A Multi Criteria Decision Model for Alternative Selection in Reverse Logistics System

S. Wadhwa, J. Madaan

Indian Institute of Technology—Delhi (IIT-D),

Hauz Khas, New Delhi, India

Abstract: Enterprises are challenged to integrate environmental standards into their business policies to maintain their competitiveness. Management research area, so-called reverse logistics, has evolved to assist in recognizing potential benefits and overcoming challenges associated with enterprise system. Determining the most favorable reverse manufacturing alternative arriving to collection centers has always been a key strategic consideration. However, the nature of these decisions usually is multidimensional, interdisciplinary, complex, and unstructured. Designing a decision making model for the same 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. In this paper, we propose a multiple criteria decision-making (MCDM) model based on fuzzy-set theory. Proposed model can help in designing effective and efficient return policy depending on the various criteria. Further companies can use this analysis as strategic decision making tool to develop fresh reprocessing facilities or efficiently use the already exiting facility. This model can also act as a strategic decision support tool by using computer based implementation. Finally, an example is illustrated to highlight the procedural implementation of proposed model. This paper makes an attempt to bring fuzzy based multi criteria decision making and reverse logistics together as a well suited as a group decision support tool for alternative selections.

Keywords: Fuzzy, Alternative Selection, Supply chain management, MCDM

1. Introduction

Nowadays, enterprises are constantly working on the improvement of their operations. Globalization, forces the enterprises to think about many issues that were not considered in the past: competitiveness, productivity, quality, equity and sustainability are now common terms in the companies speech. But more than just talking about that, enterprises are implementing permanently new strategies to survive in an increasing competitive market. Reverse Logistics (RL) is one of the issues emerging as a consequence of the increasing pressure made by the competitive forces and specially, by the governments, which are involved in the preservation of the environment. This paper considers reverse logistics part of an enterprise system to capture value benefit from returned products. In general reverse logistics can be defined as the process of moving goods from their typical final destination for the purpose of capturing value, or proper disposal (Rogers and Tibben-Lembke, 1998). Moving goods from their point of origin towards their final destination has long been the focus of logistics systems. A reverse logistics system incorporates a supply chain that has been redesigned to manage the flow of products or parts destined for remanufacturing, repairing, or disposal and to effectively use resources (Dowlatshahi, 2000). Today product return has become endemic for almost all product categories, with rates as high as 20% in some sectors. Therefore, developing a comprehensive and cost-effective decision system for product return handling is a daunting challenge that reaches well beyond the operational level. Thus, a well-developed reverse logistics and management plan can be a vital strategic asset (Wadhwa & Madaan, 2004). According to a past survey conducted by the Reverse Logistics Executive Council (RLEC), the average returns rate is 8.46% with individual expected return shown in table 1. Looking across the entire manufacturing value chain, one finds return rates are as high as 20-30% or more in the year 2005-06 and these rates are expected to increase in the near future.

Table 1. Expected Rate of Return (Survey by RLEC)

Product category	Return % in Year 2004
White goods	8 %
House Hold appliances	7 %
TV's	8 %
Computers and accessories	15%
Brown Goods	6%

To cater the need for this emerging field with interdisciplinary, multi-criteria decision making complexity, designing a framework has always been a challenging issue. Specially, when there are number of reprocessing alternatives available (remanufacturing, repair, resell, refurbishing cannibalization etc.). With a high variability in evaluation these alternative with respect to alternatives either tangible or intangible no crisp data is available.

No matter how, when and in what condition products are returned, the primary problem in designing an effective logistics system is the high degree of quantity, timing and quality variability inherent in a recoverable product environment (Guide et al., 2000). The presence of multiple criteria (both managerial and technical (time/cost, market, legislative factor, quality, and environment impact)) and the involvement of multiple decision-makers will expand decisions from one to many dimensions, thus increasing the complexity of the alternative selection process. It seems obvious that we cannot solve the selection problem simply by grinding through a mathematical model or algorithm. We need new approaches, which could handle multi-criteria decision-making problems of choice and prioritization, to support these types of complex and unstructured selection problems. These selection decisions regarding the can help companies to prioritize and develop reverse manufacturing facilities accordingly. This paper makes an attempt to bring fuzzy decision-making method and Reverse logistics once again together by making the reverse manufacturing alternative selection decision structure explicit and by quantifying preferences based on the decision structure. This formal decision analysis allows decision makers in setting to rank order the alternatives based on the results of the analysis.

2. Review of Literature

Although products have been returned since the early days of commerce but reverse logistics has only attracted academic attention since the early 1990's. Reverse logistics (RL) commonly refers to the backward movement of materials in the supply chain (Rogers and et al, 2002). This does not imply that materials are necessarily ending up at their original manufacturers, but refers to the collection of product returns, disassembly, and disposal aspects of RL, regardless of their final destination (Carter and Ellram, 1998). While some authors limit reverse logistics to the sum of those activities that ensure a sustainable or environment-friendly recovery of products and materials (Kopicki et al., 1993; Murphy and Poist, 2000), broader definitions extend this to the handling of all kinds of product returns, including the take-back of unwanted products, recalls and warranty returns (Stock, 1998; Rogers and Tibben-Lembke, 1999; Fleischmann, 2001). Here we can use the broader definition of reverse logistics as a reverse enterprise system in the sense that we include products flowing backwards for all kinds of reasons (Wadhwa & Madaan, 2004 b). Furthermore, the term 'product-returns' and 'reverse logistics' have been used interchangeably in this paper. Thierry et al. (1995) proposed the term Product Recovery Management (PRM) to recover as much of the economic (and ecological) value as reasonably possible, thereby reducing the quantities of waste.

