

January 01, 2004

Efficient design and effective marketing of a reverse supply chain : a fuzzy logic approach

Kishore K. Pochampally
Northeastern University

Surendra M. Gupta
Northeastern University

Recommended Citation

Pochampally, Kishore K. and Gupta, Surendra M., "Efficient design and effective marketing of a reverse supply chain : a fuzzy logic approach" (2004). *Mechanical and Industrial Engineering Faculty Publications*. Paper 23. <http://hdl.handle.net/2047/d20000305>

This work is available open access, hosted by Northeastern University.



Laboratory for Responsible Manufacturing

Bibliographic Information

Pochampally, K. K. and Gupta, S. M., "Efficient Design and Effective Marketing of a Reverse Supply Chain: A Fuzzy Logic Approach", ***Proceedings of the 2004 IEEE International Symposium on Electronics and the Environment***, Phoenix, Arizona, pp. 321-326, May 10-13, 2004.

Copyright Information

(c) 2004 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other users, including reprinting/ republishing this material for advertising or promotional purposes, creating new collective works for resale or redistribution to servers or lists, or reuse of any copyrighted components of this work in other works.

Contact Information

Dr. Surendra M. Gupta, P.E.
Professor of Mechanical and Industrial Engineering and
Director of Laboratory for Responsible Manufacturing
334 SN, Department of MIE
Northeastern University
360 Huntington Avenue
Boston, MA 02115, U.S.A.

(617)-373-4846 **Phone**
(617)-373-2921 **Fax**
gupta@neu.edu **e-mail address**

<http://www.coe.neu.edu/~smgupta/> **Home Page**

Phase-I (Fuzzy Cost-Benefit Function)

A fuzzy cost-benefit function that can be used to select the most economical product to re-process, from a set of candidate used products, is proposed here (see [4] for a good introduction of fuzzy logic).

Nomenclature for Fuzzy Cost-Benefit Function

| | |
|-------------|--|
| b_{ij} | probability of bad quality (broken, worn-out, low-performing, etc) of component j in product i ; |
| CC_i | total collection cost of product i per period (\$); |
| CD | cost of re-processing per unit time (\$/unit time); |
| CF | recycling revenue factor (\$/unit weight); |
| CR_i | total recycle revenue of product i per period (\$); |
| CO_i | cost to collect one product i (\$); |
| DC_i | total disposal cost of product i per period (\$); |
| DI_{ij} | disposal cost index of component j in product i (index scale 0 = lowest, 10 = highest); |
| DF | disposal cost factor (\$/unit weight); |
| E_{ik} | subassembly k in product i ; |
| FCB_i | fuzzy cost-benefit function for product i ; |
| i | product type; |
| IC_i | investment cost of product i (\$); |
| j | component type; |
| LC_i | loss-of-sale cost of product i (\$); |
| M_i | total number of subassemblies in product i ; |
| m_{ij} | probability of missing component j in product i ; |
| N_{ij} | multiplicity of component j in product i ; |
| RCP_{ij} | percentage of recyclable contents by weight in component j of product i ; |
| RC_i | total re-processing cost of product i per period (\$); |
| RI_{ij} | recycling revenue index of component j in product i (index scale 0 = lowest, 10 = highest); |
| $Root_i$ | root node (for example, outer casing) of product i ; |
| RV_{ij} | resale value of component j in product i (\$); |
| SU_i | supply of product i per period in the reverse supply chain (# of products); |
| $T(Root_i)$ | time to disassemble $Root_i$ (time units); |
| $T(E_{ik})$ | time to disassemble subassembly k in product i (time units); |
| UR_i | total reuse revenue of product i per period (\$); |
| W_{ij} | weight of component j in product i (lb); |
| ΔBZ | incremental total revenues (between the challenger and the defender); |
| ΔCZ | incremental total costs (between the challenger and the defender). |

Formulation of Fuzzy Cost-Benefit Function

The fuzzy cost-benefit function (FCB) of used product i of interest consists of equivalent values (EV) of seven terms (*viz.*, total reuse revenue per period (UR_i), total recycle revenue per period (CR_i), total collection cost per period (CC_i), total re-processing cost per period (RC_i), total disposal cost per period (DC_i), loss-of-sale cost (LC_i), and investment cost (IC_i)) as follows:

$$FCB_i = \frac{EV \text{ of } (UR_i + CR_i)}{EV \text{ of } (CC_i + RC_i + DC_i + LC_i + IC_i)}; \quad (1)$$

The following sub-sections explain how the above seven terms are calculated [7].

