of the attributes, statistical variance method is used in this paper. Rao *et al.* (2011) stated that statistical variance gives a measure of dispersion of a set of data points around their mean value. Unlike statistical analyses that look at the extremes, the variance looks at all the data points and then determines their distribution. It is a mathematical expectation of the average squared deviations from the mean. It is observed that calculation of objective weights using entropy method suggested by Shannon and Weaver (1947) requires more computation than the statistical variance method.

The statistical variance for determining the objective weights of importance of the attributes is given by the following equation:

$$v_j = (1/n)\sum_{i=1}^{n}\left(x^*_{ij} - \left(x^*_{ij}\right)_{\text{mean}}\right)^2 \tag{8}$$

where v_j is the variance of the data corresponding to the jth attribute and $(x^*_{ij})_{\text{mean}}$ is the average value of x^*_{ij}.

The objective weight of the jth attribute w^0_j can be computed by dividing the statistical variance of the jth attribute with the total value of the statistical variances of m number of attributes. Thus, w^o_j can be computed by the following equation:

$$w^o_j = v_j / \sum_{j=1}^{m} v_j \tag{9}$$

3.3.2 Computation of subjective weights of importance of the attributes. For assigning weights of relative importance of the attributes, AHP method given by Saaty (1980) is proposed here. The AHP technique obtains quantitative results by transforming the comparative weight between elements to ratio scale. By doing pair- wise comparisons of the attributes using the scales suggested by Saaty, reciprocal matrices ($m \times m$) can be formulated. After doing all the pair-wise comparisons, the consistency is checked by using the following computations:

$$\text{Consistency Index}, CI = (\lambda_{\max} - m)/(m-1) \tag{10}$$

where $\lambda_{\max}$ is the maximum Eigen value of the matrix and m is matrix size:

$$\text{Consistency Ratio}, CR = \left(CI/RI\right) \tag{11}$$

Consistency ratio (CR) is basically the ratio of consistency index (CI) to random index (RI). The value of RI can be taken using Table III.

If CR does not exceed 0.10, then the values are acceptable. Otherwise, the judgment matrix is inconsistent and needed to be reviewed and improved.

3.3.3 Computation of integrated weights of importance of the attributes. Considering the different weightings of the objective and subjective weights of the attributes, the integrated weights of importance are calculated using the following equation:

$$w_j^i = w^o \times w_j^o + w^s \times w_j^s \tag{12}$$

Here, w_j^i, w_j^o and w_j^s denote the integrated, objective and subjective weight of the jth attribute respectively. w^o and w^s represents the weightings considered for objective and subjective weights, respectively. The weightings are taken between 0 and 1.

3.4 Ranking of alternatives using SIR method

The SIR method given by Xu (2001) is used to determine final ranking of alternatives. The method derives two types of flows, the superiority flow (S-flow) and inferiority flow (I-flow), through which ranking of the alternatives is done. The two types of flow express the intensity of superiority and inferiority of each alternative. In SIR method, such scores are used obtained by comparison of values of alternatives under different criteria.

From decision matrix the criteria values of each criteria (of two alternatives for a criteria) is compared. If $C_m(a)$ and $C_m(b)$ are the criteria values of alternates R_a and R_b for criteria C_m then the difference between criteria values are used to estimate the intensity of the preference of R_a over R_b:

$$\text{Difference } d = [C_m(a) - C_m(b)]$$

$$\text{Preference index } P(R_a, Rb) = f(d) = f[C_m(a) - C_m(b)] \tag{13}$$

Here $f(d)$ is a non-decreasing function which is a real number to [0, 1] and is called generalized criteria. Brans *et al.* (1986) proposed six generalized criterion types which

Table III.
Value of RI

m	1	2	3	4	5	6	7	8	9
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46

can be used to capture the characteristics of functions that represent the specified criteria. According to the attitude toward the preference structure and intensity of preference, the decision maker selects the generalized criteria (along with its associated parameter). Table IV lists the types of generalized criteria.