A lot of previous research on product returns has concentrated on technical issues such as network design (Krikke, 1998), shop floor control (Guide and Srivastava, 1998) and inventory control (Inderfurth, 1997). Therefore present literature show the advances in analytical modeling from an operational decision making perspective to be more advanced than analytical models to support strategic decision making. We propose a strategic model that links with operational characteristics, in the selection of most favorable reverse manufacturing alternative. Here by focusing on various recovery options, five different alternatives can be found: cannibalization, remanufacturing, refurbishing, repair and reselling, listed in order of the required degree of disassembly. These alternatives can be explained following:

Repair and reuse is to return used products in working order. The quality of the repaired products could be less than that of the new products.

Refurbishing is to bring the quality of used products up to a specified level by disassembly to the upgraded level, inspection, and replacement of broken components. Refurbishing could also involve technology upgrading by replacing outdated modules or components with technologically superior ones.

Remanufacturing is to bring used products up to quality standards that are as rigorous as those for new products by complete disassembly down to the component level and extensive inspection and replacement of broken/outdated parts.

Cannibalization is to recover a relatively small number of reusable parts and modules from the used products, to be used in any of the three operations mentioned above. Finally recycling to reuse materials from used products and parts by various separation processes and reusing them in the production of the original or other products.

Figure 1 is a visual representation of generic product return network, where the retailers, collection stations, and evaluation point serve as decision making nodes for opting reverse manufacturing facilities. This figure attempts to incorporate entire possible facilities and transportation links in a forward and reverse logistics network.

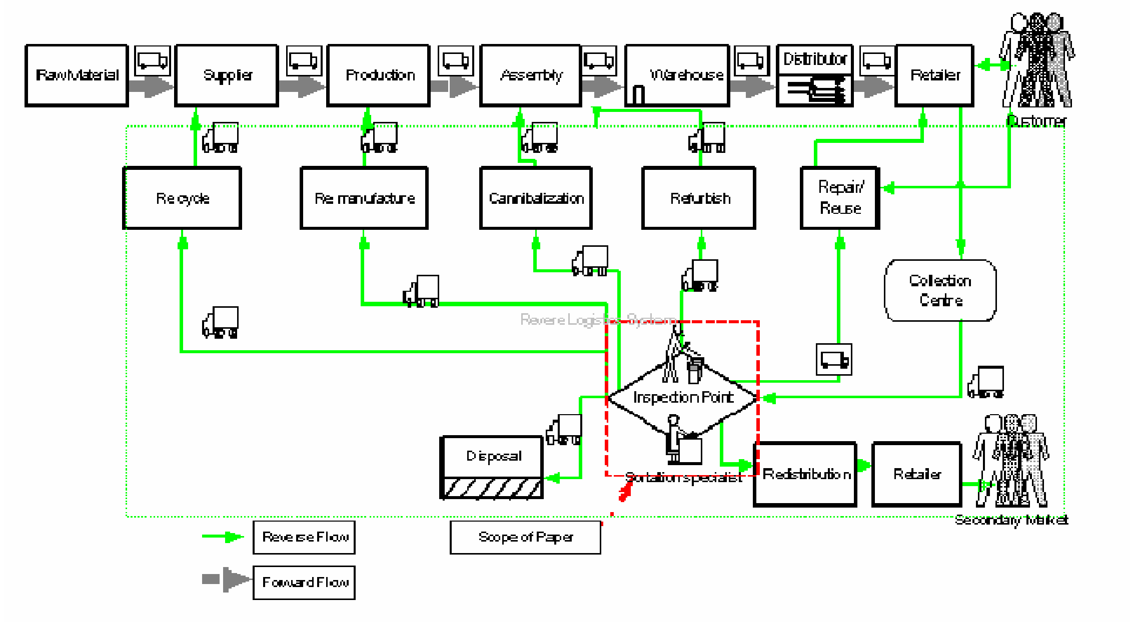

Figure 1. Generic Flow in Reverse Logistics Systems

If all of these reprocessing facilities have been developed, then depending upon market, environmental, legislative conditions etc one can route the products to various nodes of reverse logistics. This can also be further viewed as type of routing flexibility problem which is external factor dependent. In this direction Wadhwa & Brawn (1989) have shown the benefits of routing flexibility in manufacturing system. These flexibility concepts can also be discussed in multiple entity flows (Wadhwa and Rao, (2003), Wadhwa et al., 2006) from enterprise synchronization perspective in the context of reverse logistics. It can be suggested that routing flexibility can play a vital role in designing a reverse logistics system also. Our future research will involve development of simulation model for reverse logistics systems. Here in this paper we are dealing with problem of selection of most appropriate alternative for reprocessing. Situation here is bit further complex in choosing the right option because the alternative selection parameters have considerable degree of fuzziness associated with them. Few models have been proposed in literature to handle this fuzzy decision-making process. These models have either been single criterion- or bi-criteria-based. Some of these works include those of Chen et al. (1993), Cramer (1996), & Low et al. (1997). Owing to the complexity of the decision and profusion of alternatives, a systematic process of selection can be formidable and expensive. For this condition when we have multiple alternatives, one has to choose for favorable alternative based on a range of criteria.

This paper proposes a framework for a decision model for developing reverse manufacturing options to aid in the designing, planning and controlling of logistics and related activities in advance. This model collects the knowledge of experts (evaluators or sortation specialists) to investigate most appropriate alternative(s) for product reprocessing with respect to existing criterions.

Since the crisp evaluation of these criteria is difficult, verbal values from a set of product return experts are used to assess the ratings of these criteria. These verbal ratings can be expressed in trapezoidal or triangular fuzzy numbers. Therefore, a hierarchy multiple criteria decision-making (MCDM) model based on fuzzy-set theory is proposed to deal with the reverse manufacturing alternative. Further according to the concept of the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) (Hwang, 1981), a closeness coefficient is defined to determine the ranking order of the alternatives by calculating the distances to the both fuzzy positive-ideal solution and fuzzy negative-ideal solution simultaneously. Based on this ranking order we develop the best alternative facility for reprocessing the returned product.