Total reuse revenue per period (UR)

UR of product i is influenced by the fuzzy supply of the product per period (SU_i) and the following data of component of each type j in the product: the resale value (RV_{ij}), the number of components (N_{ij}), the fuzzy probability of missing (m_{ij}) and the fuzzy probability of bad quality (broken, worn-out, low-performing, etc) (b_{ij}). This revenue equation can be written as follows:

$$UR_i = \sum_j SU_i.RV_{ij}.N_{ij}.(1 - b_{ij} - m_{ij}); \quad (2)$$

Since SU_i , b_{ij} and m_{ij} are expressed as fuzzy numbers, the resulting UR_i is a fuzzy number too.

Total recycle revenue per period (CR)

CR of product i is calculated by multiplying the component recycling revenue factors by the number of components recycled for materials content as follows:

$$CR_i = \sum_j \left[\frac{SU_i.RI_{ij}.W_{ij}.RCP_{ij}}{\{N_{ij}(1 - m_{ij}) - N_{ij}.(1 - b_{ij} - m_{ij})\}} \right] CF; \quad (3)$$

Note that each component has a percentage of recyclable contents (RCP_{ij}). RI_{ij} is the recycling revenue index (varying in value from one to ten) representing the degree of benefit generated by the recycling of component of type j (the higher the value of the index, the more profitable it is to recycle the component), W_{ij} is the weight of the component of type j and CF is the recycling revenue factor.

Since SU_i , b_{ij} and m_{ij} are expressed as fuzzy numbers, the resulting CR_i is a fuzzy number too.

Total collection cost per period (CC)

CC of product i is calculated by multiplying the fuzzy supply of the product per period (SU_i) by the cost of collecting one used product from consumers (CO_i)

$$CC_i = SU_i.CO_i; \quad (4)$$

Since SU_i is expressed as a fuzzy number, the resulting CC_i is a fuzzy number too.

Total re-processing cost per period (RC)

RC of product i can be calculated from the disassembly time of the root node (for example, outer casing) of the product ($T(Root_i)$), the disassembly time of each sub-assembly in the product ($T(E_{ik})$) and the re-processing cost per unit time (CD) as follows:

$$RC_i = \left[T(Root_i) + \sum_{k=1}^{M_i} T(E_{ik}) \right].CD; \quad (5)$$

Depending on the type (vague or objective) of data available of the disassembly times, RC_i is a fuzzy or crisp real number.

Total disposal cost per period (DC)

DC of product i is calculated by multiplying the component disposal cost by the number of component units disposed as follows:

$$DC_i = \sum_j \left[\frac{SU_i.DI_{ij}.W_{ij}.(1 - RCP_{ij})}{\{N_{ij}(1 - m_{ij}) - N_{ij}.(1 - b_{ij} - m_{ij})\}} \right].DF; \quad (6)$$

Note that DI_{ij} is the disposal cost index (varying in value from one to ten) representing the degree of nuisance created by the disposal of component of type j (the higher the value of the index, the more nuisance the component creates and hence it costs more to dispose it of), W_{ij} is the weight of the component of type j and DF is the disposal cost factor.

Since SU_i , b_{ij} and m_{ij} are expressed as fuzzy numbers, the resulting CR_i is a fuzzy number too.

Loss-of-sale cost (LC)

LC of product i represents the cost of not meeting its demand on the market for re-processed goods, in a timely manner. This occurs because of the unpredictable supply of used products, as consumers do not discard them in a predictable manner. LC is difficult to predict and thus is usually guessed by “experts”, for a particular period of interest.

Due to the involvement of the experts’ guesses, LC_i is expressed as a fuzzy number.

Investment cost (IC)

IC of product i is the fixed cost of the recovery facility and the machinery required to process product i . Depending on the type (vague or objective) of data available of the product and of the region where the recovery facility exists or is planned to be built, IC_i is a fuzzy or crisp real number.

