ISEIS

Journal of Environmental Informatics 39(1) 11-21 (2022)

Journal of Environmental Informatics

www.iseis.org/jei

Integrating Linear Physical Programming and Fuzzy Programming for the Management of Third Party Reverse Logistics Providers

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Received 25 December 2017; revised 29 November 2018; accepted 20 January 2021; published online 25 November 2021

ABSTRACT. Shorter product lifecycles, more liberal return policies and the rise of internet marketing increased the amount of product returns in recent years. Companies must have a well-managed reverse logistics system to ensure the timely and cost-effective collection, processing and disposal of returned products. However, high fixed cost of reverse logistics infrastructure and high level of uncertainty associated with product returns force companies to outsource their reverse logistics operations to third party reverse logistics providers (3PRLPs). The success of outsourcing largely depends on the selection of suitable 3PRLP(s). Although there are many 3PRLP evaluation methodologies, the research on the determination of order quantities from 3PRLPs considering uncertainties associated with budget allocation and capacity is very limited. In addition, the previous studies do not allow decision makers to express their preferences for 3PRLP selection criteria in a physically meaningful way. This study fills these research gaps by proposing a novel 3PRLP evaluation methodology which integrates linear physical programming (LPP) and fuzzy programming (FP). First, an LPP model is constructed based on decision makers' preferences and alternative 3PRLPs are ranked according to their total LPP scores. Then, an FP model takes total LPP scores, budget allocation and capacity constraints as input and determines the number of returned products to be processed by each 3PRLP. A numerical example is also provided to illustrate the feasibility and practicality of the proposed method. The results from this example are analyzed by considering the effects of capacity and budget limitations on order quantities and several managerial insights are proposed.

Keywords: reverse logistics, third-party reverse logistics providers, linear physical programming, fuzzy programming

1. Introduction

Traditional logistics, also known as forward logistics, involves the flow of raw materials, work-in-progress inventory, and finished products from point of origin to the point of consumption. However, there are many cases (e.g., repair, warranty returns) that require the flow of materials and finished products from consumers to the point of origin. In order to operate effectively at these cases, companies must establish an effective system for reverse logistics which involves all the activities related to the collection and treatment of product returns.

There is an increasing interest towards reverse logistics in both industry and academia in recent years due to a number of environmental and economical reasons. Governments try to cope with various environmental problems (e.g., ozone depletion, global warming) by forcing manufacturers to establish reverse logistics networks for the management of product returns. Moreover, implementation of a suitable product recovery option (e.g., recycling, remanufacturing) may be profitable for a manufacturer. An effective reverse logistics program leads to decreased resource investment levels and reduces various costs (viz., holding, distribution and disposal). Reverse logistics-related product recovery operations (viz., remanufacturing, repair, reconfiguration, and recycling) positively impact a company's bottom line through value reclamation (Autry, 2005). More liberal return policies and higher number of customers buying products through e-commerce also increase the amount of product returns. Hence, companies must ensure the cost-effective design and operation of a reverse logistics system in order to handle customer returns profitably and increase the loyalty of their customers.

Reverse logistics operations cannot be performed using the forward logistics infrastructure. Because, collection and transportation of returned products and product recovery operations require the use of sophisticated equipment and a dedicated workforce. Moreover, high level of uncertainty associated with the product returns and processing times complicates the planning of reverse logistics operations. Outsourcing of reverse logistics operations to a third party reverse logistic provider (3PRLP) is a frequently used method to deal with the above-cited complications (Kumar and Putnam, 2008).

3PRLPs can be beneficial to companies in many ways. They have sophisticated equipment for transportation, material handling and product recovery operations together with a dedicated workforce. Hence, they can carry out complete set

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ISSN: 1726-2135 print/1684-8799 online
 doi:10.3808/jei.202100466

of reverse logistics operations letting companies focus on their core competencies. They also increase customer satisfaction in after-sale service by responding promptly to customers' repair and warranty-related requests. Lastly, they reduce the total cost of reverse logistics operations by achieving economies of scale. According to Krumwiede and Sheu (2002), annual logistics costs could be reduced up to 10% by out-sourcing reverse logistics operations to 3PRLPs.

The most crucial decision in the outsourcing of reverse logistics operations is to determine the most suitable 3PRLP(s). The methodology employed in 3PRLP evaluation process should consider decision makers' preferences and the high level of uncertainty associated with reverse logistics operations. In this study, a novel 3PRLP evaluation methodology integrating linear physical programming (LPP) and fuzzy programming (FP) is proposed. First, an LPP model is constructed based on decision makers' preferences and the alternative 3PRLPs are ranked according to their total LPP scores. Then, an FP model takes total LPP scores, budget allocation and capacity constraints as input and determines the number of returned products to be processed by each 3PRLP.

The rest of the paper is organized as follows. Section 2 presents a literature review on reverse logistics and 3PRLP evaluation. The proposed methodology is explained in Section 3. Section 4 provides an example to illustrate the working mechanism of the methodology. Conclusions and directions for future research are presented in Section 5.

2. Literature Review

Researchers developed various Multi-Criteria Decision Making (MCDM) methodologies for the selection of 3PRLPs (Guarnieri et al., 2015; Ilgin et al., 2015; Gupta and Ilgin, 2018; Zhang et al., 2020). Weight-based MCDM techniques such as analytic network process (ANP), analytic hierarchy process (AHP) and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) are frequently used in these methodologies. Meade and Sarkis (2002) and Tavana et al. (2016b) proposed ANP-based 3PRLP evaluation and selection methodologies. Presley et al. (2007) presented an approach integrating four techniques, viz., activity based costing (ABC), balanced scorecard (BSC), AHP and quality function deployment (QFD). Efendigil et al. (2008) considered the vagueness associated with the selection of a suitable 3PRLP by developing an integrated methodology based on fuzzy AHP and neural networks (NNs). Objective and subjective factors associated with 3PRLP selection process were considered by the approach proposed by Kannan et al. (2009a). This approach combined AHP and linear programming (LP) and determined the best 3PRLP as well as the optimum quantities to be ordered from alternative 3PRLPs. The interactions among 3PRLP evaluation criteria were analyzed by Kannan et al. (2012) using Interpretive Structural Modeling (ISM). The methodology proposed by Kannan et al. (2009b) integrated fuzzy TOPSIS and ISM. Kannan (2009) and Kannan and Murugesan (2011) used fuzzy AHP in order to evaluate alternative 3PRLPs. Percin and Min (2013) developed an integrated methodology involving three steps. In the first step, specific customer service needs are determined and those needs are matched to the characteristics of alternative 3PRLPs. Fuzzy linear regression is then used to determine a functional relationship between the 3PRLP user's logistics service needs and the 3PRLP characteristics. Finally, alternative 3PRLPs are ranked by solving a zero-one goal programming model. Senthil et al. (2014) determined criteria weights by employing fuzzy AHP. Then fuzzy TOPSIS was used in order to obtain the final ranking of alternative 3PRLPs. Tavana et al. (2016a) integrated intuitionistic fuzzy AHP and SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis in order to determine the importance levels of 3PRLP selection criteria. There are two main problems associated with the weight-based techniques. First, there is a high level of subjectivity involved in pairwise comparison process. Second, as the number of alternatives increases, the inconsistency of pair-wise comparisons also increases.