When dealing with ordinal data, only true criterion is considered. In dealing with cardinal data, one can not only consider the difference between the criteria values but also the amplitude of difference (Roy *et al.*, 1992). For such data, the decision maker has to carefully choose the criteria to use. For the present work true criteria has been chosen.

For each alternative R_i ($i=1, 2, \ldots, n$) the superiority index $S_j(R_i)$ and inferiority index $I_j(R_i)$ with respect to the jth ($j=1, 2, \ldots, m$) criterion are calculated using the following equations:

$$S_j(R_i) = \sum_{k=1}^{n} P_j(R_i, R_k) = \sum_{k=1}^{n} f_j\left(C_j(R_i) - C_j(R_k)\right) \tag{14}$$

$$I_j(R_i) = \sum_{k=1}^{n} P_j(R_i, R_k) = \sum_{k=1}^{n} f_j\left(C_j(R_k) - C_j(R_i)\right) \tag{15}$$

The superiority and inferiority indices are used to form superiority matrix (S-matrix) and inferiority matrix (I-matrix). S-matrix provides information about the intensity of superiority of each alternative on each criterion whereas I-matrix provides information about the intensity of inferiority:

$$S = S_j(R_i)_{m\times n} = \begin{bmatrix} S_1(R_1) & S_2(R_1) & .. & S_m(R_1) \\ S_1(R_2) & S_2(R_2) & .. & S_m(R_2) \\ : & : & : & : \\ S_1(R_n) & S_2(R_n) & .. & S_m(R_n) \end{bmatrix}$$

$$I = I_j(R_i)_{m\times n} = \begin{bmatrix} I_1(R_1) & I_2(R_1) & .. & I_m(R_1) \\ I_1(R_2) & I_2(R_2) & .. & I_m(R_2) \\ : & : & : & : \\ I_1(R_n) & I_2(R_n) & .. & I_m(R_n) \end{bmatrix}$$

Table IV. Generalized criteria

Type 1 true criterion $f(d) = \begin{cases} 1 & \text{if } d > 0 \\ 0 & \text{if } d \leqslant 0 \end{cases}$	Type 2 quasi criterion $f(d) = \begin{cases} 1 & \text{if } d > q \\ 0 & \text{if } d \leqslant q \end{cases}$	Type 3 criterion with linear preference $f(d) = \begin{cases} 1 & \text{if } d > p \\ d/p & \text{if } 0 < d \leqslant p \\ 0 & \text{if } d \leqslant 0 \end{cases}$
Type 4 level criterion $f(d) = \begin{cases} 1 & \text{if } d > p \\ 1/2 & \text{if } q < d \leqslant p \\ 0 & \text{if } d \leqslant q \end{cases}$	Type 5 criterion with linear preference and indifference criterion $f(d) = \begin{cases} 1 & \text{if } d > p \\ (d-q)/(p-q) & \text{if } q < d \leqslant p \\ 0 & \text{if } d \leqslant q \end{cases}$	Type 6 Gaussian criterion $f(d) = \begin{cases} 1-\exp\left(-d^2/2\sigma^2\right) & \text{if } d > 0 \\ 0 \text{ if } d \leqslant 0 & \text{if } d \leqslant 0 \end{cases}$

This procedure uses the superiority scores and inferiority scores in the *S*- and *I*-matrix and weightings of criteria defined by decision makers to formulate the superiority flow $\varphi^{>}(R_i)$ and the inferiority flow $\varphi^{<}(R_i)$. The following Equation (16) gives the calculation:

$$\varphi^{>}(R_i) = \sum_{j=1}^{m} w_j S_j(R_i) \text{ and } \varphi^{<}(R_i) = \sum_{j=1}^{m} w_j I_j(R_i) \tag{16}$$

where w_j in the integrated weight of the criteria. Thus for different proportion of objective weight (w^o) and subjective weight (w^s), *S*- and *I*-flow will be obtained which represents the global intensity of superiority and inferiority of each alternative. Therefore the higher $\varphi^{>}(R_i)$ and the lower $\varphi^{<}(R_i)$, the more preferred the alternative R_i is. This gives the partial ranking of alternatives. To determine the complete ranking synthesizing flow, i.e. *n*-flow $\varphi_n(R_i)$ is calculated as follows:

$$\varphi_n(R_i) = \varphi^{>}(R_i) - \varphi^{<}(R_i) \tag{17}$$

The alternative which has highest value of *n*-flow is given top ranking in the order. Ranking is done for different weighting taking into account different proportions of objective and subjective weights. The best possible alternative can be assessed through the final ranking matrix.

