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PERFORMANCE APPRAISAL OF REVERSE LOGISTICS USING INTERVAL-VALUED FUZZY NUMBERS SET

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ABSTRACT

Reverse logistics (RL) is the process of moving goods from their typical final destination for the purpose of capturing value, or proper disposal. Reverse logistics also includes processing returned merchandise due to damage, seasonal inventory, restock, salvage, recalls, and excess inventory. It also includes recycling programs, hazardous material programs, obsolete equipment disposition, and asset recovery. In relation to reverse supply chain management, reverse logistics performance appraisal is highly essential. To this end, the present paper presents a fuzzy based RL performance appraisal platform, applied in a case study. Interval-Valued Fuzzy Numbers Set (IVFNS) has been explored here to facilitate such a decision-modeling.

Keywords: Reverse Logistics and Interval-Valued (IV) Fuzzy Numbers Set.

1. Introduction

Reverse Logistics 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. Organizations that implement reverse logistics are able to improve customer service and response times; reduce environmental impact by reducing waste and improve overall corporate citizenship. Reconditioning, refurbishing, remanufacturing, reselling, recycling and cannibalization etc may be considered as reverse logistics alternatives.

Enterprises around the world are employing reverse supply chain practices to overcome the regulations and generate profit making opportunities. As a result of the rapid progress in technology the product lifecycles are shrinking faster than ever. In the face of global competition, heightened environmental regulations and a wealth of additional profits and improved corporate image opportunities, performing the reverse supply chain operations at a world class level is becoming quintessential. These factors in addition to the inherent complexity of reverse supply chains due to the uncertainties associated with the quantity, quality, and timing of returns make returns management all the more complicated. Existing literature on reverse supply chains focuses on how organizations are effectively using reverse logistics practices to sustain competition and how to optimize the overall reverse supply chain, but there is little investigation into how organizations are able to evaluate their reverse supply chain operations [1]. The growing environmental concern worldwide, forced companies to engage in reverse logistics, such as re-use of products and materials, and recycling. Practically, most of the companies deal with returns of some nature because of issues such as marketing returns, damage or quality problems, overstocks, refurbishing, or remanufacturing. Handling returns present a great challenge for companies, while in many cases becomes a necessity for keeping customers' satisfaction to a certain level. Reverse logistics operations in a supply chain may be considered as an introduction to innovative services of a company's portfolio. They may have an important impact on a firm's strategic performance in terms of market effectiveness, as well as, internal cost efficiency. Through reverse logistics innovation, it may be possible to expand revenue through market growth due to account customization, service augmentation, and improved customer satisfaction. Reverse logistics is becoming an area of competitive advantage [2].

Trappey et al. [3] proposed a decision support model that integrated fuzzy cognitive maps trained using a genetic algorithm for Evaluation of RFID-based Reverse Logistics Services.Gülfem et al. [4] proposed a multi-objective model for the reverse logistics network design (RLND) problem. The proposed methodology was comprised of two stages: the centralized return centre (CRC) evaluation stage and the reverse logistics network design (RLND) stage. In the first stage an integrated ANP and fuzzy-TOPSIS methodology was utilized. In the second stage, using the CRC weights obtained in the first stage, the RLND model was solved

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via genetic algorithms (GAs). Olugu and Wong [5] adopted a fuzzy based approach applicable in evaluating the reverse logistics performance of the automotive industry. Geethan et al. [6] developed a Performance Evaluation Analytic for Reverse Logistics Methodology to facilitate decision making from the perspective of an enterprise engaged in reverse logistics. It explored the various reverse logistics functions and product lifecycle stages. It also developed some key business strategies and performance metrics that could be effectively employed to be successful in returns handling.

In reverse supply chain management, performance evaluation of reverse logistics has gained vital importance in today's global competitive marketplace. There are a number of mutually correlated performance measures and metrics (also called capabilities-attributes and criterions) which in turn influence the overall RL performance index. Most of the performance estimates being subjective in nature, expert opinion is indeed essential to facilitate such a decision-cum-appraisement modeling. Fuzzy logic has been found fruitful in dealing with linguistic evaluation of the decision-makers in relation to appropriateness towards performance as well as importance weights of each of the RL metrics. Compared to generalized positive fuzzy numbers (trapezoidal or triangular), it has been viewed that Interval-Valued Fuzzy Numbers (IVFN) can provide more reliable decision-evaluation result. Therefore, present analysis has explored Interval-Valued Fuzzy Numbers (IVFN) [7-11] followed by a decision-cum evaluation hierarchy to estimate the extent of RL performance practices of a particular industry at eastern part of India.