As an alternative to the weight-based MCDM techniques, data envelopment analysis (DEA) was used in various 3PRLP selection methodologies. Saen (2009, 2010, 2011) proposed DEA-based methodologies. Azadi and Saen (2011) proposed a chance-constrained DEA approach considering both dual-role factors and stochastic data. Although these methodologies eliminate the weight assignment process, they fail to provide decision makers with a natural problem formulation process. Moreover, they cannot specify the order quantities from alternative 3PRLPs.

3PRLP evaluation and selection studies can be categorized into two main categories based on the consideration of uncertainty. The papers in the first category (Meade and Sarkis, 2002; Presley et al., 2007; Kannan et al., 2009a; Saen, 2010; Kannan et al., 2012; Tavana et al., 2016b) simply do not consider the effect of uncertainty in 3PRLP evaluation and selection process. The papers in the second category take the uncertainty into consideration by employing fuzzy or stochastic analysis techniques. As can be seen from the third column of Table 1, weight-based techniques such as Fuzzy AHP (Efendigil et al., 2008; Kannan and Murugesan, 2011; Tavana et al., 2016a) and Fuzzy TOPSIS (Kannan et al., 2009b; Senthil et al., 2014) consider the uncertainty in the comparison and evaluation process by building fuzzy comparison and evaluation matrices. DEA-based methodologies (Saen, 2009, 2010, 2011; Azadi and Saen, 2011) consider imprecise or stochastic inputs and outputs. There is one study employing fuzzy regression analysis (Percin and Min, 2013).

Table 1 summarizes the important details about the previous studies and the proposed approach. According to Table 1, there is no study focusing on the determination of order quantities from 3PRLPs considering uncertainties associated with budget allocation and capacity. In addition, the previous studies do not let decision makers convey their preferences for 3PRLP selection criteria in a physically meaningful manner. In this study, we try to fill these gaps by integrating LPP and FP. The subjective and tedious weight assignment process required by weight-based techniques is eliminated by using the class functions of LPP. In LPP, the decision maker specifies appropriate class functions and the associated ranges of

Table 1. Previous Studies and the Proposed Approach

Study	Techniques	Consideration of Uncertainty?	DM's Role in Determination of Criteria Weights	Determination of Order Quantities?
Meade and Sarkis (2002)	ANP	No	DM compares criteria subjectively using Saaty's scale.	No
Presley et al., (2007)	ABC, BSC, AHP, QFD	No	DM compares criteria subjectively using Saaty's scale.	No
Efendigil et al., (2008)	Fuzzy AHP, NNs	Fuzzy pairwise comparisons	DM compares criteria subjectively using fuzzy version of Saaty's scale.	No
Kannan et al., (2009a)	AHP, LP	No	DM compares criteria subjectively using Saaty's scale.	LP determines order quantities
Kannan et al., (2009b)	ISM, Fuzzy TOPSIS	Fuzzy evaluation matrix	DM compares criteria subjectively using fuzzy version of Saaty's scale.	No
Kannan (2009)	AHP, Fuzzy AHP	Fuzzy pairwise comparisons	DM compares criteria subjectively using classical and fuzzy versions of Saaty's scale.	No
Saen (2009)	DEA	Imprecise inputs and outputs	DM determines the inputs and outputs of alternatives.	No
Saen (2010)	DEA	No	DM determines the inputs and outputs of alternatives.	No
Saen (2011)	DEA	Imprecise inputs and outputs	DM determines the inputs and outputs of alternatives.	No
Azadi and Saen (2011)	DEA	Stochastic inputs and outputs	DM determines the inputs and outputs of alternatives.	No
Kannan and Murugesan (2011)	Fuzzy AHP	Fuzzy pairwise comparisons	DM compares criteria subjectively using fuzzy version of Saaty's scale.	No
Kannan et al., (2012)	ISM	No	There is no weight assignment.	No
Percin and Min (2013)	QFD, AHP, Fuzzy LR, GP	Fuzzy linear regression	DM compares criteria subjectively using Saaty's scale.	No
Senthil et al., (2014)	AHP, Fuzzy TOPSIS	Fuzzy evaluation matrix	DM compares criteria subjectively using Saaty's scale.	No
Tavana et al., (2016a)	Fuzzy AHP, SWOT	Fuzzy pairwise comparisons	DM compares criteria subjectively using fuzzy version of Saaty's scale.	No
Tavana et al., (2016b)	ANP	No	DM compares criteria subjectively using Saaty's scale.	No
Proposed Approach	LPP, FP	Fuzzy budget and capacity constraints	DM determines physically meaningful preference ranges.	FP determines order quantities

ABC: Activity Based Costing; **AHP:** Analytical Hierarchy Process; **ANP:** Analytical Network Process; **BSC:** Balanced Score Card; **DEA:** Data Envelopment Analysis; **DM:** Decision Maker; **FP:** Fuzzy Programming; **GP:** Goal Programming; **ISM:** Interpretive Structural Modeling; **LP:** Linear Programming; **LPP:** Linear Physical Programming; **LR:** Linear Regression**; NNs:** Neural Networks; **QFD:** Quality Function Deployment; **SWOT:** Strengths, Weaknesses, Opportunities and Threats; **TOPSIS:** Technique for Order of Preference by Similarity to Ideal Solution.

different degrees of desirability instead of assigning weights. FP determines the order quantities from alternative 3PRLPs considering fuzzy budget allocation and capacity constraints.

3. Proposed 3PRLP Evaluation Methodology

Outline of the proposed methodology is presented in Figure 1. Following the determination of alternative 3PRLPs and selection criteria, LPP class functions and associated limits are specified based on the decision makers' preferences. Then LPP weight algorithm is employed to calculate criteria weights. Next, total LPP scores of alternative 3PRLPs are determined by constructing and solving an LPP model. Finally, using normalized LPP scores, budget allocation and capacity constraints, an FP model calculates the amount of returned products to be processed by each 3PRLP. The knowledge about 3PRLPs and their performance have a vital importance in the successful implementation of the proposed methodology. That is why the performance of 3PRLPs must be tracked and various inputs of the methodology (viz., 3PRLP alternatives, selection criteria, limits of class functions) must be updated regularly. The feedback loops in Figure 1 represent this tracking and updating process. The following sections present the working mechanisms of LPP and FP.

