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Full Length Research Paper

Fuzzy logic evaluation of reverse logistics performance in the automotive industry

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This study was aimed at evaluating the performance of the reverse logistics process in the automotive industry. Fuzzy logic was applied in assessing the performance of the reverse logistics process using a case study. Linguistic variables were used to represent the performance of the metrics, and the variables were converted into fuzzy numbers. Fuzzy operators were applied to these numbers to obtain the performance of the measures and the entire process. From the results obtained, it was found that the approach adopted is applicable in evaluating the reverse logistics performance of the automotive industry. Based on this study, managers can assess their reverse logistics processes with ease and identify areas which are deficient, thus improving the overall performance of their reverse logistics. This will in turn support environmental management through waste reduction. In essence, this paper contributes to knowledge in performance measurement at large, thus putting forth a measurement approach for reverse logistics operations in the automotive industry. It also gives guidelines for future research in reverse logistics management.

Key words: Supply chain management, performance evaluation, reverse logistics, fuzzy logic, automotive industry.

INTRODUCTION

Reverse logistics is a process that involves the movement of goods from their typical final destinations which are the customers or end users back to the manufacturers or suppliers, for the purpose of recapturing value through remanufacturing, reuse, refurbishment or recycling, and proper disposal of accrued waste. According to Ilgin and Gupta (2010), reverse logistics encompasses every operation geared towards collection, recovery and/or disposal of end-of-life products. The importance and value attached to reverse logistics stem chiefly from strict environmental regulations and diminishing raw material resources (Ravi and Shankar, 2005; Olugu et al., 2010a; Ilgin and Gupta, 2010). These have led to an intensified drive towards reverse logistics practices across various organizational supply chains. It is also observed that for an effective green supply chain management, there is a need to effectively coordinate the flow and reprocessing of end-of-life products, and integration of recyclates back into the main manufacturing stream (Olugu et al., 2010b; Nunes et al., 2009).

There are seemingly plenty of benefits accruable to an organization from reverse logistics. It has been posited that despite being environmentally responsible, an effective management of reverse logistics operations will result in higher profitability through reduction in transportation, inventory and warehousing costs (Ilgin and Gupta, 2010). Some other studies have considered reverse logistics as value adding by helping to meet regulatory requirements, boosting organizational corporate images and improving savings on raw materials and landfills issues (Autry, 2005; Nunes et al., 2009). Efficient reverse logistics operations are believed to yield a significant return on investment, as well as a significantly increased

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competitiveness in the industry (Efendigil et al., 2008). It has been further highlighted that reverse logistics operations influence forward logistics activities in the aspect of creation of storage space and transportation capacity. There is an observation that reverse logistics is very instrumental towards achieving a green supply chain (Efendigil et al., 2008; Olugu et al., 2010b).

Pokharel and Mutha (2009) and Nunes et al. (2009) asserted that, the focus of reverse logistics is on waste management, material recovery through recycling, and part or product recovery through remanufacturing, refurbishment and reuse. It can therefore be summarized that reverse logistics in the automotive industry involves the process of planning, implementing, and controlling the efficient flow of end-of-life vehicles (ELVs) from the point of use (customer) through the process of remanufacturing, refurbishment, reuse and recycling, aimed at recapturing value as well as proper waste disposal (Kumar and Putnam, 2009; Olugu et al., 2010b). It has been observed that making the forward chain of an automotive supply chain becomes green does not guarantee a green supply chain.

Therefore, the effort of greening the forward chain must be complemented with a sound reverse logistics, in order to achieve a successful green supply chain. The only means of revealing the performance of the reversed logistics process is through the evaluation of its key performance measures. Till date, no study has used a set of measures and metrics to conduct the performance evaluation of reverse logistics process. Since such a process is characterized by vague information, uncertainties and imprecise data, fuzzy logic becomes the most appropriate tool for its performance evaluation (Lin et al., 2006b; Alex, 2007; Dweiri and Kablan, 2006).

The rest of the paper is organized as follows, a brief review of some previous studies related to reverse logistics is presented. This is followed by a description of the fuzzy set concept. Subsequently, the research methodology as well as the fuzzy logic measurement approach is explained. The study culminates with a case study conducted to illustrate and assess the use of the fuzzy logic approach in measuring the performance of reverse logistics. The results obtained are discussed and finally, the paper ends with conclusions and directions for future studies.

Review on previous studies

To date, most of the studies in the field of reverse logistics have focused on the competitive advantage available to companies that proactively incorporate environmental goals into their business practices and strategic plans (Newman and Hanna, 1996; Johnson, 1998; Autry, 2005; Gonza´lez-Torre and Adenso-Dı´az, 2006; Nunes, 2009). On the other hand, studies which focus on performance optimization of the reverse logistics operation have been mainly related to network design. Examples of these include Schultmann et al. (2006), in which reverse logistics was modeled with vehicle routing planning to form a tailored algorithm. It was tested using several scenarios based on real case data from German automotive industries.