Multi-Criteria Economic Analysis

In order to select the most economical product to re-process in a reverse supply chain, from a set of candidate used products, we use the following steps:

Step 1: Eliminate every candidate used product whose FCB is less than 1.0.

Step 2: Assign the candidate used product that has the lowest IC as the defender and the product with the next-lowest IC as the challenger.

Step 3: Calculate the ratio of the EV of incremental total revenue ΔBZ (between the challenger and the defender) to the EV of incremental total cost ΔCZ (between the challenger and the defender). If the ratio is less than 1.0, eliminate the challenger. Otherwise, eliminate the defender.

Step 4: Repeat steps 2 and 3 until only one used product (which is the most economical one in the set) is left.

Numerical Example

We take three different used products (Product-1, Product-2 and Product-3) whose structures are shown in Figures 2, 3, and 4 respectively. We assume that the supplies of all these products are perpetual. Hence, we take capitalized worth (CW) [4] as the EV. Therefore, FCB is the ratio of total revenues to CW of total costs. Some of the data that we use to calculate FCB of the products are: $T(Root_1) = 2$ min; $T(Root_2) = 1.5$ min; $T(Root_3) = 1.5$ min; $T(E_{11}) = 9$ min; $T(E_{21}) = 7$ min; $T(E_{22}) = 8$ min; $T(E_{31}) = 7$ min; $T(E_{32}) = 8$ min; $CO_1 = \$20$; $CO_2 = \$21$; $CO_3 = \$18$; $IC_1 = \$20000$; $IC_2 = \$25000$; $IC_3 = \$30000$; $SP_1 = \$70$; $SP_2 = \$28$; $SP_3 = \$58$; $LC_1 = \$(1000, 1500, 1700)$ per 3 years; $LC_2 = \$(1000, 1200, 1500)$ per 3 years; $LC_3 = \$(1900, 2000, 2100)$; $CF = 0.2$ \$/lb; $DF = 0.1$ \$/lb; $CD = 0.55$ \$/min. Also, the supplies of the three products are expressed in triangular fuzzy

numbers [4] as follows: $SU_1 = (200, 230, 250)$ products per year; $SU_2 = (210, 220, 230)$ products per year; $SU_3 = (600, 650, 700)$ products per year.

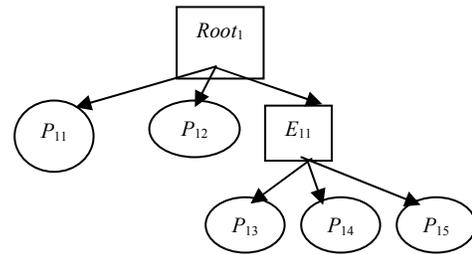


Figure 2. Structure of Product-1

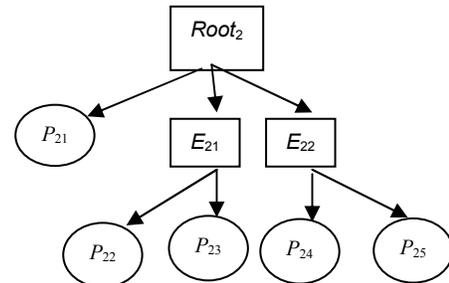


Figure 3. Structure of Product-2

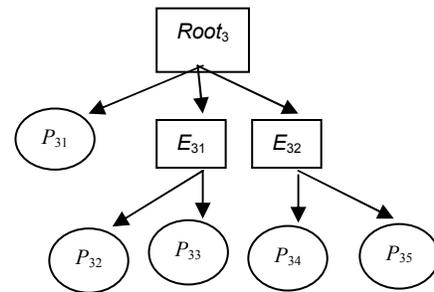


Figure 4. Structure of Product-3

Upon calculating revenues and benefits for each product, we get $FCB_1 = (0.66, 1.59, 3.11)$, $FCB_2 = (0.36, 0.59, 0.83)$ and $FCB_3 = (1.21, 1.89, 3.16)$. Defuzzifying [5] these numbers, we get $FCB_1 = 1.79$, $FCB_2 = 0.59$ and $FCB_3 = 2.09$. Since FCB_2 is less than 1.0, we eliminate it from further analysis.