3.1. Linear Physical Programming

Weight-based MCDM techniques like goal programming (Ignizio, 1976) requires decision makers to assign physically meaningless weights. LPP (Messac et al., 1996) eliminates this weight assignment process by allowing decision-maker to express his/her preferences using one of the following four classes for each criterion (Ilgin and Gupta, 2012a):

- Class 1S: smaller-is-better
- Class 2S: larger-is-better

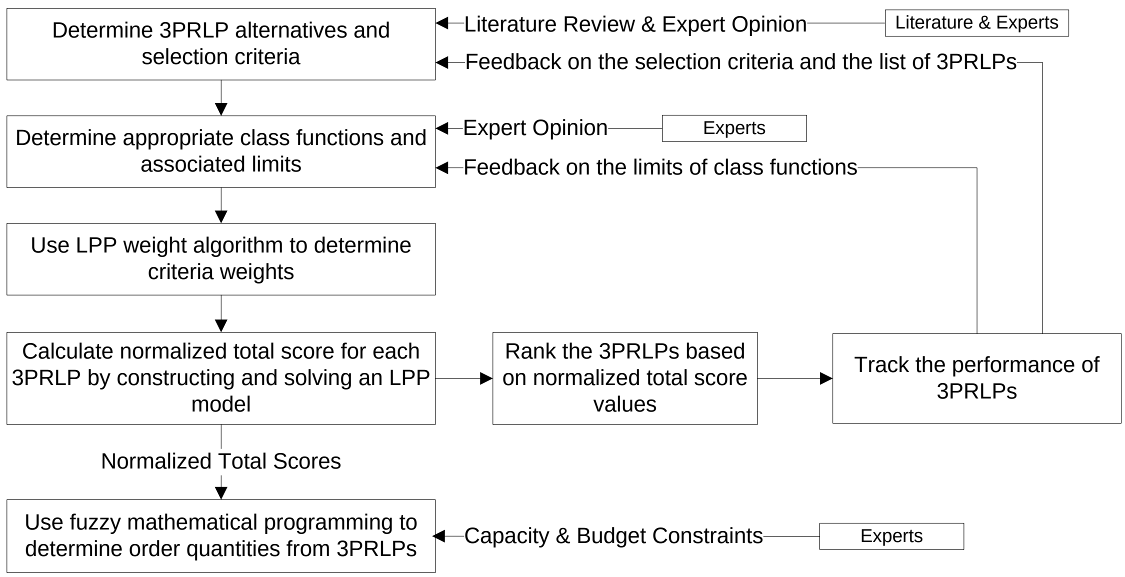

Figure 1. Flow chart for the proposed methodology.

- Class 3S: value-is-better
- Class 4S: range-is-better

A qualitative and quantitative representation of LPP class functions are presented in Figure 2. The vertical axis presents the value of the class function and the value of the criterion is presented on the horizontal axis. The smaller values of a class function are preferred and the ideal value of this function is zero. The preference ranges presented in the horizontal axis are used by the decision maker to categorize the value of the c^{th} criterion. The desirability ranges of Class 2S can be presented as given below:

- Unacceptable range: $g_c \le t_{c5}^-$
- Highly undesirable range: $t_{c5}^- \le g_c \le t_{c4}^-$
- Undesirable range: $t_{c4}^- \le g_c \le t_{c3}^-$
- Tolerable range: $t_{c3}^- \le g_c \le t_{c2}^-$
- Desirable range: $t_{c2}^- \le g_c \le t_{c1}^-$
- Ideal range: $g_c \ge t_{c1}^-$

A decision maker states his/her preferences for the c^{th} generic criterion by specifying the quantities t_{c1}^- through t_{c5}^-. Assuming that the criterion being evaluated is to be mini- mized (Class 1S) and the decision maker specifies the values of t_{c1}^+ through t_{c5}^+ as 50, 100, 150, 200, and 250, respectively. If the alternative under consideration has a criterion value of 65, it would be in the desirable range. If it has a value of 225, it would locate in the highly undesirable range, and so on (Ilgin and Gupta, 2012b).

The criterion value, g_c is mapped into a real, positive and dimensionless parameter using the class function, z_c, on the vertical axis in Figure 2. This ensures that a common scale is used for different criteria values with different meanings. For instance, for Class 1S, the value of the class function is zero if the value of a criterion, g_c, is in the ideal range. On the other hand, if the value of a criterion is in the unacceptable range, the value of the class function is very high (Pochampally et al., 2009).

Application of LPP involves the following four steps (Ilgin and Gupta, 2012a):

1. The decision maker specifies one of the four classes for each criterion.

2. The decision maker specifies the limits of the ranges of differing degrees of desirability for each criterion.

3. Incremental weights are calculated using LPP weight algorithm (Messac et al., 1996) as follows:

I. Initialize. β = 1.1; $w_{c1}^+ = 0$, $w_{c1}^- = 0$, $\tilde{z}^2 =$ small positive number (i.e., 0.1), $c = 0$; $i = 1$; n_c = number of criteria.

II. Set $c = c + 1$.

III. Set $i = i + 1$. Evaluate the following parameters sequentially: $\tilde{z}^i, \tilde{t}_{ci}^+, \tilde{t}_{ci}^-, w_{ci}^+, w_{ci}^-, \tilde{w}_{ci}^+, \tilde{w}_{ci}^-, \tilde{w}_{\min}$; if $\tilde{w}_{\min}$ is less than some chosen small positive number (i.e., 0.01), then increase β, and go to II.

IV. If $i \neq 5$, go to III.

V. If $c \neq n_c$, go to II.

where w_{ci}^+ and w_{ci}^- are positive and negative weights, respectively, for criterion c in the i^{th} range (These weights represent the slope increments of the class function for different desirability ranges), $\tilde{z}^i$ represents the change in the value of the class function along the i^{th} range, $\tilde{t}_{ci}^+$ and $\tilde{t}_{ci}^-$ are the lengths of the i^{th} ranges on the positive and negative sides of the c^{th} criterion, $\tilde{w}_{ci}^+$ and $\tilde{w}_{ci}^-$ are positive and negative normalized weights, respectively, $\tilde{w}_{\min}$ is calculated by taking the minimum of $\tilde{w}_{ci}^+$ and $\tilde{w}_{ci}^-$ and β is a convexity parameter.

The following equations are employed to calculate the various parameters appeared in the weight algorithm:

$$\tilde{z}^i = \beta(n_c - 1)\tilde{z}^{i-1} \tag{1}$$

$$\tilde{t}_{ci}^{+} = \tilde{t}_{ci}^{+} - \tilde{t}_{c(i-1)}^{+} \tag{2}$$

$$\tilde{t}_{ci}^{-} = \tilde{t}_{ci}^{-} - \tilde{t}_{c(i-1)}^{-} \tag{3}$$

$$w_{ci}^{+} = \tilde{z}^i / \tilde{t}_{ci}^{+} \tag{4}$$

$$w_{ci}^{-} = \tilde{z}^i / \tilde{t}_{ci}^{-} \tag{5}$$

$$\tilde{w}_{ci}^{+} = w_{ci}^{+} \Big/ \sum_{i=2}^{5} w_{ci}^{+} \tag{6}$$

$$\tilde{w}_{ci}^{-} = w_{ci}^{-} \Big/ \sum_{i=2}^{5} w_{ci}^{-} \tag{7}$$

Equation 1 calculates the change in the value of class function along the i^{th} range. A given initial value of $\tilde{z}^2$ must be determined in order to apply Equation 1. In practice, small positive value, such as 0.1, will be appropriate. The lengths of the i^{th} ranges on the positive and negative sides of the c^{th} criterion are calculated using Equations 2 and 3, respectively. Equations 4 and 5 are employed for the calculation of positive and negative weights, respectively. Positive and negative normalized weights are calculated using Equations 6 and 7, respectively.