Finally, a case example is shown to highlight the procedure of the proposed method at the end. This paper shows that the proposed model is very well suited as a multi dimensional decision making tool for reverse manufacturing process selection decisions.

The paper is organized as follows. Next section formulates problem definition in reverse logistics system; and a fuzzy decision-making methodology to cope with the alternative selection problem. Further, the proposed method is illustrated with an application example. And then we suggest scope for computer based implementation of the proposed model as decision support tool in reverse logistics**.** Finally, interesting some conclusions is pointed out at the end of this paper.

3. Proposed Method for Reverse Manufacturing Alternative Selection

Here we propose a systematic methodology to extend the TOPSIS approach for solving the reverse manufacturing alternative-selection problem under a fuzzy environment.

Since the quantitative evaluation of all the criteria motivating for product return is difficult, verbal values are used by experts (evaluator or sortation specialist) to assess the ratings of criteria. This linguistic evaluation of these criteria takes place at various levels of decision hierarchy in a company which already have or about develop a reprocessing facility to take back returns. Here we consider importance weights of 'return evaluation criterion' and the quality ratings of each decision maker as linguistic variables. Since linguistic assessments of these criteria is merely approximate, we can consider linear trapezoidal membership functions to be adequate for capturing the vagueness of these linguistic assessments (Delgado et al., 1998; Herrera et al., 1996; Herrera and Herrera-Viedma, 2000). These linguistic variables can be expressed in positive trapezoidal fuzzy numbers, as in Figures. 2 and 3. The importance weight of each criterion can be by either directly assigning or indirectly using pair wise comparison (Cook, 1992).

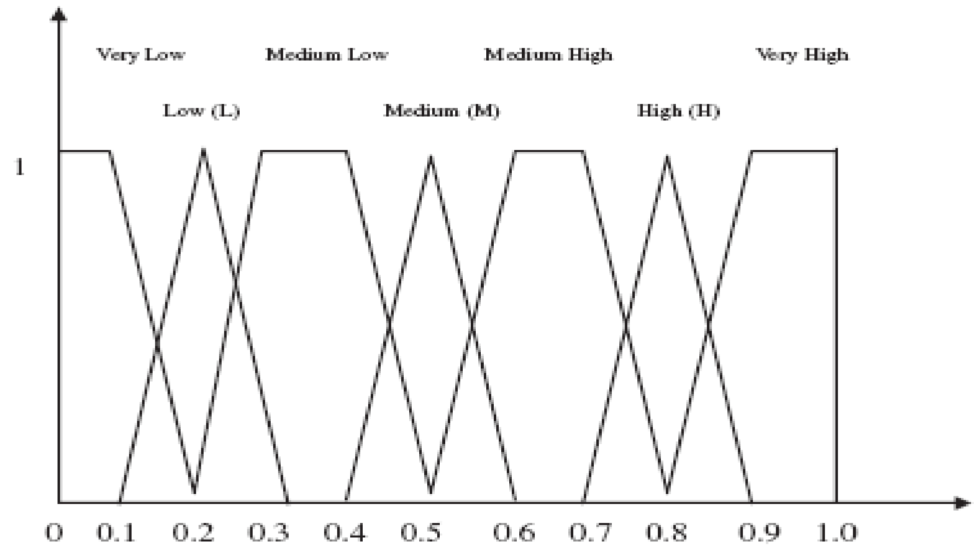

Figure 2. Importance variable weight of each criterion

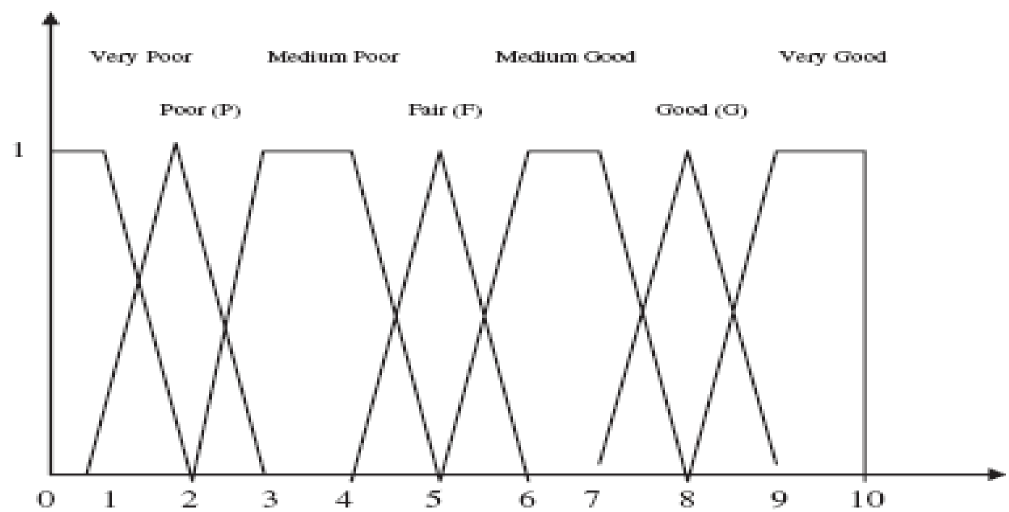

Figure 3. Rating variable of each returned product

Fig. 2 and 3 shows the evaluation of the importance weights of the product take back criteria and the ratings of reverse manufacturing alternatives with respect to product take back criteria. For example, the linguistic variable "Medium High (MH)' showing the weight of each given criteria' can be represented as (0.5, 0.6, 0.7, 0.8), the membership function of which is represented as

$$\mu_{MH}(x) = \begin{bmatrix} 0, & x < 0.5, \\ (x-0.5)/(06-0.5), & 0.5 \le x \le 0.6, \\ 1, & 0.6 \le x \le 0.7, \\ (x-0.8)/(0.7-0.8), & 0.7 \le x \le 0.8, \\ 0, & x > 0.8 \end{bmatrix}$$