Another study was done by Kara et al. (2007). They presented a simulation model of a reverse logistics network for collecting end-of-life appliances in Sydney. Their study provided a tool which aids the understanding of the operation of the system and identification of the most important factors for detailed analysis of the system. Ravi et al. (2005) designed an analytic network process based on decision model which structures different problems in reverse logistics for end-of-life computers in a hierarchical form. This system links the determinants, dimensions, and enablers of the reverse logistics process with alternatives available to the decision maker. El-Sayed et al. (2008) presented a multi-period, multi-echelon forward-reverse logistics network design model, and stochastic mixed integer linear programming was applied to form a multi-stage stochastic program aimed at maximizing the total expected profit. Other studies include Biehl et al. (2007), in which a simulation model was used in a design of experiment to analyze the impact of system design and environmental factors on the reverse logistics performance in the carpet industry.

Lee et al. (2009) proposed a mathematical model of remanufacturing system as a three-stage logistics network model for minimizing the total cost using genetic algorithm with a priority-based encoding method. Lee and Dong (2009) came up with dynamic location and allocation models to cope with reverse logistics network configurations and associated factors. They used a two-stage stochastic programming model for multi-period reverse logistics network design. A numerical experiment was presented to demonstrate the significance of the developed stochastic model as well as the efficiency of the proposed solution method. Sheu (2008) presented a multi-objective optimization programming approach to address the issue of nuclear power generation, using a linear multi-objective optimization model to optimize the operations of both the nuclear power generation and the accompanying reverse logistics process. Likewise, a model based on incapacitated facility location problems was used by Cruz-Rivera and Ertel (2009) to assess the features of closed loop reverse logistics.

A study by Hernández et al. (2009) focused on evaluation of the relationship between reverse logistics practices and corporate performance in Brazilian automotive industry using analytic hierarchy process (AHP) and analytic network process (ANP). The indicators employed in the study are mainly corporate indicators and not those directly borne out of the processes in reverse logistics operations. It was pointed out that as the volume of data involved increases in ANP; the process becomes cumbersome and time consuming (Hernandez et al., 2009).

To date, there has not been a focused study which applied measures and metrics directly related to the reverse logistics operations in measuring the performance of the reverse logistics process in the automotive industry. It is an established fact that, scoring techniques as well as simulations techniques have some shortcomings such as inability to incorporate ambiguity and multi-possibility that goes with mapping people's decisions to numbers, and subjectivity in judgments and individual preferences of evaluators (Lin et al., 2006; Ordoobadi, 2008). Thus, experts' perceptions which are characterized by subjectivity require fuzzy logic for assessment. On this ground, linguistics approximation and fuzzy arithmetic have been applied to achieve this purpose.

Fuzzy set concept

Fuzzy set theory which was first presented by Zadeh (1978) is applied in the representation of human reasoning. Fuzzy logic is a superset of conventional logic that has been extended to represent the concept of partial truth (Ordoobadi, 2008). It is described as a problem solving methodology which provides definite conclusions from imprecise, vague and uncertain information (Dweiri and Kablan, 2006; Alex, 2007). This fuzzy concept is anchored on the fact that, human reasoning is based on knowledge and concepts which do not conform to well-defined boundaries (Kumar and Ravi, 2007). Thus, fuzzy logic uses its ability to generate precise solutions from certain approximate information for solving problems in engineering and operations management which could not be solved using purely mathematical and logic-based approaches in system design.

Fuzzy logic is basically a multi-value logic which permits intermediate values to be defined between conventional ones like true/false, low/high, good/bad, etc. It is an established fact that, as the complexities surrounding a system increase, making a precise statement about the state of the system becomes very difficult. This complexity can only be best handled by applying the fuzzy logic method inherent in human beings. This is supported by Zadeh's (1978) assertion that, as the complexities of a system increase, precision of our knowledge about the system decreases, until a stage is attained at which the precision and significance become mutually exclusive.

Thus, fuzzy decision making involves a process of selecting one or more alternatives or solutions from a finite set of alternatives which suits a set of constraints (Ganesh, 2006; Lin et al., 2006). Fuzzy logic provides mathematical strengths to capture the uncertainties associated with human cognitive and judgmental processes, such as thinking and reasoning (Zadeh, 1978). Therefore, it provides an inference mechanism that enables approximate human reasoning capabilities to be applied to knowledge-based systems (Alex, 2007; Ordoobadi, 2008).