4. A total score (T) is determined for each alternative by calculating a weighted sum of deviations over all ranges and criteria as given below:

$$\min_{d_{ci}^{-}, d_{ci}^{+}} T = \sum_{c=1}^{n_c} \sum_{i=2}^{5} (\tilde{w}_{ci}^{-} \cdot d_{ci}^{-} + \tilde{w}_{ci}^{+} \cdot d_{ci}^{+}) \tag{8}$$

where d_{ci}^{-} and d_{ci}^{+} represent the deviations of the c^{th} criterion value from the corresponding target values. The most desirable alternative is the one with the lowest total score.

3.2. Fuzzy Programming

A great deal of uncertainty is involved in 3PRLP selection process. Since the deterministic models are not effective in dealing with such vagueness, FP models are often employed. Instead of strictly satisfying the constraints, these models maximize the overall aspiration level (Kumar et al., 2006). They also have the capability of handling multiple objectives. There are successful applications of FP in many areas including waste management (Chen et al., 2017), closed-loop supply chain network design (Pourjavad and Mayorga, 2019), water and land resources management (Ren et al., 2017), supplier evaluation (Nakashima and Gupta, 2013) and warehouse management (Mohammed et al., 2017).

Zimmermann (1978) proposed a method for the solution of multi-objective fuzzy mathematical programming models. According to this method, first, a multi-objective programming problem with fuzzy goals and constraints is transformed into a crisp linear programming formulation. Then conventional optimization tools are employed to solve the crisp model. In this section, first, 3PRLP selection problem is modeled as a multi objective problem with fuzzy goals and constraints. Then the solution methodology proposed by Zimmerman (1978) is discussed.

The multi-objective integer programming 3PRLP selection problem (MIP-3PRLP) for two objectives, namely, total normalized LPP score (TNS) and total cost (TOC) and four relevant system constraints can be written as follows:

Goal 1:

$$\text{Minimize TNS:} \quad \sum_{i=1}^{n} NS_i \cdot X_i = TNS \tag{9}$$

Goal 2:

$$\text{Minimize TOC:} \quad \sum_{i=1}^{n} UC_i \cdot X_i = TOC \tag{10}$$

Capacity Constraint:

$$X_i \leq CAP_i \tag{11}$$

Returned Product Constraint:

$$\sum_i X_i = R \tag{12}$$

Budget Allocation Constraint:

$$\sum_i UC_i \cdot X_i \leq B_i \tag{13}$$

Non-negativity Constraint:

$$X_i \geq 0 \tag{14}$$

where:

i: 3PRLP index, $i = 1, 2, \ldots, n$

B_i: Budget allocated for 3PRLPi

UC_i: Unit cost of 3PRLPi

R: Number of products returned by customers

NS_i: Normalized LPP score of 3PRLPi

CAP_i: Capacity of 3PRLPi

X_i: Quantity to be processed by 3PRLPi

n: Number of alternative 3PRLPs

Equation 9 minimizes the total normalized LPP score. Equation 10 minimizes total cost (TOC). Equation 11 ensures that the amount of returned products allocated to a 3PRLP may not exceed its capacity. According to Equation 12, total amount of returned products allocated to alternative 3PRLPs must be equal to the total amount of products returned by customers.

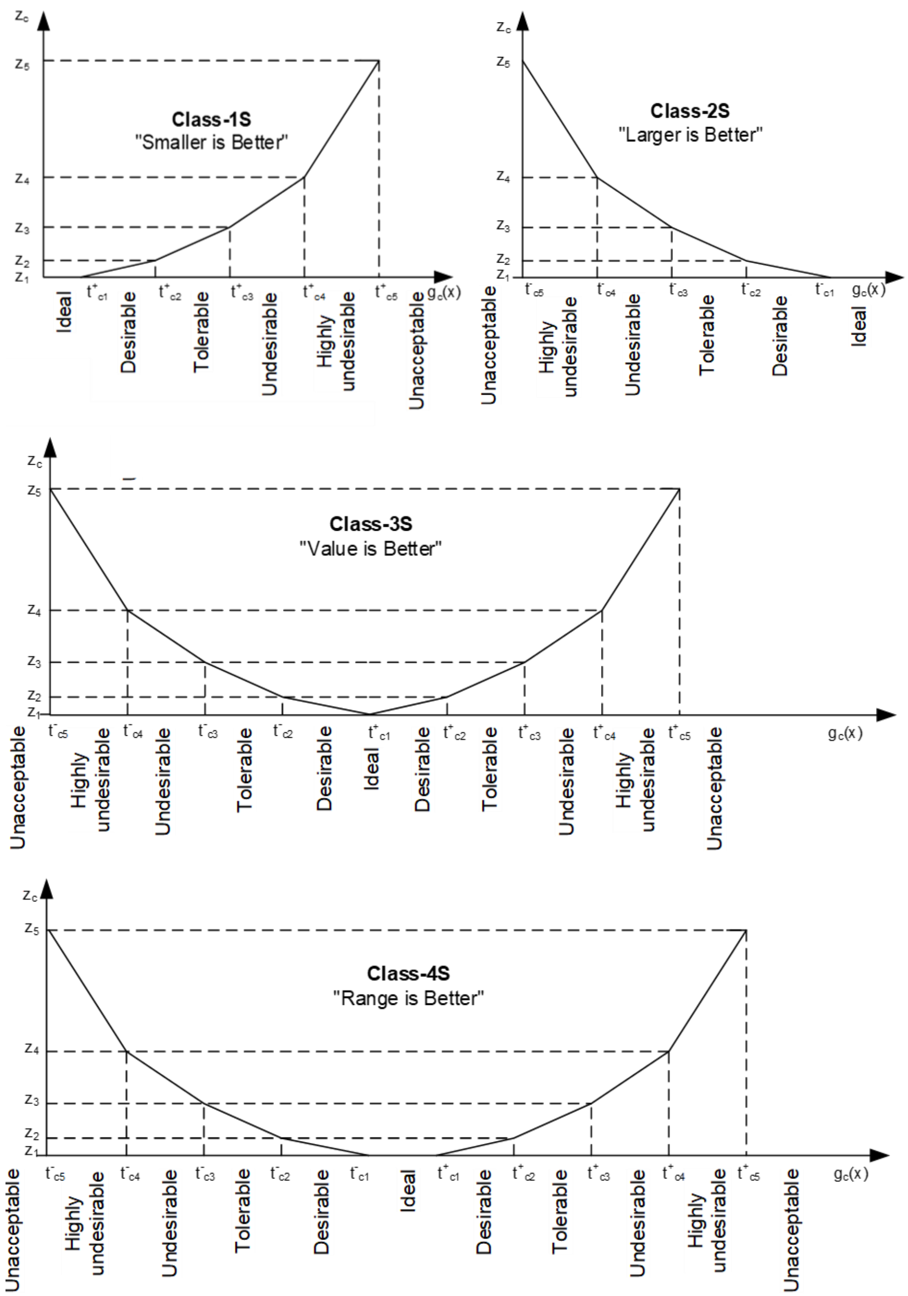

Figure 2. Class functions for LPP.

Equation 13 guarantees that the budget used by a 3PRLP may not exceed the budget allocated for that 3PRLP. Equation 14 represents the non-negativity constraints.