Similarly, linguistic ratings by the experts describing criteria with respect to alternatives can be described as ''Very Good (VG)'' in the range of (8, 9, 9, 10), the membership function of which is

$$\mu_{VG}(x) = \begin{bmatrix} 0, & x < 8, \\ (x-8)/(9-8), & 8 \le x \le 9, \\ 1, & 9 \le x \le 10 \end{bmatrix}$$

Here, in this case of selecting reverse manufacturing alternative can be considered as a group multiple-criteria decision-making (GMCDM) problem, which may be described by means of the following sets:

i. a set of N decision makers (management experts or sortation specialists) called $P = \{P_1, P_2........P_N\}$;
ii. a set of n possible alternatives for reverse manufacturing called $R = \{R_{1,}, R_2......R_n\}$;
iii. a set of criteria for which products are taken back $C = \{C_{1,}, C_2........C_f\}$, with which performance of reverse manufacturing function can be assessed;
iv. a set of performance ratings of alternative $R_i(i = 1,2,....n)$, with respect to criteria $C_j(j = 1,2,.....f)$,called $X = \{x_{ij}, i = 1.2.......n, j = 1,2,......f\}$

Assume that there are "N" decisions makers are returned at various level of management, and the fuzzy rating of them $P_n(n = 1,2,3....N)$ can be represented as a positive trapezoidal fuzzy number $\tilde{F}_n(n = 1,2,....N)$ with membership function $\mu_{\tilde{F}n}(x)$. A good aggregation method should be considered for the range of fuzzy ratings of each returned product. It means that the range of aggregated fuzzy rating must include the ranges of all the evaluator's fuzzy ratings. Let the fuzzy ratings of all evaluation experts or sortation specialists be trapezoidal fuzzy numbers $\tilde{F}_n = (a_n, b_n, c_n, d_n)$, n=1, 2….N. Then the aggregated fuzzy rating can be defined as $\tilde{F} = (a, b, c, d)$, n=1, 2...N.

Here

$$a = \min\{a_n), b = \frac{1}{N}\sum_{n=1}^{N} b_n$$

$$c = \frac{1}{N}\sum_{n=1}^{N} c_n, d = \max_n\{d_{n\}}$$

Let the fuzzy rating and importance weight of the N[th] sortation specialists be $\tilde{x}_{ijn} = (a_{ijn}, b_{ijn}, c_{ijn}, d_{ijn})$ and $\tilde{w}_{jn} = (w_{jn1}, w_{jn2}, w_{jn3}, w_{jn4})$; i=1, 2 …n, and j=1.2……..f respectively. Hence the aggregated fuzzy ratings $(\tilde{x}_{ij})$ of alternatives with respect to each criterion can be calculated.

As stated above, a supplier-selection problem can be concisely expressed in matrix format as follows:

$$\tilde{P} = \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots\dots\dots \tilde{x}_{1f} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots\dots \tilde{x}_{2f} \\ & & \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \dots\dots\dots \tilde{x}_{nf} \end{pmatrix}$$

$$\tilde{W} = (\tilde{w}_1, \tilde{w}_2, \tilde{w}_3, \tilde{w}_n)$$

Where $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij})$ and $\tilde{w}_j = (w_{j1}, w_{j2}, w_{j3}, w_{j4})$

Here i=1, 2 ….n, j=1, 2...f can be approximated by positive trapezoidal fuzzy numbers. To avoid complexity of mathematical operations in a decision process, the linear scale transformation is used here to convert the various criteria scales into comparable scales.

The set of criteria can be divided into benefit criteria (the larger the rating, the greater the preference) and cost criteria (the smaller the rating, the greater the preference). Therefore, the normalized fuzzy-decision matrix can be represented as

$$\tilde{F} = [\tilde{F}_{ij}]_{m*n}$$

Where B and C are the sets of benefit criteria and cost criteria, respectively, and

$$d_j^* = \max_i (d_{ij}), j \in B$$

$$a_j^- = \min_i (a_{ij}), j \in C$$

The normalization is done to preserve the property in which the elements $NFD_{ij}, \forall i, j$ are standardized (normalized) trapezoidal fuzzy numbers. Considering the different importance of each take back criterion, the weighted normalized fuzzy-decision matrix is constructed as

$$\tilde{N}_{FD} = [\tilde{N}_{FD}]_{n*f}$$

i=1, 2…….n, &j=1, 2.........f.

Where $\tilde{N}_{FD} = \tilde{F}_{ij}(.)\tilde{w}_{ij}$

According to the weighted normalized fuzzy decision matrix, Normalized positive Trapezoidal Fuzzy Numbers can also approximate the elements $NFD_{ij}, \forall i, j$ .Then, the fuzzy positive-ideal solution (FPIS, R^*) and fuzzy negative-ideal solution (FNIS, R^-) can be defined as

$$R^* = (\tilde{n}_1^*, \tilde{n}_2^* \dots\dots\dots \tilde{n}_n^*) \ \& \ R^- = (\tilde{n}_1^-, \tilde{n}_2^- \dots\dots\dots \tilde{n}_n^-)$$

Where, $n^*_{fd} = \max\{n_{fd4}\}$ & $n^-_{fd} = \min\{n_{fd1}\}$

i=1, 2………n

j=1, 2…….f

The distance of each alternative from R^* and R^- can be currently calculated as

$$d_i^* = \sum_{j=1}^{n} d_v(nfd_{ij}, nfd_j^*), i = 1,2,\dots\dots n \ \& \ d_i^- = \sum_{j=1}^{n} d_v(nfd_{ij}, nfd_j^*), i = 1,2,\dots\dots f$$

Here $d_v(.,.)$ is the distance measurement between two fuzzy numbers.