Now, since IC_1 is less than IC_3 , we consider Product-1 the defender and Product-3 the challenger. The defuzzified ratio of CW of ΔBZ to CW of ΔCZ is now calculated and is found to be 2.81, which is greater than 1.0. Hence, we eliminate the defender, i.e., Product-1. Therefore, the remaining product, i.e., Product-3 is the most economical product amongst the three products.

Phase-II (Integer Goal Programming Model)

In this phase, we formulate a linear integer goal programming model that not only identifies potential recovery facilities but also leads to transportation of the right mix and quantities of products - used as well as re-processed (re-manufactured, here) - across the supply chain.

Nomenclature for Goal Programming Model

| | |
|-----------|--|
| a_1 | space occupied by one unit of used product (square units/product); |
| a_2 | space occupied by one unit of remanufactured product (square units/product); |
| C_u | cost per used product retrieved at collection center u (\$/product); |
| DEM_w | demand of remanufactured products at demand center w (products); |
| DT_v | average disassembly time at recovery facility v ; |
| I_{uv} | decision variable representing the number of used products to be transported from collection center u to recovery facility v ; |
| $MINCOL$ | total minimum collection cost; |
| $MINQ$ | minimum increment in quality after remanufacturing; |
| $MINREC$ | total minimum recovery cost; |
| $MINTD$ | minimum value of throughput multiplied by supply; |
| $MINTRI$ | total minimum cost for transportation between collection centers and recovery facilities; |
| $MINTRO$ | total minimum cost for transportation between recovery facilities and demand centers; |
| $MINTS$ | minimum throughput per supply; |
| O_{vw} | decision variable representing the number of remanufactured products to be transported from recovery facility v to demand center w ; |
| QI_v | average quality of used products at recovery facility v ; |
| QO_v | average quality of remanufactured products at recovery facility v ; |
| R_v | cost of re-processing per product at recovery facility v (\$/product); |
| S_{1v} | storage capacity of recovery facility v for used products (square units); |
| S_{2v} | storage capacity of recovery facility v for remanufactured products (square units); |
| SUP_u | supply at collection center u (products); |
| SU_v | supply to recovery facility v ; |
| TI_{uv} | cost of transporting one used product from collection center u to recovery facility v (\$/product); |
| TO_{vw} | cost of transporting one remanufactured product from recovery facility v to demand facility w (\$/product); |
| TP_v | throughput of recovery facility v ; |
| U | total number of collection centers; |
| W | total number of demand centers; |
| Y_v | selection variable for recovery facility v ; |

Formulation of Goal Programming Model

Minimize the following expression representing the sum of all deviations:

$$d_1 + d_2 + d_3 + d_4 + \sum_{u=1}^U du_u + \sum_{w=1}^W dw_w; \quad (7)$$

Subject to the following constraints:

$$\sum_u \sum_v TI_{uv} I_{uv} - d_1 = MINTRI; \quad (8)$$

$$\sum_v \sum_w TO_{vw} O_{vw} - d_2 = MINTRO; \quad (9)$$

$$\sum_u \sum_v C_u I_{uv} - d_3 = MINCOL; \quad (10)$$

$$\sum_v \sum_w R_v O_{vw} - d_4 = MINREC; \quad (11)$$

$$\sum_v I_{uv} - du_u = SUP_u \forall u; \quad (12)$$

$$\sum_w O_{vw} - dw_w = DEM_w \forall w; \quad (13)$$

$$\sum_w O_{vw} = \sum_u I_{uv} \forall v; \quad (14)$$

$$\sum_w a_{1v} O_{vw} \leq S_{1v} Y_v; \forall v \quad (15)$$

$$\sum_u a_{2v} I_{uv} \leq S_{2v} Y_v; \forall v \quad (16)$$

$$\left(\frac{TP_v}{SU_v} \right) Y_v \geq MINTS \forall v; \quad (17)$$

$$(QO_v - QI_v) Y_v \geq MINQ \forall v; \quad (18)$$

$$(TP_v \cdot DT_v) Y_v \geq MINTD \forall v; \quad (19)$$

$$I_{uv} \geq 0 \forall u, v; \quad (20)$$

$$O_{vw} \geq 0 \forall v, w; \quad (21)$$

$$Y_v \in \{0,1\} \forall v; \quad (22)$$

$$d_1, d_2, d_3, d_4 \geq 0; \quad (23)$$

$$du_u \geq 0 \forall u; \quad (24)$$

$$dw_w \geq 0 \forall w. \quad (25)$$

Illustrative Example

In our example, we consider two collection centers, three recovery facilities, and three demand centers. The example data we take to implement the goal programming model are: $TP_1 = 200$; $SU_1 = 250$; $TP_2 = 250$; $SU_2 = 600$; $TP_3 = 225$; $SU_3 = 250$; $DT_1 = 0.5$; $DT_2 = 0.1$; $DT_3 = 0.5$; $QO_1 = 0.90$; $QI_1 = 0.60$; $QO_2 = 0.80$; $QI_2 = 0.60$; $QO_3 = 0.75$; $QI_3 = 0.25$; $MINTRI = 1000$; $MINTRO = 800$; $MINCOL = 950$; $R_1 = 4$; $R_2 = 4.5$; $R_3 = 5$; $MININO = 500$; $MINTS = 0.5$; $MINQ = 0.25$; $MINTD = 25$; $SUP_1 = 200$; $SUP_2 = 250$; $DEM_1 = 60$; $DEM_2 = 70$; $DEM_3 = 80$; $a_1 = a_2 = 0.5$; $S_{11} = S_{12} = S_{13} = S_{21} = S_{22} = S_{23} = 400$. Upon solving the linear integer goal programming model, we get the following optimal solution:

$$Y_1 = Y_3 = 1; Y_2 = 0; I_{11} = 200; I_{12} = I_{13} = 0; I_{21} = 167; I_{22} = 0; I_{23} = 83; O_{11} = 0; O_{12} = 47; O_{13} = 320; O_{21} = O_{22} = O_{23} = 0; O_{31} = 60; O_{32} = 23; O_{33} = 0.$$

It is obvious from the above solution that the second recovery facility is not chosen for the reverse supply chain design.

MARKETING OF REVERSE SUPPLY CHAIN

In this section, we identify all the important drivers (numerous and often conflicting with each other) of public participation, and propose a fuzzy TOPSIS (Technique for

Order Preference by Similarity to Ideal Solution) approach [2] to predict how effectively the planned marketing strategy will motivate the public.

The basic concept of the TOPSIS is that the rating of the alternative selected as the best, from a set of different alternatives, should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution in a geometrical (i.e., Euclidean) sense (see [4] for a good introduction of the TOPSIS).

Drivers of Public Participation

The following is a fairly exhaustive list of self-explanatory drivers for the public to participate in a reverse supply chain:

- i. Knowledge of drivers of implementation of the reverse supply chain program (KD)
- ii. Awareness of the reverse supply chain program being implemented (AR)
- iii. Simplicity of the reverse supply chain program (SR)
- iv. Convenience for disposal of used products at collection centers (CD)
- v. Incentives for disposal of used products (ID)
- vi. Effectiveness of collection methods (EC)
- vii. Information supplied about used products being collected (IU)
- viii. Regularity of collection of used products (RC)
- ix. Design of special methods for abusers of the reverse supply chain program (AB)
- x. Good locations of centers where re-processed goods are sold (LR)
- xi. Incentives to buyers of re-processed goods (IB)
- xii. Co-operation of the program organizers with the local government (CL)

Evaluation of Marketing Strategy

Suppose that we have three representatives from a community to weigh the drivers of public participation, depending on what driver greatly motivates them to participate, what driver is not so important for them, and so on. Since it is difficult for them to assign numerical weights, they give *linguistic* weights like “very high”, “low”, “medium”, etc. Table 1 illustrates the linguistic weights. Using fuzzy set theory, these linguistic weights are converted into triangular fuzzy numbers [4]. Table 2 shows one of the many ways for such a conversion. Then, the average fuzzy weight and hence the normalized fuzzy weight is calculated for each driver. The normalized fuzzy weights that we obtain are as follows: KD - (0.03, 0.07, 0.16); AR - (0.06, 0.10, 0.20); SR - (0.03, 0.07, 0.16); CD - (0.06, 0.11, 0.21); ID - (0.03, 0.06, 0.12); EC - (0.07, 0.10, 0.20); IU - ((0.03, 0.06, 0.15); RC - (0.02, 0.05, 0.13); AB - (0.02, 0.06, 0.15); LR - (0.06, 0.11, 0.22); IB - (0.05, 0.09, 0.20); CL - (0.03, 0.07, 0.16).