A linear membership function is defined for all fuzzy parameters in order to formulate the fuzzy multi-objective integer programming 3PRLP selection problem (f-MIP-3PRLP). The lower and upper values of the acceptability for a parameter are used to define a linear membership function and this function has a continuously increasing or decreasing value over the range of the parameter.

A fuzzy objective $\tilde{Z} \in X$ is a fuzzy subset of X characterized by its membership function $\mu_Z(x)\colon x \rightarrow [0, 1]$. The linear membership function for the fuzzy objectives is given by:

$$\mu_{z_j}(x) = \begin{cases} 1 & \text{if} \quad Z_j(x) \le Z_j^{\min} \\ [Z_j^{\max} - Z_j(x)]/[Z_j^{\max} - Z_j^{\min}] & \text{if} \quad Z_j^{\min} \le Z_j(x) \le Z_j^{\max} \\ 0 & \text{if} \quad Z_j(x) \ge Z_j^{\max} \end{cases} \tag{15}$$

where j is the index for the objectives (j = 1, 2, …, J), $Z_j^{\min}$ is $\min_j Z_j(x^*)$, $Z_j^{\max}$ is $\max_j Z_j(x^*)$ and x^* is the optimum solution.

A fuzzy constraint $\tilde{C} \in X$ is a fuzzy subset of X characterized by its membership function $\mu_C(x): x \rightarrow [0, 1]$. The linear membership function for a fuzzy constraint can be defined as follows:

$$\mu_{C_k}(x) = \begin{cases} 1 & \text{if } g_k(x) \le b_k \\ [1 - \{g_k(x) - b_k\}/d_k] & \text{if } b_k \le g_k(x) \le b_k + d_k \\ 0 & \text{if } b_k + d_k \le g_k(x) \end{cases} \quad (16)$$

where k is the index for constraints (k = 1, 2, …, K) and d_k is the tolerance interval for constraint k.

The following crisp formulation is obtained by transforming the FP model with J objectives and K constraints (Kumar et al., 2006):

$$\text{Maximize } \lambda \quad (17)$$

subject to:

$$\lambda \cdot (Z_j^{\max} - Z_j^{\min}) + Z_j(x) \le Z_j^{\max},\ j = 1, 2, ..., J \quad (18)$$

$$\lambda \cdot (\ d_k) + g_k(x) \le b_k + d_k,\ k = 1, 2, ..., K \quad (19)$$

$$Ax \le b \text{ for all deterministic constraints} \quad (20)$$

$$x \ge 0 \text{ and } x \text{ is integer} \quad (21)$$

$$0 \le \lambda \le 1 \quad (22)$$

where λ is the overall degree of satisfaction.

According to the solution procedure proposed by Zimmermann (1978), the individual optima is used as lower bound ($Z_j^{\min}$) and upper bound ($Z_j^{\max}$) of the optimal values for each objective. MIP-3PRLP problem is solved as a linear programming model in order to obtain the lower bound ($Z_j^{\min}$) and upper bound ($Z_j^{\max}$) of the optimal values. It must be noted, while solving the problem, one objective is considered each time by ignoring other objectives:

$$\text{Minimize/Maximize } Z_j(x),\ \ j = 1, 2, ..., J \quad (23)$$

subject to:

$$g_k(x) \le b_k + d_k,\ k = 1,\ 2,\ ...,\ K \quad (24)$$

$$Ax \le b \text{ for all deterministic constraints} \quad (25)$$

$$x \ge 0 \text{ and } x \text{ is integer} \quad (26)$$

The three-step solution methodology can be summarized as follows:

1. For each objective, a linear programming problem with the system constraints is solved. The maximization of the objective gives the upper bound of the optimal values of the objective while the minimization of the objective gives the lower bound.

2. An equivalent crisp formulation of the fuzzy optimization problem is created by using the lower and upper bound values determined in step 1.

3. The equivalent crisp formulation is solved based on the maximization of the overall satisfaction level.

Section 4 provides a numerical example for better understanding of the proposed 3PRLP evaluation methodology.

4. Illustrative Example

Suppose that a manufacturer wants to determine suitable 3PRLP(s) and associated quantities of returned products to be processed. The product structure is presented in Figure 3. There are two subassemblies (SA) and six components (C). Disassembly times of alternative 3PRLPs are presented in Table 2.

Table 2. Disassembly Times of Alternative 3PRLPs (minutes)

3PRLPs	Root	SA_1	SA_2
$3PRLP_1$	4.0	3.0	3.0
$3PRLP_2$	5.0	4.5	4.5
$3PRLP_3$	4.0	4.0	3.0

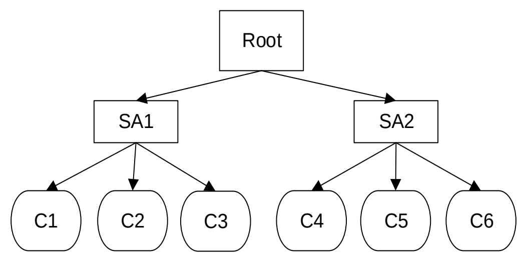

Figure 3. Product structure

Table 3. Criteria Values for Each 3PRLP

3PRLPs	g_1	g_2	g_3	g_4	g_5	g_6
$3RLP_1$	25.00	**10.00**	0.20	0.10	0.75	0.85
$3RLP_2$	15.00	14.00	0.60	0.20	0.60	0.80
$3RLP_3$	20.00	11.00	1.00	0.50	0.90	0.95

Table 4. Target Values for LPP Model

Criterion	t^+_{c1}	t^+_{c2}	t^+_{c3}	t^+_{c4}	t^+_{c5}
g_1	10.00	13.00	18.00	25.00	30.00
g_2	**5.00**	7.00	10.00	12.00	15.00
g_3	0.20	0.40	0.80	1.10	1.50
g_4	0.10	0.20	0.40	0.60	0.70
Criterion	t^-_{p1}	t^-_{p2}	t^-_{p3}	t^-_{p4}	t^-_{p5}
g_5	0.50	0.60	0.75	0.90	1.00
g_6	0.60	0.70	0.80	0.95	1.00

4.1. Ranking 3PRLPs Using LPP

There are four Class 1S criteria and two Class 2S criteria. The formulations associated with each criterion can be written as follows:

Table 5. Normalized Weights for LPP

Criterion	$\tilde{w}^{+}_{c2}$	$\tilde{w}^{+}_{c3}$	$\tilde{w}^{+}_{c4}$	$\tilde{w}^{+}_{c5}$	$\tilde{w}^{-}_{c2}$	$\tilde{w}^{-}_{c3}$	$\tilde{w}^{-}_{c4}$	$\tilde{w}^{-}_{c5}$
g_1	0.046	0.045	0.125	0.784	-	-	-	-
g_2	0.042	0.050	0.363	0.545	-	-	-	-
g_3	0.056	0.036	0.312	0.596	-	-	-	-
g_4	0.028	0.018	0.106	0.848	-	-	-	-
g_5	-	-	-	-	0.285	0.004	0.150	0.561
g_6	-	-	-	-	0.142	0.074	0.003	0.781

4.1.1. Class 1S Criteria

Unit Collection Cost (UCC_i) is the average cost of collecting (retrieving) one product ($/product):

$$g_1 = UCC_i \tag{27}$$

Unit Disassembly Time is the average time of disassembling one product (minutes):

$$g_2 = RDT_i + \sum_{j=1}^{N} SDT_{ij} \tag{28}$$

where RDT_i is the root disassembly time of 3PRLP*i* and SDT_{ij} is the time required for the disassembly of subassembly *j* by 3PRLP*i*. *N* is the total number of subassemblies.