Based on the distance measurement a closeness coefficient is defined to determine the ranking order of all possible reverse manufacturing alternatives, once d^*i and d^-i of each alternative $R_i (i = 1,2......n)$ has been calculated. The closeness coefficient represents the distances of the ranking to the fuzzy positive-ideal solution (R^*) and the fuzzy negative-ideal solution (R^-) simultaneously by taking the relative closeness to the fuzzy positive-ideal solution. The closeness coefficient (CCi) of each reverse manufacturing alternative is calculated as

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-}, i = 1,2,........ n$$

It is clear that CCi =1 if $R_i = R^*$ and CCi =0 if $R_i = R^-$ In other words, alternative Ri is closer to the FPIS (R*) and farther from FNIS (R^*) as CCi approaches to 1. According to the descending order of CCi, we can determine the ranking order of all reverse manufacturing options and select the most feasible alternative. Although we can determine the ranking order of all feasible alternatives, a more realistic approach may be to use a linguistic variable to describe the current assessment status of each returned product in accordance with its closeness coefficient. In order to describe the assessment of an alternative, we divide the interval [0, 1] into five sub-intervals. Five linguistic variables with respect to the sub-intervals are defined to divide the assessment status of products into five ranks. The decision rules of these ranking are shown below.

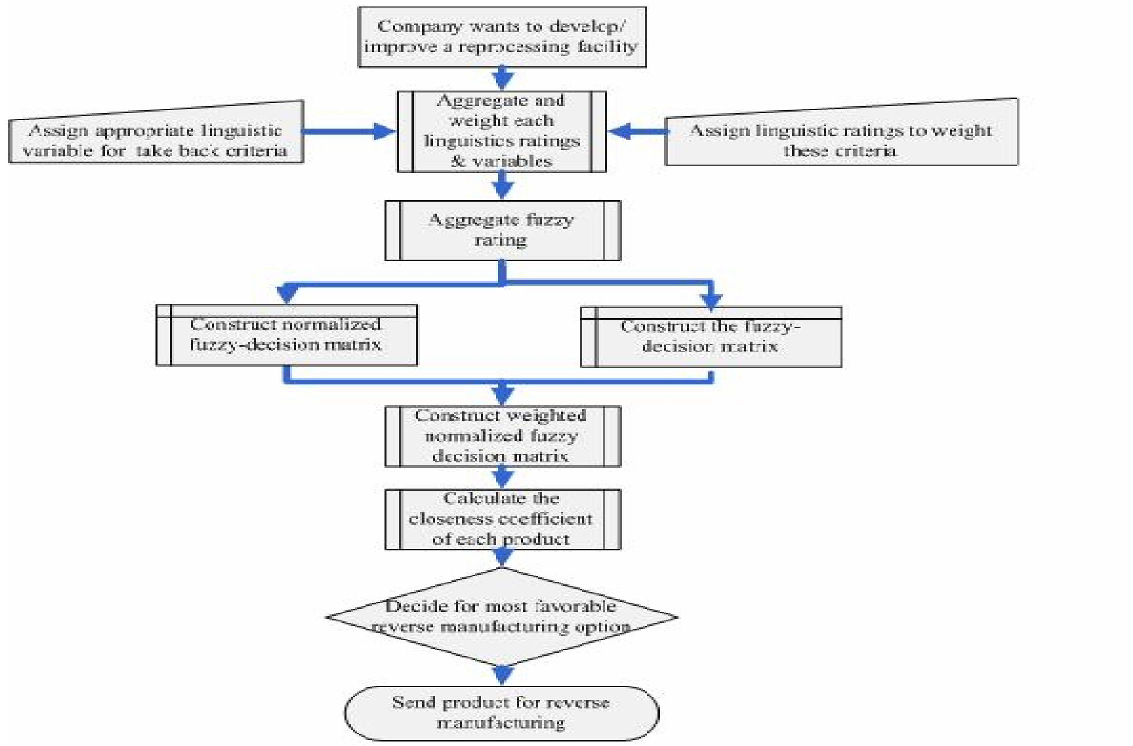

Figure 4. Algorithm of fuzzy decision-making used for alternative selection

- Company wants to develop a new reprocessing activity or improve the already existing facility.
- Identify the quantitative and qualitative criteria.
- An appropriate linguistic variable for product take back criteria and the linguistic weights of ratings is assigned for each criterion.
- Aggregate the weight of criteria to get the aggregated fuzzy weight $\tilde{w}_j$ of criterion Cj, and pool the evaluator's ratings of returned products to get the aggregated fuzzy rating $\tilde{x}_{ij}$ of each reverse manufacturing alternative Ri under criterion Cj.
- Construct the fuzzy-decision matrix and the normalized fuzzy-decision matrix.
- Construct weighted normalized fuzzy decision matrix.
- Calculate the closeness coefficient of each product .
- According to the closeness coefficient, we decide for the most favorable reverse manufacturing option.

4. A Case Example for Proposed Algorithm

Here we present a case of an OEM (Original Equipment Manufacturing) company manufacturing high value and medium volume products (brown goods) .This Company is looking forward to involve itself in product returns due to various internal and external environment demands. This company can get returns both from the end user (consumer) or the commercial returns from various nodes of forward supply chain.

For identifying the most favorable reprocessing alternative they form team experts (decision makers) from various levels of management having good knowledge forward and return supply chain process were chosen. These experts identify following criterion based on maturity of their knowledge as cost/time (C1), environmental impact (C2), market factor (C3), quality factor (C4), legislative impact (C5) etc. These criteria are weighted considering their sub criteria as shown in 5.