Fuzzy numbers

The concept of fuzzy set is an extension of the concept of crisp set. A fuzzy set is used to express a collection of elements in a universe of data in which the boundary of the set within the universe is vague, imprecise and ambiguous (Ganesh, 2006; Lin et al., 2006). Every fuzzy set is specified by a membership function of each of its elements in the universe of discourse with values ranging within the unit interval of [0,1]. The value 0 is used to represent non-membership, while the value 1 implies complete membership and those between 0 and 1 are the intermediate degrees of membership. Thus, a fuzzy set is defined by its membership function. Let X be a set of items, known as the universe, and its elements are denoted by x.

Therefore, a fuzzy subset A in X is characterized by a membership function $f_A(x)$ which is associated with each element x in A and a real number in the interval [0,1]. The membership function $f_A(x)$ maps each element x to a membership value between 0 and 1, and this value represents the level of membership of x in A. A fuzzy subset A is called a fuzzy real number. There are various fuzzy number categories that can be applied in representing imprecise information. Some of them are triangular, trapezoidal, etc (Cox, 1994; Ganesh, 2006). In this study, the triangular fuzzy is applied as it is the most suitable and convenient (Zadeh, 1978; Lin et al., 2006). Let $x, a, b, c \in R$, where R is a real number. Based on this definition, a triangular fuzzy is represented as a fuzzy number A in R, if its membership function $f_A : R \rightarrow [0,1]$ is

$$f_A(x) = \begin{cases} (x-a)/(b-a), & a \le x \le b, \\ (c-x)/(c-b), & b \le x \le c, \\ 0, & otherwise. \end{cases} \quad (1)$$

Hence, the triangular fuzzy number is represented as $A = (a,b,c)$, where the lower and upper limits of the area for data evaluation are represented by a and c respectively. The peak grade is represented by b, which is the full membership value. Thus, $f_A(b) = 1$. Triangular fuzzy numbers have been the most applied mainly because they are easily specified by experts

Table 1. Fuzzy numbers for estimating the linguistic variable values.

Importance weight		Performance rating	
Linguistic variable	**Fuzzy numbers**	**Linguistic variable**	**Fuzzy numbers**
Low	$(0.0, 0.2, 0.4)$	Poor	$(0, 2, 4)$
Moderate	$(0.3, 0.5, 0.7)$	Fair	$(3, 5, 7)$
High	$(0.6, 0.8, 1.0)$	Good	$(6, 8, 10)$

(Ganesh, 2006; Lin et al., 2006).

Fuzzy arithmetic operators

The arithmetic operators applied in fuzzy sets are synonymous to those used in regular statistical operations (Ordoobadi, 2008; Ganesh, 2006; Lin et al., 2006). Assuming that two triangular fuzzy numbers are represented by *X* and *Y,* such that $X = (a_1, b_1, c_1)$ and $Y = (a_2, b_2, c_2)$. The triangular fuzzy number arithmetic operations for *X* and *Y* using the extension principle are presented in Equations 2 and 3. According to the extension principle, the classical results of Boolean logic are recovered from fuzzy logic operations, when all fuzzy membership grades are restricted to the conventional set {0,1}. Thus, fuzzy sets and logic are true generalization of classical set theory and logic.

$$X \oplus Y = (a_1, b_1, c_1) \oplus (a_2, b_2, c_2) = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \quad (2)$$

$$X \otimes Y = (a_1, b_1, c_1) \otimes (a_2, b_2, c_2) = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2) \quad (3)$$

Linguistic variables

Since fuzzy sets are usually aimed at modeling cognitive states of human beings, their determinations are based on certain prescriptions rather than precise numbers. This is because a direct determination of vague scores indicators is virtually impractical for experts. The truth of a statement in fuzzy logic is considered to be a matter of degree, which can be viewed as a generalization of the Boolean logic (Ganesh, 2006; Alex, 2007).

Therefore, it offers tools to operate with vaguely defined parameters or concepts. In order to achieve these prescriptions, natural languages are used to convey the degree of imprecision and these are the linguistic variables (Ganesh, 2006; Efendigil et al., 2008). Such variables are in the form of very low, low, medium, high, very high etc. According to Lin et al. (2006), it is suggested that linguistic levels should be limited to nine levels, as this is the limit of human absolute discrimination.

MATERIALS AND METHODS

The objective of this study is to illustrate how managers can assess the efficiency of their reverse logistics process in the automotive industry. Since this kind of evaluation is characterized by vagueness and imprecision, linguistic expressions will be employed for the assessment (Lin et al., 2006a; 2006b; Alex, 2007). In order to evaluate the efficiency of the reverse logistics process, experts' opinions have been elicited in two different forms, which are the importance weight and performance rating of the measures and metrics. The importance of weight for the measures has been adopted from the study in Olugu et al. (2010b) and the performance measurement employed a score sheet which allowed the managers to assess their company's reverse logistics process using linguistics variables. These are presented in Table 1.