Unit Disassembly Cost ($UDAC_i$) is the cost of disassembly per unit time ($/minute):

$$g_3 = UDAC_i \tag{29}$$

Unit Disposal Cost ($UDSC_i$) is the disposal cost per unit weight ($/lb):

$$g_4 = UDSC_i \tag{30}$$

4.1.2. Class 2S Criteria

On Time Delivery Ratio (ODR_i) is the ratio of the orders that were received on or before the due date against the total number of orders received:

$$g_5 = ODR_i \tag{31}$$

Confirmed Fill Rate (CFR_i) is the ratio of the orders that were received in right *amount* and right size against the total number of orders received:

$$g_6 = CFR_i \tag{32}$$

Table 3 presents criteria values for alternative 3PRLPs. Target values are provided in Table 4. Normalized weights used in LPP were determined using the LPP weight algorithm described in Section 3.1. (see Table 5). The weight algorithm was written in C++.

Deviations of criteria values from target values are presented in Tables 6 ~ 8. For instance, consider the second criterion (g_2) and the first 3PRLP (3PRLP1). The deviation for i = 2 can be determined in two steps. First, the value of the criterion (i.e., 10, see the bolded number in Table 3) is subtracted from the target value (i.e., 5, see the bolded number in Table 4). Then the absolute value (i.e., 5, see the bolded number in Table 6) of this difference is taken.

The total score for each 3PRLP is calculated using Equation 8. Table 9 presents the score, normalized score and rank of each 3PRLP.

Table 6. Deviations of Criteria from Target Values for $3PRLP_1$

Criterion	i = 2	i = 3	i = 4	i = 5
g_1	15.00	12.00	7.00	0.00
g_2	**5.00**	3.00	0.00	0.00
g_3	0.00	0.00	0.00	0.00
g_4	0.00	0.00	0.00	0.00
g_5	0.25	0.15	0.00	0.00
g_6	0.15	0.10	0.00	0.00

Table 7. Deviations of Criteria from Target Values for $3PRLP_2$

Criterion	i = 2	i = 3	i = 4	i = 5
g_1	5.00	2.00	0.00	0.00
g_2	9.00	7.00	4.00	2.00
g_3	0.40	0.20	0.00	0.00
g_4	0.10	0.00	0.00	0.00
g_5	0.40	0.30	0.15	0.00
g_6	0.20	0.15	0.00	0.00

Table 8. Deviations of Criteria from Target Values for $3PRLP_3$

Criterion	i = 2	i = 3	i = 4	i = 5
g_1	10.00	7.00	2.00	0.00
g_2	6.00	4.00	1.00	0.00
g_3	0.80	0.60	0.20	0.00
g_4	0.40	0.30	0.10	0.00
g_5	0.10	0.00	0.00	0.00
g_6	0.05	0.00	0.00	0.00

4.2. Determination of Order Quantities Using FP

Characteristics of the 3PRLPs considered in the illustrative example are presented in Table 10. Number of products returned by customers is considered to be a deterministic constraint and the numerical value of this parameter was taken as 2250. There are two fuzzy parameters: capacities and budget allocations. The uncertainty levels for both parameters were considered as 20% of the deterministic model. Table 11 shows the membership function values for fuzzy objective functions and fuzzy constraints at the lowest and highest aspiration levels.

Unit cost for a 3PRLP is calculated using the following expression:

$$UC_i = UCC_i + UDT_i \cdot UDAC_i + W \cdot UDSC_i \tag{33}$$

where UCC_i is unit collection cost of 3PRLPi, UDT_i is the unit disassembly time of 3PRLPi, $UDAC_i$ is the unit disassembly cost of 3PRLPi, $UDSC_i$ is the unit disposal cost of 3PRLPi and W is the weight of the product. Numerical values of the first five parameters are taken from Table 2. The weight of the product is 10 lbs. For instance, the unit cost of $3PRLP_1$ is calculated as follows:

$$UC_1 = 25 + 10 \cdot 0.2 + 10 \cdot 0.1 = 28 \tag{34}$$

The equivalent crisp formulation of the fuzzy optimization problem formulated using Equations 17 ~ 22 is as follows:

$$\text{Maximize } \lambda \tag{35}$$

subject to:

$$53.2\lambda + 0.31X_1 + 0.45X_2 + 0.24X_3 \leq 641.5 \tag{36}$$

$$1756\lambda + 28X_1 + 25.4X_2 + 36X_3 \leq 72220 \tag{37}$$

$$X_1 + X_2 + X_3 = 2250 \tag{38}$$

$$140\lambda + X_1 \leq 840 \tag{39}$$

$$60\lambda + X_2 \leq 360 \tag{40}$$

$$260\lambda + X_3 \leq 1560 \tag{41}$$

$$6000\lambda + 28X_1 \leq 36000 \tag{42}$$

$$4000\lambda + 25.4X_2 \leq 24000 \tag{43}$$

$$10000\lambda + 36X_3 \leq 60000 \tag{44}$$

$$X_1, X_2, X_3 \geq 0 \text{ and integers} \tag{45}$$

The above model was solved using Lingo 11 and the maximum degree of overall satisfaction achieved is $\lambda_{max} = 0.017$. The number of returned products to be processed by 3PRLPs was determined as follows: $X_1 = 837$, $X_2 = 200$ and $X_3 = 1,213$. *TNS* is 640.59 and *TOC* is 72,184.

The effect of uncertainty level was analyzed by increasing the uncertainty level in steps of 10%. Table 12 presents the results of this analysis. According to Table 12, at higher uncertainty levels, the number of returned products to be processed by $3PRLP_1$ increases due to its low unit cost and low normalized score. $3PRLP_2$ experiences drastic reductions due to its high normalized score. Although $3PRLP_3$ has the highest capacity, its high unit cost causes reductions in the number of returned products to be processed by this 3PRLP.