2. Proposed Evaluation Model: Case Study

When something is vague, using type-1 fuzzy sets, which represent uncertainty by numbers in the range (0, 1), makes more sense than using conventional sets. However, it may not be practical to use an accurate membership function for something that is not only uncertain but also complex (Sepulveda et al., 2007). The concept of type-2 fuzzy sets has thus been proposed by Zadeh (1975), which may better handle linguistic uncertainties in complex situations. In fuzzy set theory, an expert often find it difficult to identify the opinion as a number in interval (0, 1). Therefore, to represent the degree of certainty of opinions by an interval is more proper for the real world that is the characteristic of IVFNs. therefore, present analysis has explored Interval-Valued Fuzzy Numbers (IVFN) to estimate the extent of RL performance practices.

Wang and Li [7] defined IVFNs and presented their extended operational rules. From [7-10], the trapezoidal IVFN $\overset{\approx}{A}$, can be represented by $\overset{\approx}{A} = \left[\overset{\approx}{A}^{L}, \overset{\approx}{A}^{U}\right]$

$= \left[\left(a_1^L, a_2^L, a_3^L, a_4^L; w_{\overset{\approx}{A}}^L\right), \left(a_1^U, a_2^U, a_3^U, a_4^U; w_{\overset{\approx}{A}}^U\right)\right]$,

Here $a_1^L \le a_2^L \le a_3^L \le a_4^L$, $a_1^U \le a_2^U \le a_3^U \le a_4^U$, $\overset{\approx}{A}^{L}$ denotes the lower IVFN, $\overset{\approx}{A}^{U}$ denotes the upper IVFN, and $\overset{\approx}{A}^{L} \subset \overset{\approx}{A}^{U}$, as shown in Figure 1.

Assume that there are two IVFNs $\overset{\approx}{A}$ and $\overset{\approx}{B}$, where;

$$\overset{\approx}{A} = \left[\overset{\approx}{A}^{L}, \overset{\approx}{A}^{U}\right] = \begin{bmatrix} \left(a_1^L, a_2^L, a_3^L, a_4^L; w_{\overset{\approx}{A}}^L\right), \\ \left(a_1^U, a_2^U, a_3^U, a_4^U; w_{\overset{\approx}{A}}^U\right) \end{bmatrix}, \text{ and}$$

$$\overset{\approx}{B} = \left[\overset{\approx}{B}^{L}, \overset{\approx}{B}^{U}\right] = \begin{bmatrix} \left(b_1^L, b_2^L, b_3^L, b_4^L; w_{\overset{\approx}{B}}^L\right), \\ \left(b_1^U, b_2^U, b_3^U, b_4^U; w_{\overset{\approx}{B}}^U\right) \end{bmatrix},$$

$0 \le w_{\overset{\approx}{A}}^L \le w_{\overset{\approx}{A}}^U \le 1$, $\overset{\approx}{A}^{L} \subset \overset{\approx}{A}^{U}$, $0 \le w_{\overset{\approx}{B}}^L \le w_{\overset{\approx}{B}}^U \le 1$, and $\overset{\approx}{B}^{L} \subset \overset{\approx}{B}^{U}$.

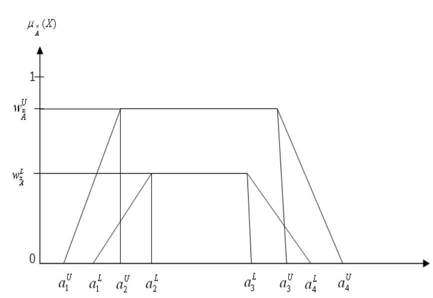

Fig. 1 An Interval-Valued Trapezoidal Fuzzy Number

The reverse logistics performance evaluation index platform adapted in this paper has been shown in Table 1 [5]. The 2-level hierarchical model consists of various indices: measures and metrics. Supplier Commitment (SC), Customer Involvement (CI), Management Commitment (MC), Material Features (MF), Recycling Efficiency (RE) and Recycling Cost (RC) have been considered as the 1st level indices (called measures) followed by 2nd level indices which encompass a number of reverse logistics metrics. An approach based on Interval-Valued Fuzzy Numbers Set (IVFNS) has been used to evaluate an overall performance index. This method has been found fruitful for solving the group decision-making problem under uncertain environment due to vagueness, inconsistency and incompleteness associated with decision-makers' subjective evaluation. The proposed evaluation index platform has been explored by the reverse supply chain of an Indian automobile part manufacturing company at eastern part of India. The analysis has been carried out using numerical illustrations on a case study presented as follows.