4. Results and discussions

For validating the proposed MADM approach, real-life data from an original equipment manufacturer company manufacturing high value and high volume consumer goods is obtained. Through exhaustive literature review and discussion with a focus group in the manufacturing company, five manufacturing alternatives such as remanufacturing (R_1), reselling (R_2), repairing (R_3), cannibalization (R_4) and refurbishing (R_5) are considered. The focus group consists of managers from various levels of management having expertise in forward and reverse supply chain. Remanufacturing entails complete disassembly of used products into its parts and components for ultimate use of them in the production of new products after reconditioning if necessary. Reselling refers to selling of old/end-of-life products after minor adjustments at discounted price. Repairing is fixing or replacement of old/end-of-life components to bring back the products to working condition. Cannibalization recovers a limited set of reusable parts from used products or components. These parts may be reused in repair, refurbishing or remanufacturing of other products and components. Refurbishing denotes higher degree of repair in terms of reprocessing undertaken and it involves fixing the improper modules and replacing them with working or technological ones. The alternatives are decided based on five attributes of conflicting nature such as cost/time (C_1), environmental impact (C_2), market factor (C_3), quality factor (C_4) and legislative impact (C_5). Out of five attributes, C_1, C_2 and C_5 are non-beneficial and C_3 and C_4 are beneficial attributes. A group of four decision makers (DM_1, DM_2, DM_3 and DM_4) are considered for the decision making and linguistic values for ratings are extracted from them using the scale shown in Table II. The linguistic values for five manufacturing alternatives under various criteria are shown in Table V. It may be noted that only qualitative measures of the attributes are available in the above table. The linguistic rating values are transformed to crisp using Table II and the corresponding values are shown in Table VI.

Decision makers	Reverse manufacturing alternatives	Criteria for selection C_1	C_2	C_3	C_4	C_5
DM_1	R_1	MP	MF	MP	F	MP
	R_2	MF	MG	F	MP	MP
	R_3	F	F	F	F	F
	R_4	F	MP	F	MP	MP
	R_5	MP	MP	F	MP	F
DM_2	R_1	MP	MG	MG	MG	MG
	R_2	MG	G	G	G	MG
	R_3	MG	G	MG	MG	MG
	R_4	MG	MG	MG	MG	MG
	R_5	F	MG	MG	MG	MG
DM_3	R_1	MF	G	MG	G	G
	R_2	MG	G	VG	G	G
	R_3	G	VG	G	MG	G
	R_4	MG	MG	G	G	G
	R_5	F	G	G	G	G
DM_4	R_1	MG	G	G	G	G
	R_2	MG	VG	VG	G	G
	R_3	G	VG	G	G	VG
	R_4	G	G	G	G	VG
	R_5	G	VG	G	G	VG