Suppose that we evaluate marketing strategies of two different reverse supply chains. Now that we have the weights of the drivers of public participation, we rate the two marketing strategies with respect to each driver. Assuming that the three representatives come to a consensus about the linguistic rating of each marketing strategy with

respect to each driver, we arrive at the decision matrix shown in Table 3 (S1 and S2 are the marketing strategies). Table 4 is used for conversion of linguistic ratings into triangular fuzzy ratings.

The normalized decision matrix $\{r_{ij}\}$ is constructed using the following equation.

$$r_{ij} = \frac{z_{ij}}{\sqrt{\sum_{j=1}^m z_{ij}^2}} \quad (26)$$

where z_{ij} represents each element of the decision matrix shown in Table 3 (after conversion of its elements to triangular fuzzy numbers), and m represents the number of drivers. $\{r_{ij}\}$ is shown in Table 5.

Table 1. Linguistic Weights of Drivers

| Driver | Rep.1 | Rep.2 | Rep.3 |
|--------|-----------|-----------|-----------|
| KD | Low | Medium | High |
| AR | Medium | High | Very High |
| SR | Low | Low | Very High |
| CD | Very High | Very High | Medium |
| ID | Low | High | Low |
| EC | High | Medium | Very High |
| IU | Low | Low | High |
| RC | Medium | Low | Low |
| AB | Medium | Low | Medium |
| LR | Very High | High | High |
| IB | High | High | Medium |
| CL | Medium | High | Low |

Table 2. Conversion Table for Weights of Drivers

| Linguistic weight | Triangular fuzzy weight |
|-------------------|-------------------------|
| Very High | (0.7, 0.9, 1.0) |
| High | (0.5, 0.7, 0.9) |
| Medium | (0.3, 0.5, 0.7) |
| Low | (0.1, 0.3, 0.5) |
| Very Low | (0.0, 0.1, 0.3) |

The weighted normalized decision matrix defined by $V = (v_{ij}) = (r_{ij}w_j)$, is constructed next. Here, w_j represents the normalized fuzzy weight of each driver. Table 6 shows the matrix V . For each row i in the matrix V , the largest fuzzy number is represented as p_i and the smallest fuzzy number is represented as q_i . Then, the positive Euclidean distance (separation from the ideal solution) D_{j+} and the negative Euclidean distance (separation from the negative-ideal solution) D_{j-} for each marketing strategy is calculated using the following equations:

$$D_{j+} = \sqrt{\sum (v_{ij} - p_i)^2} \quad \text{for } j = 1, 2, 3, \dots, m \quad (27)$$

$$D_{j-} = \sqrt{\sum (v_{ij} - q_i)^2} \quad \text{for } j = 1, 2, 3, \dots, m \quad (28)$$

Using the following equation, relative closeness to the ideal solution is calculated.

$$C_{j+} = \frac{D_{j-}}{D_{j+} + D_{j-}} \quad (29)$$

In this example, C_{1+} is 0.31, and C_{2+} is 0.69. S2 is better than S1 because C_{2+} is higher than C_{1+} .

Table 3. Decision Matrix

| Driver | S1 | S2 |
|--------|-----------|-----------|
| KD | Very Good | Very Poor |
| AR | Fair | Very Good |
| SR | Fair | Fair |
| CD | Very Poor | Very Good |
| ID | Very Good | Good |
| EC | Good | Fair |
| IU | Poor | Fair |
| RC | Very Poor | Very Good |
| AB | Fair | Good |
| LR | Good | Good |
| IB | Poor | Very Good |
| CL | Very Poor | Good |

Table 4. Conversion for Ratings of Marketing Strategies

| Linguistic rating | Triangular fuzzy rating |
|-------------------|-------------------------|
| Very Good | (7, 10, 10) |
| Good | (5, 7, 10) |
| Fair | (2, 5, 8) |
| Poor | (0, 3, 5) |
| Very Poor | (0, 0, 3) |