Table 1: Conceptual Model for Leanness Assessment

Goal	Measures (1st level indices)	Metrics (2nd level indices)
Reverse logistics perfor-mance	Supplier Commitment (SC)	Extent of delivery from suppliers back to manufactures (SC_1)
		Level of certification of suppliers(SC_2)
		Number of supplier initiatives in recycling (SC_3)
	Customer Involvement (CI)	Level of customer co-operation in returning ELVs (CI_1)
		Level of customer dissemination of information (CI_2)
		Level of understanding of reverse logistics (CI_3)
	Management Commitment (MC)	Level of management motivation to customers for returning their ELVs (MC_1)
		Availability of a standard procedure (MC_2)
		Availability of a waste management scheme (MC_3)
	Material Features (MF)	Level of waste generated (MF_1)
		Ratio of materials recycled to recyclables (MF_2)
		Material recovery time (MF_3)
	Recycling Efficiency (RE)	Percent Decrease in recycling time (RE_1)
		Availability of a recycling standard (RE_2)
		Percent Reduction in emission and waste (RE_3)
	Recycling Cost (RC)	Cost associated with returning ELVs (RC_1)
		Cost associated with processing recyclables (RC_2)
		Cost of disposal for unprocessed waste (RC_3)

In this paper, the priority weights against performance measures-metrics and corresponding appropriateness ratings have been considered as linguistic variables which have been further transformed into IV-trapezoidal fuzzy numbers. Here, these linguistic variables corresponding to weight assignment of various performance measures-metrics (both in 1st and 2nd level) has been expressed in fuzzy numbers by 1-9 scale as shown in Table 2. Similarly, the fuzzy performance ratings of individual reverse logistics metrics in 2nd level have also been expressed in fuzzy numbers by 1-9 scale shown in Table 2. The procedural steps and its implementation results have been summarized as follows.

Table 2: Linguistic Variables (A-9 Member Interval Linguistic Term Set)

Linguistic terms for weight assignment	Linguistic terms for ratings	Interval-Valued trapezoidal fuzzy numbers
Absolutely low, AL	Absolutely poor, AP	[(0.0, 0.0, 0.0, 0.0; 1.0), (0.0, 0.0, 0.0, 0.0; 1.0)]
Very low, VL	Very poor, VP	[(0.0075, 0.0075, 0.015, 0.0525; 0.5), (0.0, 0.0, 0.02, 0.07; 1.0)]
Low, L	Poor, P	[(0.0875, 0.12, 0.16, 0.1825; 0.5), (0.04, 0.10, 0.18, 0.23; 1.0)]
Fairly low, FL	Fairly poor, FP	[(0.2325, 0.255, 0.325, 0.3575; 0.5), (0.17, 0.22, 0.36, 0.42; 1.0)]
Medium, M	Medium, M	[(0.4025, 0.4525, 0.5375, 0.5676; 0.5), (0.32, 0.41, 0.58, 0.65; 1.0)]
Fairly High, FH	Fairly satisfactory, FS	[(0.65, 0.6725, 0.7575, 0.79; 0.5), (0.58, 0.63, 0.80, 0.86; 1.0)]
High, H	Satisfactory, S	[(0.7825, 0.815, 0.885, 0.9075; 0.5), (0.72, 0.78, 0.92, 0.97; 1.0)]
Very High, VH	Very Impressive, VI	[(0.9475, 0.985, 0.9925, 0.9925; 0.5), (0.93, 0.98, 1.0, 1.0; 1.0)]
Absolutely high, AH	Absolutely impressive, AI	[(1.0, 1.0, 1.0, 1.0; 1.0), (1.0, 1.0, 1.0, 1.0; 1.0)]

Step 1: Measurement of performance ratings and importance weights of measures/metrics using linguistic terms

For evaluating importance weights of various RL measures/metrics, as well as appropriateness rating of RL metrics; a committee of three decision-makers (DMs), DM_1, DM_2, DM_3 has been formed to express their subjective preferences (priority importance) in linguistic terms (Tables 2) which have been further transformed into IV-fuzzy numbers.