Table V. Linguistic rating for reverse manufacturing alternatives selection

Decision makers	Reverse manufacturing alternatives	Criteria for selection C_1	C_2	C_3	C_4	C_5
DM_1	R_1	0.136	0.318	0.136	0.500	0.136
	R_2	0.318	0.682	0.500	0.136	0.136
	R_3	0.500	0.500	0.500	0.500	0.500
	R_4	0.500	0.136	0.500	0.136	0.136
	R_5	0.136	0.136	0.500	0.136	0.500
DM_2	R_1	0.136	0.682	0.682	0.682	0.682
	R_2	0.682	0.864	0.864	0.864	0.682
	R_3	0.682	0.864	0.682	0.682	0.682
	R_4	0.682	0.682	0.682	0.682	0.682
	R_5	0.500	0.682	0.682	0.682	0.682
DM_3	R_1	0.318	0.864	0.682	0.864	0.864
	R_2	0.682	0.864	1.000	0.864	0.864
	R_3	0.864	1.000	0.864	0.682	0.864
	R_4	0.682	0.682	0.864	0.864	0.864
	R_5	0.500	0.864	0.864	0.864	0.864
DM_4	R_1	0.682	0.864	0.864	0.864	0.864
	R_2	0.682	1.000	1.000	0.864	0.864
	R_3	0.864	1.000	0.864	0.864	1.000
	R_4	0.864	0.864	0.864	0.864	1.000
	R_5	0.864	1.000	0.864	0.864	1.000

Table VI. Crisp ratings for reverse manufacturing alternatives selection attributes

The assigned ratings given by the decision makers to each alternative under various criteria are averaged to obtain aggregate values as shown in Table VII. The attribute values are now normalized using Equations (6) and (7) depending on type of criteria. The normalized decision matrix is shown in Table VIII.

On the basis of statistical variance method, the objective weights of the attributes are computed using Equation (8). The variance of the data of normalized decision matrix is given in Table VIII. The objective weights for different attributes (criteria) are obtained using Equation (9) as shown Table IX.

AHP is used here to calculate subjective weights of criteria. Table X shows the pair-wise comparison matrix for the given attributes obtained from the decision makers using average method aggregating data. The value of CR is 0.035 which is less than 0.1 and hence the result is acceptable. The subjective weights are calculated using geometric means and the result is shown in Table XI.

Table VII. Aggregate crisp ratings for reverse manufacturing alternatives

			Criteria		
Alternatives	C_1	C_2	C_3	C_4	C_5
R_1	0.3182	0.6818	0.5909	0.7274	0.6364
R_2	0.5909	0.8523	0.8409	0.6818	0.6364
R_3	0.7273	0.8409	0.7273	0.6818	0.7614
R_4	0.6818	0.5909	0.7273	0.6364	0.6705
R_5	0.5000	0.6705	0.7273	0.6364	0.7614

Table VIII. Normalized decision matrix for reverse manufacturing alternatives selection

			Criteria		
Alternatives	C_1	C_2	C_3	C_4	C_5
R_1	1.0000	0.8667	0.7027	1.0000	1.0000
R_2	0.5385	0.6933	1.0000	0.9375	1.0000
R_3	0.4375	0.7027	0.8648	0.9375	0.8358
R_4	0.4667	1.0000	0.8648	0.8750	0.9491
R_5	0.6364	0.8813	0.8648	0.8750	0.8358

Table IX. Objective weights of criteria

Criteria	C_1	C_2	C_3	C_4	C_5
Variance	$v_{c_1} = 0.2145$	$v_{c_2} = 0.4089$	$v_{c_3} = 0.4438$	$v_{c_4} = 0.5278$	$v_{c_5} = 0.5299$
Objective weights	$w^o_{c_1} = 0.101$	$w^o_{c_2} = 0.192$	$w^o_{c_3} = 0.209$	$w^o_{c_4} = 0.248$	$w^o_{c_5} = 0.249$

Table X. Pair-wise comparison matrix for reverse manufacturing alternatives selection attributes

			Criteria		
Criteria	C_1	C_2	C_3	C_4	C_5
C_1	1	3	4	9	7
C_2	0.333	1	2	6	2
C_3	0.250	0.500	1	5	2
C_4	0.100	0.167	0.200	1	0.200
C_5	0.143	0.500	0.500	5	1

Table XI. Subjective weights of attributes

Criteria	C_1	C_2	C_3	C_4	C_5
Subjective weight	$w^s_{c_1} = 0.518$	$w^s_{c_2} = 0.209$	$w^s_{c_3} = 0.144$	$w^s_{c_4} = 0.032$	$w^s_{c_5} = 0.098$

The integrated weights of attributes are obtained using Equation (12). Table XII gives the integrated weights of attributes considering the different weightings of the objective and subjective weights of the five criteria within the range 0-1.