The evaluations are carried out using the linguistic variables in terms of very good, good, medium good etc. The hierarchical structure of this decision problem has already been shown in Fig. 5. The most suitable alternative to reprocess the returned products can be judged by the experts P_1; P_2 P_3, and P_n on the basis of these linguistic ratings and proposed method can be applied, using the computational algorithm of which can be summarized as follows:

Step 1: Specialists/Experts/Decision makers use the linguistic weighting variables to assess the importance of the criteria with respect as given in Table 2.

Table 2. Importance weight of criteria from n decision makers

Criteria	Importance of Each Criteria with respect to Returned Product			
	P_1	P_2	P_3	P_n
Cost/Time	VH	VH	VH	VH
Environmental impact	VH	H	H	H
Market factor	VH	VH	H	MH
Quality Factor	MH	H	H	H
Legislative factor	H	H	H	H

Table 3. Linguistic ratings for five reverse manufacturing alternatives under various criteria.

Criteria	Reverse Manufacturing Alternatives	Ratings by Experts			
		P_1	P_2	P_3	P_n
Cost/Time (C1)	Remanufacturing R_1	MP	MP	MF	MG
	Reselling R_2	MF	MG	MG	MG
	Repairing R_3	F	MG	G	G
	Cannibalization R_4	F	MG	MG	G
	Refurbishing R_5	MP	F	F	G
Environmental impact (C2)	Remanufacturing R_1	MF	MG	G	G
	Reselling R_2	MG	G	G	VG
	Repairing R_3	F	G	VG	VG
	Cannibalization R_4	MP	MG	MG	G
	Refurbishing R_5	MP	MG	G	VG
Market Factor (C3)	Remanufacturing R_1	MP	MG	MG	G
	Reselling R_2	F	G	VG	VG
	Repairing R_3	F	MG	G	G
	Cannibalization R_4	F	MG	G	G
	Refurbishing R_5	F	MG	G	G
Quality Factor (C4)	Remanufacturing R_1	F	MG	G	G
	Reselling R_2	MP	G	G	G
	Repairing R_3	F	MG	MG	G
	Cannibalization R_4	MP	MG	G	G
	Refurbishing R_5	MP	MG	G	G
Legislative impact (C5)	Remanufacturing R_1	MP	MG	G	G
	Reselling R_2	MP	MG	G	G
	Repairing R_3	F	MG	G	VG
	Cannibalization R_4	MP	MG	G	VG
	Refurbishing R_5	F	MG	G	VG

Step 2: Here experts uses the linguistic rating variables to evaluate the each alternative as shown in Fig. 3 with respect to given criterion.

The linguistic ratings of the reprocessing alternatives by the sortation specialists under the various criteria are shown in Table 3.

Table 4. Normalized fuzzy-decision matrix and weight of five candidates

	Cost/Time Factor (C1)	Environmental impact (C2)	Market Factor (C3)	Quality Factor (C4)	Legislative impact (C5)
Remanufacturing R_1	(0.4,0.40,0.55,0.70)	(0.40,0.65,0.80,1)	(0.45,0.70,0.80,0.90)	(0.5 ,0.6,0.60,0.80)	(0. 8,0.8,0.82,1)
Reselling R_2	(0.45,0.65,0.65,0.80)	(0.60,0.80,0.80,1)	(0.50,0.70,1,1)	(0.40,0.60,0.8,0.80)	(0.4,0.7,0.80,1)
Repairing R_3	(0.45,0.7,0.70,0.93)	(0.55,0.70,0.90,1)	(0.50,0.70,0.80,0.90)	(0.5,0.60,0.7,0.80)	(0.5,0.65,0.80,1)
Cannibalization R_4	(0.40,0.65,0.65,0.80)	(0.40,0.60,0.7,0.9)	(0.5,0.70,0.80,0.90)	(0. 5,0.5,0.5,0.5)	(0.40,0.60,0.80,1)
Refurbishing R_5	(0.35,0.45,0.55,0.70)	(0.44,0.63,0.70,0.9)	(0.5,0.7,0.80,0.90)	(0.40,0.65,0.65,0.5)	(0.5,0.60,0.80,1)
Weight	(1,1,1,1)	(1,0.8,0.8,0.8)	(1,1,0.8,0.65)	(0.65,0.8,0.8,0..8)	(0.8,0.8,0.8,0.8)