After the linguistic variables for assessing the performance ratings and importance weights of various RL indices has been accepted by the decision-makers (DMs), the decision-makers have been asked to use aforesaid linguistic scales to subjective fuzzy priority weight of these indices (both at 1st and 2nd level). Similarly appropriateness ratings of 2nd level indices have been assessed by the DMs (Tables 3-5).

Table 3: Appropriateness Ratings Assigned by DMs

Metrics	Linguistic Rating by DMs		
	DM1	DM2	DM3
(SC_1)	S	FS	S
(SC_2)	VI	VI	AI
(SC_3)	AI	AI	VI
(CI_1)	S	VI	S
(CI_2)	FS	M	M
(CI_3)	FS	S	FS
(MC_1)	VI	S	S
(MC_2)	AI	VI	S
(MC_3)	M	FP	M
(MF_1)	FS	FS	S
(MF_2)	S	S	S
(MF_3)	P	FP	P
(RE_1)	S	S	VI
(RE_2)	M	FS	FS
(RE_3)	M	M	M
(RC_1)	VI	VI	AI
(RC_2)	S	FS	S
(RC_3)	AI	VI	VI

Table 4: Priority Weight (metrics) Assigned by DMs

Metrics	Linguistic Weight assigned by DMs		
	DM1	DM2	DM3
(SC_1)	H	H	VH
(SC_2)	FH	M	FH
(SC_3)	H	VH	VH
(CI_1)	AH	VH	AH
(CI_2)	VH	VH	VH
(CI_3)	FH	H	H
(MC_1)	M	FH	FH
(MC_2)	VH	H	VH
(MC_3)	AH	H	H
(MF_1)	M	FH	FH
(MF_2)	H	H	VH
(MF_3)	FH	H	H
(RE_1)	M	FH	H
(RE_2)	FH	FH	H
(RE_3)	VH	H	AH
(RC_1)	H	H	VH
(RC_2)	FH	FH	H
(RC_3)	H	H	H

Step 2: Approximation of the linguistic terms by IV trapezoidal fuzzy numbers

Using the concept of generalized positive trapezoidal Interval-Valued fuzzy numbers in fuzzy set theory, the linguistic variables have been approximated by fuzzy numbers (as shown in Table 2). Next, based on average rule, the aggregated decision-making cum evaluation matrix has been constructed reflecting pulled opinion of the group of decision-makers. The aggregated fuzzy appropriateness rating against individual 2nd level indices with corresponding importance weight have been computed. Similarly, aggregated fuzzy priority weight of various 1st level indices has also been obtained.

Table 5: Priority Weight (Measures) Assigned by DMs

Measures	Linguistic Weight assigned by DMs		
	DM1	DM2	DM3
(SC)	VH	AH	H
(CI)	VH	H	VH
(MC)	AH	VH	VH
(MF)	H	H	H
(RE)	H	VH	H
(RC)	AH	H	FH

Step 3: Estimation of appraisement index

FPI represents the *Fuzzy Performance Index*. The fuzzy performance index of 1st level RL measures can be calculated as follows:

$$U_i = \frac{\sum_{j=1}^{m}\left(w_{ij} \otimes U_{ij}\right)}{\sum_{j=1}^{n} w_{ij}} \qquad (1)$$

Here U_{ij} represent aggregated performance measure (rating) and w_{ij} represent aggregated fuzzy weight for priority importance corresponding to 2nd level index C_{ij} which is under i_{th} 1st level index C_i. Here, m is the total number of RL metrics.

Thus, overall fuzzy performance index $U(FPI)$ can be obtained as follows.

$$U(FPI) = \frac{\sum_{i=1}^{n}\left(w_i \otimes U_i\right)}{\sum_{i=1}^{n} w_i} \qquad (2)$$

Here U_i = Rating of i^{th} 1st level index C_i; w_i = Weight of i^{th} 1st level index, and $i = 1, 2, 3, ...n$. Here, n is the total number of RL measures.

The FPI thus becomes [(0.575, 0.666, 0.886, 1.007; 0.500), (0.438, 0.574, 1.026, 1.309; 1.000)]. FPI can be compared with predefined performance estimate fuzzy scale set by the management to check the existing performance level for the said supply chain reverse logistics and to seek for week performing areas which need future improvement.