The next step is to find out the ranking values of alternatives. The criteria values of the alternatives from Table VII is used to calculate the superiority and inferiority index (using Equations (13)-(15) of each alternative according the preferred generalized function type (see Table IV) to obtain superiority(S) matrix and inferiority (I) matrix. The S and I matrix is shown in Tables XIII and XIV.

The next step is to determine the superiority and inferiority flow for each criterion using Equation (16). Here the values are calculated using integrated weight of each alternative with different proportion of objective weights and subjective weights. The S- and I-flow matrix are shown in Tables XV and XVI, respectively. Ranking of the alternatives can be assessed through these matrixes but the result will be partial in nature. For complete ranking the next step is to calculate n-flow matrix using Equation (16). The n-flow matrix is shown in Table XVII. The descending order of the values of alternatives expresses the ranking order.

		Integrated weights of criteria Criteria				
Importance weight of objective weight (w^o)	Importance weight of subjective weight (w_s)	C_1 $w^i_{c_1}$	C_2 $w^i_{c_2}$	C_3 $w^i_{c_3}$	C_4 $w^i_{c_4}$	C_5 $w^i_{c_5}$
1.0	0	0.101	0.192	0.209	0.248	0.249
0.8	0.2	0.184	0.196	0.196	0.205	0.219
0.6	0.4	0.268	0.199	0.183	0.162	0.189
0.4	0.6	0.351	0.202	0.170	0.118	0.158
0.2	0.8	0.435	0.205	0.157	0.075	0.128
0	1.0	0.518	0.209	0.144	0.032	0.098

Table XII. Integrated weights of importance of the criteria

			Criteria		
Alternative	C_1	C_2	C_3	C_4	C_5
R_1	0	2	0	4	0
R_2	2	4	4	2	0
R_3	4	3	1	2	3
R_4	3	0	1	0	2
R_5	1	2	1	0	3

Table XIII. Superiority (S) matrix

			Criteria		
Alternative	C_1	C_2	C_3	C_4	C_5
R_1	4	2	4	0	3
R_2	2	0	0	1	3
R_3	0	1	1	1	0
R_4	1	4	1	3	2
R_5	3	3	1	3	0

Table XIV. Inferiority (I) matrix

From Table XVII, it can be observed that the value of n-flow measured, when considering only objective weight, is highest for alternative 3 and lowest for alternative 4. Therefore one can rank alternative 3 as most suitable for the case. In the similar manner, one can rank the product recovery alternative in the order of preference considering descending order of values of n-flow matrix. The final ranking taking into account different proportions of objective and subjective weights is given in Table XVIII. From the table one can easily conclude that alternative 3 (repairing) is the best among all. Thus the

Table XV. Superiority flow matrix $[\varphi^{>}(R_i)]$

	Proportion of objective and subjective weights of criteria					
Alternative	$w^o=1$ $w^s=0$	$w^o=0.8$ $w^s=0.2$	$w^o=0.6$ $w^s=0.4$	$w^o=0.4$ $w^s=0.6$	$w^o=0.2$ $w^s=0.8$	$w^o=0$ $w^s=1$
R_1	1.376	1.21	1.046	0.876	0.712	0.546
R_2	2.302	2.342	2.388	2.426	2.472	2.512
R_3	2.432	2.554	2.743	2.89	3.049	3.201
R_4	1.01	1.166	1.365	1.539	1.718	1.894
R_5	1.441	1.397	1.416	1.399	1.388	1.374

Table XVI. Inferiority flow matrix $[\varphi^{<}(R_i)]$

	Proportion of objective and subjective weights of criteria					
Alternatives	$w^o=1$ $w^s=0$	$w^o=0.8$ $w^s=0.2$	$w^o=0.6$ $w^s=0.4$	$w^o=0.4$ $w^s=0.6$	$w^o=0.2$ $w^s=0.8$	$w^o=0$ $w^s=1$
R_1	2.371	1.763	1.818	1.864	1.919	1.968
R_2	1.197	0.811	0.669	0.524	0.382	0.24
R_3	0.649	0.575	0.65	0.723	0.798	0.871
R_4	2.32	1.929	2.144	2.352	2.567	2.777
R_5	1.832	1.335	1.552	1.765	1.982	2.195