Table 9. Ranking of 3PRLPs

3PRLPs	Score	Normalized Score	Rank
$3PRLP_1$	2.573	0.306	2.000
$3PRLP_2$	3.800	0.452	3.000
$3PRLP_3$	2.036	0.242	1.000

Table 10. Characteristics of 3PRLPs

3PRLPs	Allocated Budget ($)	Capacity	Unit Cost ($)
$3PRLP_1$	30,000.0	700.0	28.0
$3PRLP_2$	20,000.0	300.0	25.4
$3PRLP_3$	50,000.0	1,300.0	36.0

Table 11. Limiting Values in Membership Function for Fuzzy Objectives and Fuzzy Constraints

	μ = 0	μ = 1
Total Normalized LPP Score (*TNS*)	641.5	588.3
Total Cost (*TOC*)	72,220.0	70,464.0
Capacity Constraints		
$3PRLP_1$	700.0	840.0
$3PRLP_2$	300.0	360.0
$3PRLP_3$	1,300.0	1,560.0
Budget Constraints		
$3PRLP_1$	30,000.0	36,000.0
$3PRLP_2$	20,000.0	24,000.0
$3PRLP_3$	50,000.0	60,000.0

Table 12. The Number of Returned Products to be Processed by 3PRLPs under Different Uncertainty Levels

3PRLPs	Uncertainty Level						
	0.20	0.30	0.40	0.50	0.60	0.70	0.80
$3PRLP_1$	837	896	955	1014	1075	1139	1200
$3PRLP_2$	200	167	136	106	81	55	32
$3PRLP_3$	1213	1187	1159	1130	1094	1056	1018

The effect of budget allocation changes was analyzed by decreasing and increasing the budget allocations of all 3PRLPs in steps of 5%. The results of this analysis are provided in Table 13. According to Table 13, when the budget allocations of all 3PRLPs were decreased 10%, the number of products to be processed by $3PRLP_2$ increases. This result can be attributed to the fact that $3PRLP_2$ has the lowest unit cost. In other words, the model tries to satisfy the constraint on the total number of returned products to be collected by 3PRLPs ($X_1 + X_2 + X_3 =$ 2,250) by increasing the amount of returned products to be collected by $3PRLP_2$ which has the lowest unit cost.

The numerical example assumes that each 3PRLP has a different capacity and budget allocation. In this setting, a 3PRLP with higher capacity and budget allocation will be more advantageous. Considering this detail, another sensitivity analysis was carried out. In this analysis, the capacities and buget allocation

Table 13. The Impact of Budget Allocation Changes on the Number of Returned Products to be Processed by 3PRLPs

3PRLPs	Change in Budgets of Alternative 3PRLPs									
	10% Decrease		5% Decrease		No Change		5% Increase		10% Increase	
	New Budget	Order Quant.	New Budget	Order Quant.	Current Budget	Order Quant.	New Budget	Order Quant.	New Budget	Order Quant.
$3PRLP_1$	27000	824	28500	837	30000	837	31500	837	33000	837
$3PRLP_2$	18000	226	19000	200	20000	200	21000	200	22000	200
$3PRLP_3$	45000	1200	47500	1213	50000	1213	52500	1213	55000	1213

Table 14. The Number of Returned Products to be Processed by 3PRLPs if Capacities and Budgets are Equal

3PRLPs	Current Setting			Equal Capacities and Budgets			
	Capacity	Budget	Order Quantity	Capacity	Budget	Order Quantity	% Change in Order Quantity
$3PRLP_1$	700.0	30,000.0	837.0	750.0	33,333.3	882.0	5.1% Increase
$3PRLP_2$	300.0	20,000.0	200.0	750.0	33,333.3	679.0	239.5% Increase
$3PRLP_3$	1,300.0	50,000.0	1,213.0	750.0	33,333.3	689.0	43.2% Decrease

of all 3PRLPs were assumed to be equal. Table 14 presents the number of returned products to be processed by each 3PRLP for both settings. According to Table 14, the 3PRLP collecting the highest number of returned products is $3PRLP_1$ when all 3PRLPs' capacities and budgets are equal. This result can be attributed to the normalized score and unit cost values presented in Tables 9 and 10, respectively. $3PRLP_1$ has the second lowest unit cost and the second lowest normalized score. $3PRLP_2$ has the lowest unit cost and the highest normalized score while $3PRLP_3$ has the lowest normalized score and the highest unit cost. Since the model has two objectives (minimization of total cost and minimization of total normalized score), it allocates more returned products to $3PRLP_1$ which ranks second in unit cost and in normalized score. Another interesting detail that can be observed from Table 14 is the fact that $3PRLP_3$ which has the highest capacity and the highest budget allocation in the current setting experiences the most drastic reduction (43.2%) in the number of returned products to be processed. This is due to the fact that there is no capacity and/or budget advantage when all 3PRLPs have equal capacity and budget values. On the other hand, $3PRLP_2$ which has the lowest capacity and the lowest budget allocation in the current setting experiences the most drastic increase (239.5%) in the number of returned products to be processed. In other words, if $3PRLP_2$ has same capacity and budget allocation values with other 3PRLPs, the model allocates more returned products to this 3PRLP due to its low unit cost.

5. Conclusions

Evaluation and selection of 3PRLPs is a key factor in the successful outsourcing of reverse logistics operations. In this paper, we propose a novel 3PRLP selection methodology by integrating LPP and FP. The methodology allows decision makers to formulate their preferences in a more natural way. In addition, reprocessing quantities of alternative 3PRLPs can be determined considering budget and capacity constraints. A numerical example is also provided to illustrate the working mechanism of the proposed methodology.

The following managerial insights can be derived based on the results of the study:

Although the numerial example involves three 3PRLPs, 3PRLP evaluation problems involving more than three 3PRLPs can be solved using the proposed methodology.

Five criteria were considered in this study. Decision makers may involve additional criteria depending on the characteristics of a specific 3PRLP evaluation problem. For each new criterion, an appropriate LPP class function must be defined and the desirability ranges of this function must be determined based on the preferences of the decision maker.

The proposed methodology was applied to an example product structure. It can also be applied to real-life products (i.e., washing machines, refrigerators). In that case, various product characteristics such as unit collection cost must be determined based on expert opinion.

As a future research topic, a computerized system can be developed in order to make the proposed methodology more user-friendly. This system should allow the user to determine the number of criteria and preference ranges for each criterion and calculate weights using LPP weight algorithm. It should also determine the rank and reprocessing quantity of each 3PRLP by automatically generating and solving an appropriate Lingo model.

References

Autry, C.W. (2005). Formalization of reverse logistics programs: A strategy for managing liberalized returns. *Ind. Mark. Manag.*, 34(7), 749-757. http://dx.doi.org/10.1016/j.indmarman.2004.12.005

Azadi, M. and Saen, R.F. (2011). A new chance-constrained data envelopment analysis for selecting third-party reverse logistics providers in the existence of dual-role factors. *Expert Syst. Appl.*, 38(10), 12231-12236. https://doi.org/10.1016/j.eswa.2011.04.001

Chen, B., Li, P., Wu, H.J., Husain, T. and Khan, F. (2017). MCFP: A Monte Carlo simulation-based fuzzy programming approach for optimization under dual uncertainties of possibility and continuous probability. *J. Environ. Inform.*, 29(2), 88-97. https://doi.org/10.3808/jei.201500293

Efendigil, T., Önüt, S. and Kongar, E. (2008). A holistic approach for selecting a third-party reverse logistics provider in the presence of vagueness. *Comput. Ind. Eng.*, 54(2), 269-287. https://doi.org/10.1016/j.cie.2007.07.009

Guarnieri, P., Sobreiro, V.A., Nagano, M.S. and Serrano, A.L.M. (2015). The challenge of selecting and evaluating third-party reverse logistics providers in a multicriteria perspective: A Brazilian case. *J. Cleaner Prod.*, 96, 209-219. http://dx.doi.org/10.1016/j.jclepro.2014.05.040

Gupta, S.M. and Ilgin, M.A. (2018). *Multiple Criteria Decision Making Applications in Environmentally Conscious Manufacturing and Product Recovery*. CRC Press. ISBN: 978-1-4987-0065-8