Step 4: Identification of week areas which need future improvement

After evaluating FPI, simultaneously it is also felt indeed necessary to identify and analyze the weak areas towards performance improvement. Fuzzy Performance Importance Index (FPII) may be used to identify these ill-performing areas. FPII combines the performance rating and importance weight of various 2nd level indices. The higher the FPII of a factor, the higher is the contribution. The FPII can be calculated as follows in Eqs. 3-4. The concept of FPII was introduced by Lin et al. [12] for agility extent measurement in supply chain.

$$FPII_{ij} = w'_{ij} \otimes U_{ij} \quad (3)$$

Here, $w'_{ij} = \left[\{(1,1,1,1;1),(1,1,1,1;1)\} - w_{ijk}\right]$ (4)

w_{ij} is the fuzzy importance weight of j_{th} 2nd level index C_{ij} which is under i_{th} 1st level index C_i.

If used directly to calculate the FPII, the importance weights w_{ij} will neutralize the performance ratings in computing FPII; in this case it will become impossible to identify the actual weak areas (low performance rating and high importance). If w_{ij} is high, then the transformation $\left[\{(1,1,1,1;1),(1,1,1,1;1)\} - w_{ijk}\right]$ is low. Consequently, to elicit a factor with low performance rating and high importance, for each 2nd level index C_{ij} (j_{th} 2nd level index under i_{th} 1st level index C_i), the fuzzy performance importance index $FPII_{ij}$, indicating the effect of each 2nd level index that contributes to overall FPI, has been defined as:

$$FPII_{ij} = \left[\{(1,1,1,1;1),(1,1,1,1;1)\} - w_{ijk}\right] \otimes U_{ij} \quad (5)$$

FPII need to be ranked to identify performance level of individual RL metrics. Based on that 2nd level indices have been ranked accordingly and ill-performing metrics have been sorted out. In future, the particular industry should pay attention towards improving those metrics aspects in order to boost up overall RL performance extent.

Fuzzy Performance Importance Index (FPII) has been computed against each of the 2nd level indices. The concept of degree of similarity (between two Interval-Valued fuzzy numbers) has been explored for attribute ranking [11]. In this computation and 'ideal FPII' has been selected as [(0.274, 0.313, 0.399, 0.430; 0.500), (0.200, 0.270, 0.443, 0.507; 1.000)]. FPIIs of individual attributes have been compared with the 'ideal FPII' chosen to estimate degree of similarity. The attributes, whose FPIIs exhibit high degree of similarity as compared with 'ideal FPII'; are said to be contributing more to the FPI. By this way, 2nd level indices have been ranked accordingly (Table 6) and thus, improvement opportunities have been verified.

Table 6: Metrics Ranging based on Degree of Similarity

Metrics	Degree of Similarity Value between $(FPIIs \approx FPII_{Ideal})$	Ranking order for metrics
(SC_1)	0.80079	11
(SC_2)	1.00000	1
(SC_3)	0.77068	12
(CI_1)	0.70830	18
(CI_2)	0.71596	17
(CI_3)	0.85834	7
(MC_1)	0.98567	2
(MC_2)	0.76919	13
(MC_3)	0.75900	14
(MF_1)	0.95562	4
(MF_2)	0.80478	10
(MF_3)	0.75254	15
(RE_1)	0.95571	3
(RE_2)	0.86124	6
(RE_3)	0.74043	16
(RC_1)	0.81177	9
(RC_2)	0.89215	5
(RC_3)	0.85183	8

3. Conclusions

Reverse logistics is the process of moving goods from their typical final destination for the purpose of capturing value, or achieving proper disposal to the satisfaction of the customer or consumer. Remanufacturing and refurbishment activities may be part of the procedure. Reverse logistics includes processing returned merchandise due to damage, seasonal inventory, restock, salvage, recalls, and excess inventory. It also includes recycling programs, hazardous material programs, obsolete equipment disposition, and asset recovery.

In recent years RL has become an important key strategic consideration for the industries and their reverse supply chains. In order to assess existing RL performance extent and to benchmark various industries (in accordance with their present RL practices) a strong performance assessment platform is indeed essential. The present study highlights such an appraisement modeling and successfully implemented in a case study. The main contributions of this research have been documented below.

1. A logical decision support cum appraisement model towards estimating RL performance extent.
2. Exploration to IVFN to support the said decision-modeling.
3. Estimation of an overall performance index of existing RL activities being practiced by the industries.

The proposed appraisement platform is capable of identifying ill-performing areas which seek future improvement.

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