Fuzzy membership functions are defined for the assessment of the importance of weight and performance rating. The former is represented by 3 membership functions for the possible data domain which are low, moderate and high, while the latter is also represented by 3 membership functions which are poor, fair and good, as shown in Figures 1 and 2. The choice of three membership functions is to avoid misrepresentation and over inclusiveness in the measurement. It is believed that, since reverse logistics is an industrial practice which is chiefly motivated by regulations and laws, it will be better to have a simple membership to depict exactly where a company falls.

Fuzzy logic evaluation methodology for reverse logistics performance

The measures and their corresponding metrics for the performance evaluation of the reverse logistics process in the automotive industry are adopted from Olugu et al. (2010b). These measures are supplier commitment, customer involvement, management commitment, material features, recycling efficiency, and recycling cost. They are grouped into two categories which are external and internal. External measures are those which are extrinsic to the manufacturing system (supplier commitment and customer involvement).

On the other hand, internal measures are those that are evaluated within the manufacturing system. The measures included under this category are management commitment, material

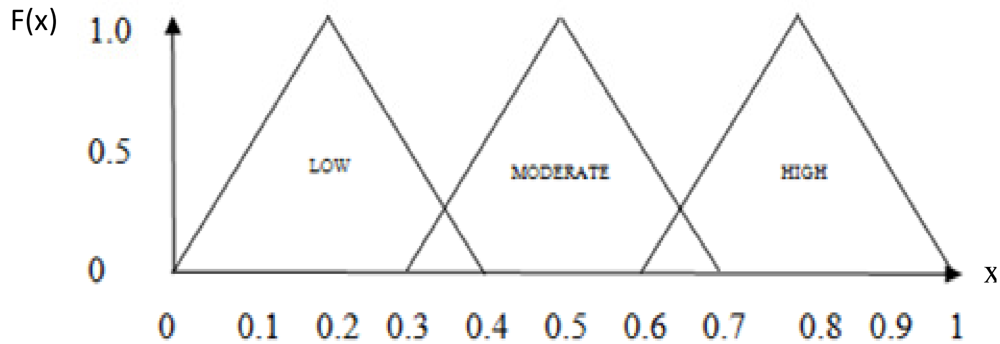

Figure 1. Linguistic importance scale.

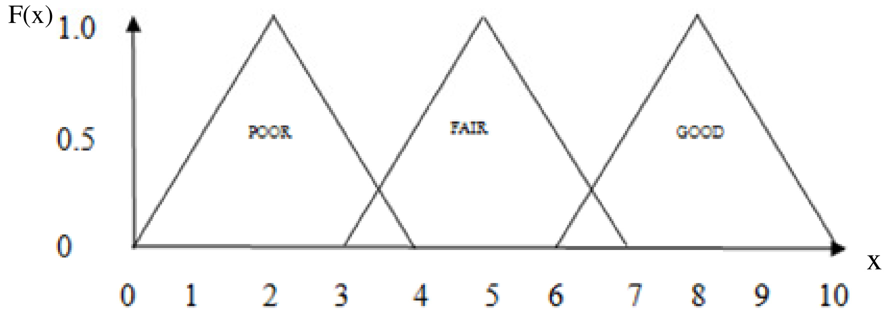

Figure 2. Linguistic performance scale.