Ignizio, J.P. (1976). *Goal Programming and Extensions*. Lexington Books. ISBN: 0669000213

Ilgin, M.A. and Gupta, S.M. (2012a). Physical programming: A review of the state of the art. *Stud. Inform. Control.*, 21(4), 349-366. https://doi.org/10.24846/v21i4y201201

Ilgin, M.A. and Gupta, S.M. (2012b). *Remanufacturing Modeling and Analysis*. CRC Press. ISBN: 978-1-4398-6308-4

Ilgin, M.A., Gupta, S.M. and Battaia, O. (2015). Use of MCDM techniques in environmentally conscious manufacturing and product recovery: State of the art. *J. Manuf. Syst.*, 37(3), 746-758. http://dx.doi.org/10.1016/j.jmsy.2015.04.010

Kannan, G. (2009). Fuzzy approach for the selection of third party reverse logistics provider. *Asia Pacific J. Market. Logist.*, 21(3), 397-416. https://doi.org/10.1108/13555850910973865

Kannan, G. and Murugesan, P. (2011). Selection of third-party reverse logistics provider using fuzzy extent analysis. *Benchmarking Int. J.*, 18(1), 149-167. https://doi.org/10.1108/14635771111109869

Kannan, G., Murugesan, P. and Haq, A.N. (2009a). 3PRLP's selection using an integrated analytic hierarchy process and linear programming. *Int. J. Serv. Technol. Manag.*, 12(1), 61-80. https://doi.org/10.1504/ijstm.2009.025036

Kannan, G., Palaniappan, M., Zhu, Q. and Kannan, D. (2012). Analysis of third party reverse logistics provider using interpretive structural modeling. *Int. J. Prod. Econ.*, 140(1), 204-211. http://dx.doi.org/10.1016/j.ijpe.2012.01.043

Kannan, G., Pokharel, S. and Sasi Kumar, P.S. (2009b). A hybrid approach using ISM and fuzzy TOPSIS for the selection of reverse logistics provider. *Resour. Conserv. Recycl.*, 54(1), 28-36. http://dx.doi.org/10.1016/j.resconrec.2009.06.004

Krumwiede, D.W. and Sheu, C. (2002). A model for reverse logistics entry by third-party providers. *Omega*, 30(5), 325-333. https://doi.org/10.1016/S0305-0483(02)00049-X

Kumar, M., Vrat, P. and Shankar, R. (2006). A fuzzy programming approach for vendor selection problem in a supply chain. *Int. J. Prod. Econ.*, 101(2), 273-285. https://doi.org/10.1016/j.ijpe.2005. 01.005

Kumar, S. and Putnam, V. (2008). Cradle to cradle: Reverse logistics strategies and opportunities across three industry sectors. *Int. J. Prod. Econ.*, 115(2), 305-315. http://dx.doi.org/10.1016/j.ijpe.2007.11.015

Meade, L. and Sarkis, J. (2002). A conceptual model for selecting and evaluating third-party reverse logistics providers. *Supply. Chain. Manag.*, 7(5), 283-295. https://doi.org/10.1108/135985402104477 28

Messac, A., Gupta, S.M. and Akbulut, B. (1996). Linear physical programming: A new approach to multiple objective optimization. *Trans. Oper. Res.*, 8(2), 39-59.

Mohammed, A., Wang, Q., Alyahya, S. and Bennett, N. (2017). Design and optimization of an RFID-enabled automated warehousing system under uncertainties: A multi-criterion fuzzy programming approach. *Int. J. Adv. Manuf. Technol.*, 91(5), 1661-1670. https://doi.org/10.1007/s00170-016-9792-9

Nakashima, K. and Gupta, S.M. (2013). *5 Modeling Supplier Selection in Reverse Supply Chains*. CRC Press, pp. 113-124. ISBN: 978-1-4398-9903-8

Percin, S. and Min, H. (2013). A hybrid quality function deployment and fuzzy decision-making methodology for the optimal selection of third-party logistics service providers. *Int. J. Logist. Res. Appl.*, 16(5), 380-397. https://doi.org/10.1080/13675567.2013.815696

Pochampally, K.K., Nukala, S. and Gupta, S.M. (2009). *Strategic Planning Models for Reverse and Closed-loop Supply Chains*. CRC Press. ISBN: 978-1-4200-5478-1

Pourjavad, E. and Mayorga, R.V. (2019). Multi-objective fuzzy programming of closed-loop supply chain considering sustainable measures. *Int. J. Fuzzy. Syst.*, 21(2), 655-673. https://doi.org/10.1007/s40815-018-0551-y

Presley, A., Meade, L. and Sarkis, J. (2007). A strategic sustainability justification methodology for organizational decisions: A reverse logistics illustration. *Int. J. Prod. Res.*, 45(18-19), 4595-4620. https://doi.org/10.1080/00207540701440220

Ren, C., Guo, P., Tan, Q. and Zhang, L. (2017). A multi-objective fuzzy programming model for optimal use of irrigation water and land resources under uncertainty in Gansu Province, China. *J. Cleaner Prod.*, 164, 85-94. https://doi.org/10.1016/j.jclepro.2017.06.185

Saen, R.F. (2009). A mathematical model for selecting third-party reverse logistics providers. *Int. J. Procure. Manag.*, 2(2), 180-190. https://doi.org/10.1504/IJPM.2009.023406

Saen, R.F. (2010). A new model for selecting third-party reverse logistics providers in the presence of multiple dual-role factors. *Int. J. Adv. Manuf. Technol.*, 46(1-4), 405-410. https://doi.org/10.1007/s00170-009-2092-x

Saen, R.F. (2011). A decision model for selecting third-party reverse logistics providers in the presence of both dual-role factors and imprecise data. *Asia-Pacific J. Oper. Res.*, 28(2), 239-254. https://doi.org/10.1142/S0217595911003156

Senthil, S., Srirangacharyulu, B. and Ramesh, A. (2014). A robust hybrid multi-criteria decision making methodology for contractor evaluation and selection in third-party reverse logistics. *Expert Syst. Appl.*, 41(1), 50-58. http://dx.doi.org/10.1016/j.eswa.2013.07.010

Tavana, M., Zareinejad, M., Di Caprio, D. and Kaviani, M.A. (2016a). An integrated intuitionistic fuzzy AHP and SWOT method for outsourcing reverse logistics. *Appl. Soft Comput.*, 40, 544-557. http://dx.doi.org/10.1016/j.asoc.2015.12.005

Tavana, M., Zareinejad, M., Santos-Arteaga, F.J. and Kaviani, M.A. (2016b). A conceptual analytic network model for evaluating and selecting third-party reverse logistics providers. *Int. J. Adv. Manuf. Technol.*, 86(5), 1705-1721. https://doi.org/10.1007/s00170-015-8208-6

Zhang, X., Li, Z. and Wang, Y. (2020). A review of the criteria and methods of reverse logistics supplier selection. *Processes*, 8(6), 705. https://doi.org/10.3390/pr8060705

Zimmermann, H.J. (1978). Fuzzy programming and linear programming with several objective functions. *Fuzzy. Sets. Syst.*, 1(1), 45-55. https://doi.org/10.1016/0165-0114(78)90031-3