Table 5. Normalized Decision Matrix

| Driver | S1 | S2 |
|--------|--------------------|--------------------|
| KD | (0.67, 1.00, 1.43) | (0.00, 0.00, 0.43) |
| AR | (0.16, 0.45, 1.10) | (0.55, 0.89, 1.37) |
| SR | (0.18, 0.71, 2.83) | (0.18, 0.71, 2.83) |
| CD | (0.00, 0.00, 0.43) | (0.67, 1.00, 1.43) |
| ID | (0.50, 0.82, 1.16) | (0.35, 0.57, 1.16) |
| EC | (0.39, 0.81, 1.86) | (0.16, 0.58, 1.49) |
| IU | (0.00, 0.51, 2.50) | (0.21, 0.86, 4.00) |
| RC | (0.00, 0.00, 0.43) | (0.67, 1.00, 1.43) |
| AB | (0.16, 0.58, 1.49) | (0.39, 0.81, 1.86) |
| LR | (0.35, 0.71, 1.41) | (0.35, 0.71, 1.41) |
| IB | (0.00, 0.29, 0.71) | (0.63, 0.96, 1.43) |
| CL | (0.00, 0.00, 0.60) | (0.48, 1.00, 2.00) |

Table 6. Weighted Normalized Decision Matrix

| Driver | S1 | S2 |
|--------|--------------------|--------------------|
| KD | (0.67, 1.00, 1.43) | (0.00, 0.00, 0.43) |
| AR | (0.16, 0.45, 1.10) | (0.55, 0.89, 1.37) |
| SR | (0.18, 0.71, 2.83) | (0.18, 0.71, 2.83) |
| CD | (0.00, 0.00, 0.43) | (0.67, 1.00, 1.43) |
| ID | (0.50, 0.82, 1.16) | (0.35, 0.57, 1.16) |
| EC | (0.39, 0.81, 1.86) | (0.16, 0.58, 1.49) |
| IU | (0.00, 0.51, 2.50) | (0.21, 0.86, 4.00) |
| RC | (0.00, 0.00, 0.43) | (0.67, 1.00, 1.43) |
| AB | (0.16, 0.58, 1.49) | (0.39, 0.81, 1.86) |
| LR | (0.35, 0.71, 1.41) | (0.35, 0.71, 1.41) |
| IB | (0.00, 0.29, 0.71) | (0.63, 0.96, 1.43) |
| CL | (0.00, 0.00, 0.60) | (0.48, 1.00, 2.00) |

REFERENCES

- [1] Fleischmann, M., *Quantitative Models for Reverse Logistics: Lecture Notes in Economics and Mathematical Systems*, Springer-Verlag, 2001.
- [2] Hwang, C. L. and Yoon, K., *Multiple attribute decision making – methods and applications: A state of the art survey*, Springer-Verlag, 1981.
- [3] Pochampally, K. K. and Gupta, S. M., “A multi-phase mathematical programming approach to strategic planning of an efficient reverse supply chain network,” *Proceedings of the 2003 IEEE International Symposium on the Electronics and the Environment*, Boston, MA, 72-78, 2003.
- [4] Pochampally, K. K., Gupta, S. M. and Kamarthi, S. V., “Evaluation of production facilities in a closed-loop supply chain: A fuzzy TOPSIS approach,” *Proceedings of the Third SPIE International Conference on Environmentally Conscious Manufacturing*, Providence, RI, 125-138, 2003.
- [5] Pochampally, K. K., Gupta, S. M. and Cullinane, T. P., “A fuzzy cost-benefit function to select economical products for processing in a closed-loop supply chain,” *Proceedings of the Third SPIE International Conference on Environmentally Conscious Manufacturing*, Providence, RI, 20-29, 2003.
- [6] Saaty, T. L., *The Analytic Hierarchy Process*, McGraw-Hill, 1980.
- [7] Veerakamolmal, P., and Gupta, S. M., “Analysis of design efficiency for the disassembly of modular electronic products,” *Journal of Electronics Manufacturing*, Vol. 9, No. 1, 79-95, 1999.
- [8] Zadeh, L. A., “Fuzzy Sets,” *Information and Control*, Vol. 8, 338-353, 1965.