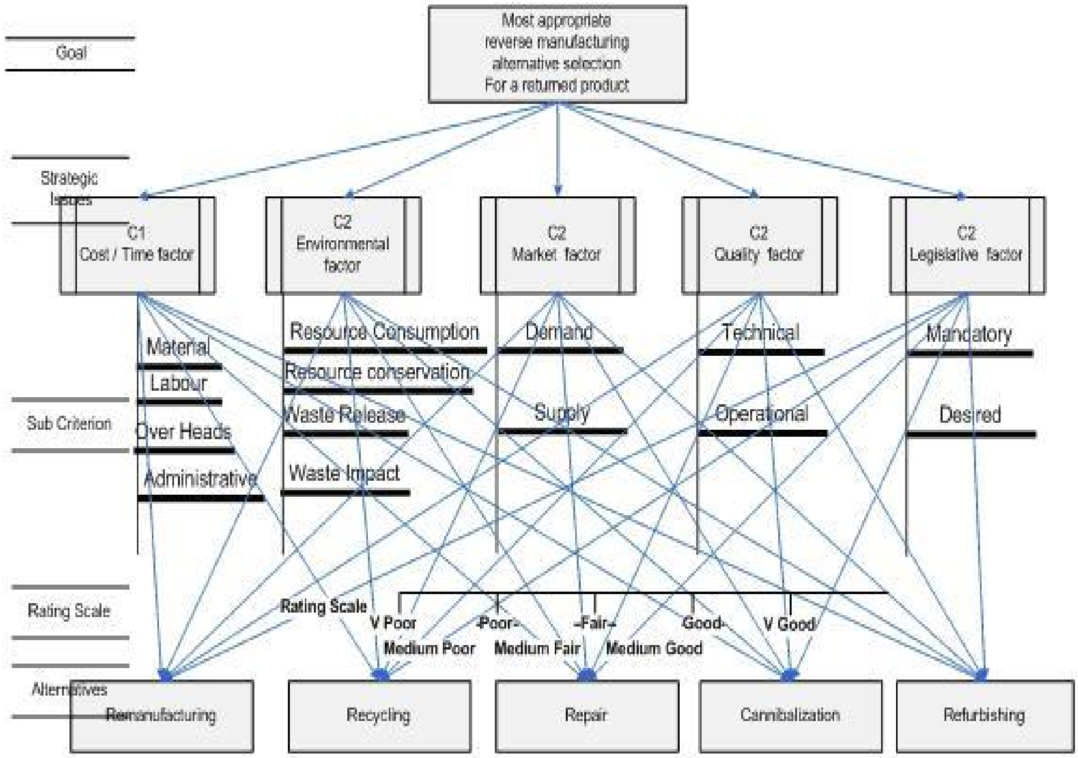

Figure 5. Hierarchical structure of alternative selection in reverse logistics system

Step 3: Then the linguistic evaluations shown in Tables 3 are used to determine weighted normalized fuzzy-decision matrix of each criterion with respect to alternatives available for reprocessing as shown in table 4.

Table 5. Weighted fuzzy-decision matrix of each criterion w.r.t alternatives

	Cost/Time Factor (C1)	Environmental impact (C2)	Market Factor (C3)	Quality Factor (C4)	Legislative impact (C5)
Remanufacturing R_1	(0.4,0.40,0.55,0.70)	(0.40,0.54,0.64,1)	(0.45,0.70,0.64,0.54)	(0.35,0.54,0.56,0.64)	(0. 64,0.64,0.64,0.8)
Reselling R_2	(0.45,0.65,0.65,0.80)	(0.60,0.64,0.64,1)	(0.50,0.70,0.8,.65)	(0.25,0.54,0.64,0.64)	(0.32,0.56,0.64,0.8)
Repairing R_3	(0.45,0.7,0.70,0.93)	(0.55,0.56,0.72,1)	(0.50,0.70,0.64,0.54)	(0.35,0.54,0.56,0.64)	(0.40,0.56,0.64,0.8)
Cannibalization R_4	(0.40,0.65,0.65,0.80)	(0.40,0.50,0.56,0.9)	(0.5,0.70,0.64,0.54)	(0. 30,0.40,0.40,0.4)	(0.32,0.56,0.64,0.8)
Refurbishing R_5	(0.35,0.45,0.55,0.70)	(0.44,0.6,0.56,0.9)	(0.5,0.7,0.64,0..54)	(0.25,0.48,0.48,0.4)	(0.40,0.48,0.64,0.8)

Step 4: Calculate the closeness coefficient of each criteria w.r.t to reverse manufacturing alternatives as

$$CC_1 = 0.56, CC_2 = 0.67, CC_3 = 0.63$$

$$CC_4 = 0.51, CC_5 = 0.43$$

Step 5: According to the closeness coefficients of the five alternatives and the approval status level we categorize them say Reselling (R2) and Repairing (R3) belong to Rank IV, the assessment status of which is ‘‘Approved’’. Alternatives Remanufacturing (R1), Cannibalization (R4) and Refurbishing (R5) belong to Rank III. This means that their assessment status is ‘‘Recommend with low risk’’. However, according to the closeness coefficients, Reselling (R2) is preferred to Repairing (R3) because CC2>CC3 in Rank IV. In Rank III, the preferred order alternatives is R4>R1>R5 because CC4>CC1>CC5. Finally, the ranking order of five alternatives for a set of prescribed criteria is Reselling>Repairing>Cannibalization>Remanufacturing>Refurbishing.

Obviously, the results of ranking order are identical when the different membership functions of linguistic variables are used in the proposed method. Later model was checked to ensure that the results reflected are happening in the real world and reasonable solutions are produced. Validating data and comparison of model results with the judgments of the experts of an OEM shows that the sample results found match to the expectations in most instances. Therefore model was examined observing its effect on the decision-making process in reverse manufacturing alternative selection. The approach follows a systematic decision-making process, which, according to involves "intelligence," "design," and "flexibility". The experience of decision makers and experts demonstrate that the developed model was very useful in strategic decision making and reprocessing facilities can well be chosen. This decision support model can help managers to developing flexible policy for returns and develop facilities for the best alternative selected.

5. Computer Based Implementation of Decision Model

The comprehensiveness of this model and the data requirements with the attendant calculations and analysis make the application of the methodology tedious. With the use of computer application we can not only quicken the implementation of this model but also facilitate easy and fine presentation of the implementation results. This model can be easily implemented on a computer by using any of the windows application such as Visual Basic, Visual C++ and others. The prototype program developed can later be upgraded to a decision support tool for reverse enterprise systems. Further, we can develop a demonstrative computer prototype that also assesses other criteria and sub-criteria.

6. Conclusion

Reverse manufacturing alternative selection problems adhere to tentative, complex and imprecise data, for which fuzzy-set theory is found to be adequate. In other words, in assessing possible reverse manufacturing alternative with respect to criteria and importance weights, it is appropriate to use linguistic variables instead of numerical values. Due to the expert’s experience, feel, and subjective estimates that often appear in the process of alternative selection problem, a fuzzy environment is proposed in this paper. In fact, the proposed method is very flexible and provides more objective information for reverse manufacturing alternative selection in a reverse logistics system. The framework proposed in this paper can be further applied to other management decision problems and developing a group decision support system.