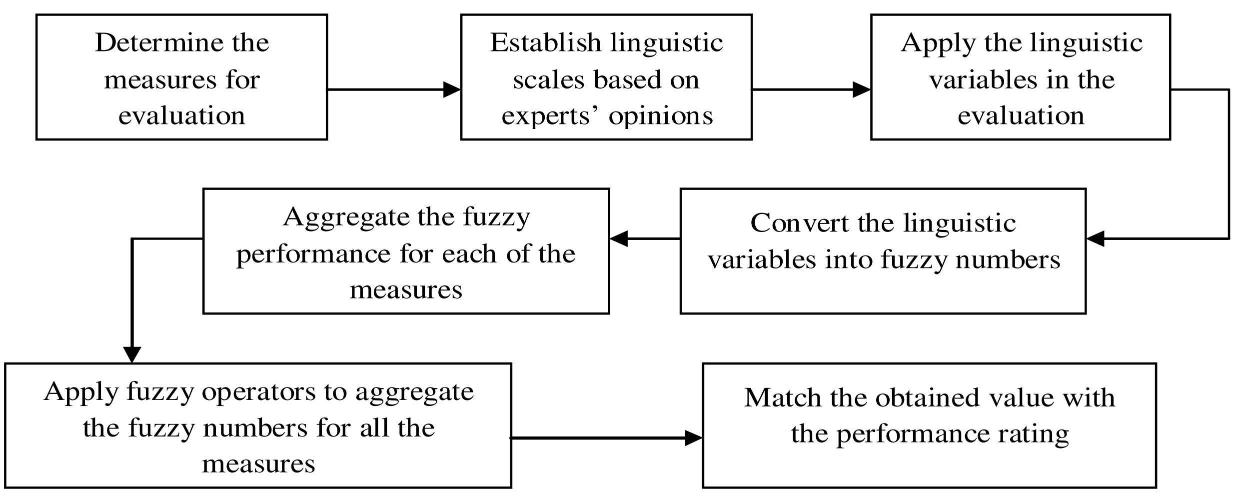

Figure 3. Methodology for the performance evaluation.

features, recycling efficiency, and recycling cost. All the measures are assessed based on their individual metrics which are used in quantifying them. The importance weights of each of the measures and their performance ratings will be synthesized to obtain the overall performance. The measurement methodology (as shown in Figure 3) is described in the ensuing steps:

1. Determine the measures for performance evaluation.
2. Establish the suitable linguistic scales upon which the importance weight and performance rating will be based on, using industrial experts' opinions.
3. Apply the linguistic variables in evaluating the importance weight and performance rating of the metrics for each of the measures.

Table 2. Measures and their metrics for reverse logistics performance evaluation.

Measures \ Metrics	1	2	3
Supplier commitment (SC)	Extent of delivery from suppliers back to manufacturers (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)	% decrease in recycling time (RE_1)	Availability of a recycling standard (RE_2)	% 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)

4. Convert the linguistic variables into fuzzy numbers for the importance weight and performance rating respectively (as presented in Table 1) based on the outcome for each metric in (3) aforestated.
5. Aggregate the fuzzy performance for each of the measures by multiplying the fuzzy performance numbers with the fuzzy importance numbers for each of the metrics and dividing by their cumulative fuzzy importance numbers.
6. Repeat step (5) for each of the measures and apply fuzzy operators to aggregate all the obtained fuzzy numbers for all the measures.
7. Match the obtained value with the performance rating to determine the overall performance level.

A case study

Here, a case study is used to illustrate the application of the proposed fuzzy logic approach in measuring the performance of the reverse logistics process of an automotive company in South-East Asia. The company was established in the early 90s. The staff strength is above 10,000, with a plant capacity of over 250,000 vehicles per annum. It has a market reach of over half a dozen countries including Malaysia, Singapore, Brunei, Fiji, Nepal, Sri Lanka, Pakistan etc. It has over 7 brands of vehicles in its list of products. As an outstanding manufacturer, it has received several awards in automotive manufacturing in the South-East Asia region. Data were collected from the company using a score sheet. The score sheet used linguistic variables which were poor, fair and good as the measurement scales for the performance. The importance of the measures has been adopted from an earlier study by Olugu et al. (2010b). The score sheets were given to the company's reverse logistics and supply chain managers. Overall, the assessment was conducted as follows:

The first stage involved the determination of the measures for evaluation. Based on the measures adopted in this study, the company was assessed according to its performance on each of the measures which were supplier commitment, customer involvement, management commitment, material features, recycling efficiency and recycling cost. These measures and their corresponding metrics as adopted from Olugu et al. (2010b) are described subsequently and presented in Table 2.

i. Supplier commitment. This involved the assessment of metrics such as the extent of delivery from suppliers back to manufacturers, that is the level of reintegration of recyclates into the main manufacturing stream, the level of certification of suppliers, and the number of initiatives put in place by them.

ii. Customer involvement. This was used to assess the level of cooperation from the customers on reverse logistics. This was based on metrics such as the level of customers' cooperation in returning their end-of-life vehicles (ELVs), the level of customers-to-customers dissemination of information, and their level of understanding of reverse logistics. It is believed that the higher the customer involvement, the more successful the entire reverse logistics process.

iii. Management commitment. This was assessed based on the following: level of management motivation to customers for returning their ELVs, availability of a standard operating procedure for the process, and availability of a waste management scheme.

Table 3. The obtained measurement grades for the company.