Table XVII. n-flow $[\varphi_n(R_i)]$ matrix

	Proportion of objective and subjective weights of criteria					
Alternatives	$w^o=1$ $w^s=0$	$w^o=0.8$ $w^s=0.2$	$w^o=0.6$ $w^s=0.4$	$w^o=0.4$ $w^s=0.6$	$w^o=0.2$ $w^s=0.8$	$w^o=0$ $w^s=1$
R_1	−0.995	−0.553	−0.772	−0.988	−1.207	−1.422
R_2	1.105	1.531	1.719	1.902	2.09	2.272
R_3	1.783	1.979	2.093	2.167	2.251	2.33
R_4	−1.31	−0.763	−0.779	−0.813	−0.849	−0.883
R_5	−0.391	0.062	−0.136	−0.366	−0.594	−0.821

Table XVIII. Ranking of alternatives considering different proportions of objective and subjective weights

$w^o=1$ $w^s=0$	$w^o=0.8$ $w^s=0.2$	$w^o=0.6$ $w^s=0.4$	$w^o=0.4$ $w^s=0.6$	$w^o=0.2$ $w^s=0.8$	$w^o=0$ $w^s=5$
R_3	R_3	R_3	R_3	R_3	R_3
R_2	R_2	R_2	R_2	R_2	R_2
R_5	R_5	R_5	R_5	R_5	R_5
R_1	R_1	R_1	R_4	R_4	R_4
R_4	R_4	R_4	R_1	R_1	R_1

method is robust enough for decision makers providing flexibility to include number of experts as well as to consider either objective weight of importance of criteria or subjective weight or both in different proportions.

5. Conclusions

In context of reverse supply chain, implementation of product recovery is always an important and crucial issue. A decision maker requires a simple and logical methodology for selection of best favorable product recovery alternative. Number of criteria also exists to decide the same. There are numerous MADM techniques available with their own merits and demerits. Many MSADM methods only consider objective weights of criteria. Several hybrid methods which consider subjective weights using AHP method only are also available. Fuzzy MADM methods available for ranking of alternatives require lengthy computation. MADM method using TOPSIS for ranking purpose uses calculation of distance of alternatives from ideal solutions without accounting for comparative analysis between set of alternatives. The proposed method provides decision makers a novel technique for selection of product recovery alternatives. It is a systematic and reliable method because it is capable of taking opinion from number of experts. It allows integration of objective weights and subjective weights in different proportions besides converting fuzzy ratings to crisp values for ease of calculation. The method also provides an option to decision makers to consider only objective weight or only subjective weights or integration of both the weights. The conversions of fuzzy scale is also beneficial for quantifying the qualitative attributes. The method uses SIR method which considers the superiority and inferiority ratings among set of alternatives. The method will provide decision makers a more realistic and rational solution for judgment. In the present example, it is observed that for almost all the proportions of objective and subjective weights the top three alternatives are same and alternative 3 (i.e. repairing) topped the list. Thus, it can be said that the proposed method offers a robust technique to decision makers. Manufacturing industries which intend to progress in the direction of product recovery, can apply it to come to a concrete solution for alternative selection. Because of frequent advancement in technologies and market competitions, industries dealing in auto parts, home appliances cellular phones, computers and its peripherals are known for short life cycles of products. Such industries always look for take-back and recovery of discarded and end-of-life products for economic and environmental/social perspectives and thus decision of a suitable recovery alternative becomes a vital issue. The proposed methodology provides the decision makers a realistic approach to handle such problems. The proposed methodology can also be applied to wide variety of problems encountering MADM where prioritization of alternatives is required which depends on number of criteria for decision making and involve number of decision makers.

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