REFERENCES

1. CARTER, C., ELLRAM, L., **Reverse Logistics: A Review of Literature and Framework for Future Investigation**, Journal of Business Logistics, 19, 1998, pp. 85-102.

2. CHEN, S.-J., HWANG, C.-L., **Fuzzy Multiple Attribute Decision Making**, Methods and Applications. Springer Verlag, 1992.

3. COOK, R. L., **Expert Systems in Purchasing Applications and Development**, International Journal of Purchasing and Management 18, 1992, pp. 20–27.

4. CRAMER J., **Pros and Cons of Optimizing the Life of Consumer Electronics Products**, In: De Ron A, Douwe-Flapper S, editors. Proc. Ist Int. Workshop on Reuse, Eindhoven, The Netherlands, 1996; pp. 73-84.

5. DELGADO, M., HERRERA, F., HERRERA-VIEDMA, E., MARTINEZ, L., **Combining Numerical and Linguistic Information in Group Decision Making,** Journal of Information Sciences 107, 1998, pp. 177–194.

6. DOWLATSHAHI, S., **Developing a Theory of Rev. Logistics. Interfaces**, 30(3), 2000, pp. 143-155.

7. FLEISCHMANN, M., **Quantitative Models for Rev Logistics**, Springer, Berlin, Germany, 2001.

8. GUIDE, V., SRIVASTAVA, R., **Inventory Buffers in Recoverable Manufacturing**, Journal of Operations Management, 16(5), 1998, pp. 551-568.

9. GUIDE, V. D. R, JAYARAMAN. V, SRIVASTAVA R, W. C. BENTON, **Supply-chain Management for Recoverable Manufacturing Systems**, Interfaces 30 (3), 2000, pp. 125–142.

10. GUIDE, JR., V.D.R., **Production Planning and Control for Re-manufacturing: Industry Practice and Research Needs**, Journal of Operations Management, 18, 2000, pp. 467–483.

11. HERRERA, F., HERRERA-VIEDMA, E., **Linguistic Decision Analysis: Steps for Solving Decision Problems under Linguistic Information,** Fuzzy Sets and Systems 115, 2000, pp. 67–82.

12. HERRERA, F., HERRERA-VIEDMA, E., VERDEGAY, J.L., **A Model of Consensus in Group Decision Making under Linguistic Assessments,** Fuzzy Sets and Systems 78, 1996, pp. 73–87.

13. HWANG, C. L., YOON. K., **Multiple Attribute Decision Making – Methods and Applications: A State of the Art Survey**, Springer-Verlag, 1981.

14. INDERFURTH, K., **Simple Optimal Replenishment and Disposal Policies for a Product Recovery System with Lead Times**, OR Spektrum, 19, 1997, pp. 111-122.

15. KOPICKI, R., BERG, M., LEGG, L., DASAPPA, V., MAGGIONI, C., **Reuse and Recycling Reverse Logistics Opportunities**, Council of Logistics Mngt, Oak Brook, IL, 1993.

16. KRIKKE, H., **Recovery Strategies and Reverse Network Design**, PhD thesis, Institute of Business Engineering and Technology Application (BETA), Universiteit Twente, The Netherlands, 1998.

17. LOW, M, WILLIAMS D., DIXON C., **The Economics of End-of-Life Management Strategy Choice: Routes to Revenue Generation from Mature Products**, IEEE, Int. Symp. Electronics and the Environment, IEEE; 1997, pp. 291-6.

18. MURPHY, P. R., POIST, R.F., **Green Logistics Strategies: An Analysis of Usage Patterns**, Transportation Journal, 40 (2), 2000, pp. 5-16.

19. Reverse Logistics Executive Council. http://www.unr.edu/coba/logis as accessed on 2 November 2006.

20. ROGERS, D., LAMBERT, D., CROXTON, K., GARCIA-DASTUGUE, S., **The Returns Management Process**, The International Journal of Logistics Management, 13, 2002, pp. 1-17.

21. ROGERS, D. S., TIBBEN-LEMBKE, R. S., **Going Backwards: R L Trends & Practices**, Reverse Logistics Executive Council, Pittsburgh, P.A, 1999.

22. STOCK, J., **Development and Implementation of Reverse Logistics Programs Council of Logistics Management**, Oak Brook, IL, 1998.

23. THIERRY, M., SALOMON, M., NUNNEN, J., WASSENHOVE, L., **Strategic Issues in Product Recovery Management,** California Management Review, 1995, Winter, 37(2), 1995, pp. 114-135.

24. WADHWA, S., BROWNE, J., **Modeling FMS with Decision Petri Nets**, International Journal of Flexible Manufacturing Systems, 1, 1989, pp. 253-280.

25. WADHWA, S., RAO K. S., **Framework for a Flexibility Maturity Model**, Global J. Flex. Syst. Manage, 3, 2002, pp. 45–55.

26. WADHWA, S., MADAAN J., **Role of Quality Management (EFQM) Model for Reverse Logistics and GP: A KM View**, ICQCC, International Convention on Quality Control Circles, Bangkok, 2004 a.

27. WADHWA, S., MADAAN J., **Reverse Enterprise System: Evolving Perspective**, Third Global Conference on Flexible System Management, New Delhi, 2004 b.

28. WADHWA, S., K. S. RAO, F. T. S. CHAN, **Comparative Influence of Three Flexibility Types on Manufacturing Lead-time Performance**, International Journal of Advanced Manufacturing Technology, 29(9-10), 2006, pp. 1002-1007.