Measures	Metrics	Importance (measures)	Importance (metrics)	Performance rating
	SC_1		High	Fair
SC	SC_2	High	High	Poor
	SC_3		Moderate	Poor
	CI_1		High	Poor
CI	CI_2	Moderate	Moderate	Poor
	CI_3		Moderate	Fair
	MC_1		High	Poor
MC	MC_2	High	Moderate	Poor
	MC_3		High	Poor
	MF_1		High	Fair
MF	MF_2	High	High	Fair
	MF_3		Moderate	Fair
	RE_1		Moderate	Fair
RE	RE_2	High	High	Fair
	RE_3		High	Fair
	RC_1		High	Poor
RC	RC_2	High	High	Fair
	RC_3		Moderate	Fair

iv. Material features. This involved the level of waste generated, the material recovery time, and the ratio of recycled to recyclable materials in the ELVs. A low level of waste generated a high ratio of recycled to recyclables, and shorter recycling times imply the material features are eco-friendly.

v. Recycling efficiency. The assessment involved the percentage decrease in the recycling time, the availability of a recycling standard, and the percentage reduction in emission and waste generated.

vi. Recycling cost. This was evaluated based on the cost incurred by the organization in the recycling processes such as cost associated with returning ELVs, cost associated with processing recyclables, and cost of disposing unprocessed waste. It is believed that the higher the capital investment in the recycling process, the better the output or efficiency of the process.

RESULTS

In the second stage, the supply chain manager, logistics manager, operations manager, and procurement managers were consulted to give their perceptions on the performance of the metrics based on the actual achievement of the company, using linguistic variables (poor, fair and good). The importance weights and performance ratings are summarized in Table 3. In the next stage, the linguistic variables were converted into fuzzy numbers based on the linguistic scales presented in Table 1, for both the importance weight and performance rating respectively. For example, the importance weight for low was represented as $(0.0, 0.2, 0.4)$ and the performance rating for poor was given as $(0, 2, 4)$.

Subsequently, the aggregation of the fuzzy importance numbers and fuzzy performance numbers of the metrics to achieve the performance for a particular measure was carried out. This was done such that,

$$P_M = \sum_{k=1}^{n} (W_m \otimes R_m) / \sum_{k=1}^{n} W_m \tag{4}$$

where, P_M is the performance of a measure, W_m and R_m are the fuzzy importance number and fuzzy performance number of the metrics respectively, and n is the number of metrics.

The next stage involved the application of fuzzy operators on the performance of each measure to determine the performance of the reverse logistics process. Therefore,

$$P_{RL} = \sum_{k=1}^{n} (W \otimes P_M) / \sum_{k=1}^{n} W \tag{5}$$

where, P_{RL} is the performance of reverse logistics, W and P_M are the fuzzy importance number and performance of each of the measures respectively, and n is the number of measures.

The final stage involved matching the P_{RL} value with the appropriate performance level using the Euclidean distance method. Based on the information presented in Table 3, each of the measures was evaluated as a product of the fuzzy importance numbers and performance numbers of their metrics. Thus:

$$P_{M(SC)}=\frac{(0.6,0.8,1)(3,5,7)\oplus(0.6,0.8,1)(0,2,4)\oplus(0.3,0.5,0.7)(0,2,4)}{((0.6,0.8,1)\oplus(0.6,0.8,1)\oplus(0.3,0.5,0.7))}$$

$$P_{M(CI)}=\frac{(0.6,0.8,1)(0,2,4)\oplus(0.3,0.5,0.7)(0,2,4)\oplus(0.3,0.5,0.7)(3,5,7)}{(0.6,0.8,1)\oplus(0.3,0.5,0.7)\oplus(0.3,0.5,0.7)}$$

$$P_{M(MC)}=\frac{(0.6,0.8,1)(0,2,4)\oplus(0.3,0.5,0.7)(0,2,4)\oplus(0.6,0.8,1)(0,2,4)}{(0.6,0.8,1)\oplus(0.3,0.5,0.7)\oplus(0.6,0.8,1)}$$

$$P_{M(MF)}=\frac{(0.6,0.8,1)(3,5,7)\oplus(0.6,0.8,1)(3,5,7)\oplus(0.3,0.5,0.7)(3,5,7)}{(0.6,0.8,1)\oplus(0.6,0.8,1)\oplus(0.3,0.5,0.7)}$$

$$P_{M(RE)}=\frac{(0.3,0.5,0.7)(3,5,7)\oplus(0.6,0.8,1)(3,5,7)\oplus(0.6,0.8,1)(3,5,7)}{(0.3,0.5,0.7)\oplus(0.6,0.8,1)\oplus(0.6,0.8,1)}$$

$$P_{M(RC)}=\frac{(0.6,0.8,1)(0,2,4)\oplus(0.6,0.8,1)(3,5,7)\oplus(0.3,0.5,0.7)(3,5,7)}{(0.6,0.8,1)\oplus(0.6,0.8,1)\oplus(0.3,0.5,0.7)}$$

Therefore,

$$P_{M(SC)}=\frac{(1.8,4.0,7)\oplus(0,1.6,4)\oplus(0,1,2.8)}{(1.5,2.1,2.7)}=\frac{(1.8,6.6,13.8)}{(1.5,2.1,2.7)}=(1.2,3.14,5.11)$$

$$P_{M(CI)}=\frac{(0,1.6,4)\oplus(0,1,2.8)\oplus(0.9,2.5,4.9)}{(1.2,1.8,2.4)}=\frac{(0.9,5.1,11.7)}{(1.2,1.8,2.4)}=(0.75,2.83,4.88)$$

$$P_{M(MC)}=\frac{(0,1.6,4)\oplus(0,1,2.8)\oplus(0,1.6,4)}{(1.5,2.1,2.7)}=\frac{(0,4.2,10.8)}{(1.5,2.1,2.7)}=(0,2,4)$$

$$P_{M(MF)}=\frac{(1.8,4,7)\oplus(1.8,4,7)\oplus(0.9,2.5,4.9)}{(1.5,2.1,2.7)}=\frac{(4.5,10.5,18.9)}{((1.5,2.1,2.7))}=(3,5,7)$$

$$P_{M(RE)}=\frac{(0.9,2.5,4.9)\oplus(1.8,4,7)\oplus(1.8,4,7)}{(1.5,2.1,2.7)}=\frac{(4.5,10.5,18.9)}{(1.5,2.1,2.7)}=(3,5,7)$$

$$P_{M(RC)}=\frac{(0,1.6,4)\oplus(1.8,4,7)\oplus(0.9,2.5,4.9)}{(1.5,2.1,2.7)}=\frac{(2.7,8.1,15.9)}{(1.5,2.1,2.7)}=(1.8,3.86,5.89)$$

Since the performance values for each of the measures have been obtained, the next step involved aggregating these values with their fuzzy importance numbers to obtain the performance of the reverse logistics operation. Thus,

P_{RL}=

$$[(0.6,0.8,1)(1.2,3.14,5.11)\oplus(0.3,0.5,0.7)(0.75,2.83,4.88)\oplus(0.6,0.8,1)(0,2,4)\oplus(0.6,0.8,1)(3,5,7)\oplus(0.6,0.8,1)(3,5,7)\oplus(0.6,0.8,1)(1.8,3.86,5.89)]$$

/

$$[(0.6,0.8,1)\oplus(0.3,0.5,0.7)\oplus(0.6,0.8,1)\oplus(0.6,0.8,1)\oplus(0.6,0.8,1)\oplus(0.6,0.8,1)]$$

$$=\frac{(0.72,2.51,5.11)\oplus(0.23,1.42,3.42)\oplus(0,1.6,4)\oplus(1.8,4,7)\oplus(1.8,4,7)\oplus(1.08,3.09,5.89)}{(3.3,4.5,5.7)}$$

$$=\frac{(5.63,16.62,32.42)}{(3.3,4.5,5.7)}=(1.71,3.69,5.69)$$

Finally, the P_{RL} value was matched with the appropriate performance level in order to deduce the suitable linguistic variable. The Euclidean distance method was adopted, since it is known to be the best approximation of human reasoning (Lin et al., 2006). Figure 4 represents the mapping using Euclidean distance.

Mathematically, this distance was evaluated from a given fuzzy number to each of the fuzzy numbers representing the performance level (Lin et al., 2006). If the fuzzy performance is expressed as P_{RL}, and the performance linguistic variable is expressed as LV, then UP_{RL} and U_{LV} represent their respective fuzzy numbers. The Euclidean distance between P_{RL} and LV was thus calculated using Equation 6.

$$D(P_{RL},LV)=\sqrt{\left\{\sum_{x\in p}(U_{P_{RL}}(x)-U_{LV}(x))^2\right\}} \quad (6)$$

where $p=\{x_0,x_1,......x_n\}\subset[1,10]$

The distance from P_{RL} to each LV was evaluated and the closest LV value having the smallest distance was identified.

For LV_{poor} = (0, 2, 4)

$$D(P_{RL}, LV_{poor})=\sqrt{(1.71-0)^2+(3.69-2)^2+(5.69-4)^2}$$
$$=\sqrt{2.9241+2.8561+2.8561}$$
$$=\sqrt{8.6363}$$
$$= 2.9388$$

For LV_{fair} = (3, 5, 7)

$$D(P_{RL}, LV_{fair})=\sqrt{(1.71-3)^2+(3.69-5)^2+(5.69-7)^2}$$

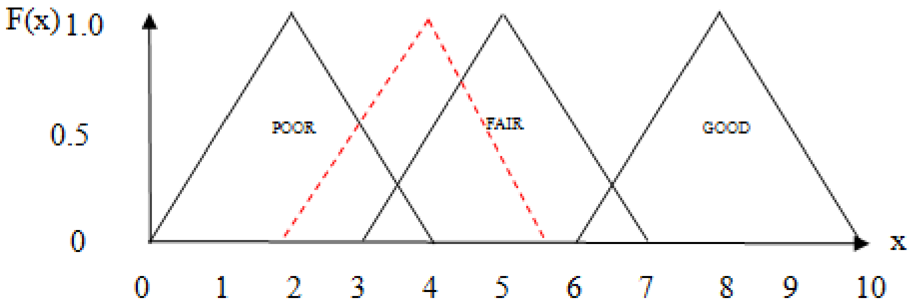

Figure 4. Mapping of the result.

$$= \sqrt{1.6641+1.7161+1.7161}$$

$$= \sqrt{5.0963}$$

= 2.2575

For LV_{good} = (6, 8, 10)

$$D(P_{RL}, LV_{good}) = \sqrt{(1.71-6)^2+(3.69-8)^2+(5.69-10)^2}$$

$$= \sqrt{18.4041+18.5761+18.5761}$$

$$= \sqrt{55.5563}$$

= 7.4536

DISCUSSION

This study has demonstrated how to evaluate the performance of the reverse logistics process of the automobile industry. Due to the fact that conventional performance evaluation methods will not be appropriate for this kind of evaluation which is characterized by vagueness and complexities (Lin et al., 2006; Alex, 2007), fuzzy logic method has been adopted. The fuzzy methodology employed linguistic approximation and fuzzy arithmetic. Hence, it can be seen from the result that, the reverse logistics performance of the company is somewhat fair. This is because LV_{fair} has the least distance from the fuzzy performance, P_{RL}. Nevertheless, from the results obtained, it can be observed that the reverse logistics operation of the company still requires a lot of commitments from the management, suppliers and customers.

Generally, reverse logistics has not been given adequate attention by the company. A closer look at the individual measures reveals that supplier commitment, customer involvement and management commitment showed poor performance. This implies that the company should put more effort in these areas. This goes to support the assertion that, the success of a reverse logistics operation requires the joint effort of the company's top management, suppliers and customers (Dyckhoff et al., 2004; Theyel, 2006; Olugu et al., 2010b). Some of these include embarking on customer enlightenment campaigns and motivation of the customers on their ELVs (Mezher and Ajam, 2006; Theyel, 2006; Dyckoff et al., 2004). Motivation could be in the form of incentives such as discounts on new cars and trade-in with their ELVs. To improve supplier commitment, the company could impose reverse logistics involvement as one of the criteria for supplier selection (Hamner, 2006). Furthermore, motivation to suppliers will boost their commitment in the reverse logistics process (Schultmann et al., 2004).

On the other hand, material features, recycling efficiency and recycling cost only showed a somewhat fair performance. The fair performance in material features could be attributed to the fact that, most of the components of the vehicles are outsourced from countries who also supply to other regions with environmental conscious manufacturing culture. Furthermore, the level of performance could be attributed to the fact that, most of the automobiles manufactured in South-East Asia are used within the same region where no serious regulation is in place, compared to the Western countries. Therefore, there is call on the government to establish regulations on ELVs and regulatory agencies, that will enforce the reverse logistics processes involving ELVs (Helms and Hervani, 2006). This will serve as an awakening call for the industry. Effort should be directed at ensuring that the recycling processes are efficient and effective. In the same light, top management should set aside sufficient fund for the reverse logistics operations.

To date, no attempt has been made to comprehensively measure the performance of the reverse logistics process in the automotive industry, using a set of well defined measures and metrics. Based on the methodology presented earlier, it is easy for managers and decision makers to have a view on the performance of their overall reverse logistics process and to know if their efforts, financially and otherwise committed into it are yielding the required dividend. It is also easier for them to realize which metrics and measures are not living up to expectation based on their performance grade. Any automotive manufacturer can easily pin-point the areas which require more attention in their reverse logistics process using this method. In essence, it will help automotive organizations to evaluate and monitor their reverse logistics performance, thus helping them to sustain the environment for future generations.

Conclusions

In this study, the issue of how to assess the performance of the collection of ELVs, recycling and subsequent integration of recyclates into the main manufacturing stream has been answered. Sequel to the fact that, the data which are involved in the assessment of the reverse logistics process are vague and imprecise; a fuzzy logic system which uses linguistic variables has been adopted. The measures used in the performance evaluation were adopted from Olugu et al. (2010b). The evaluation methodology involves defining the criteria for evaluation, selecting the suitable linguistic variables based on experts' opinions, applying the linguistic variables in the evaluation, converting them into fuzzy numbers, aggregating the fuzzy performance, and subsequently matching the obtained value with the performance level.

Future research could be directed towards implementing this methodology into a computer based program which allows the evaluation of the reverse logistics performance of an organization with less time and enhanced accuracy. This program can be built with 'if then rules" which shall be based on experts' opinions. It is also recommended that experts should be selected from the monitoring agencies for waste and emission reduction. In this manner, their opinions will represent the industry standards.

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