A Decision Support System for Managing Reverse Supply Chain

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Abstract

Reverse logistics are becoming more and more important in the overall Industry area because of the environment and business factors. Planning and implementing a suitable reverse logistics network could bring more profit, customer satisfaction, and an excellent social picture for companies. But, most of the logistics networks are not equipped to handle the return products in reverse channels. Reverse logistics processes and plans rely heavily on reversing the supply chain so that companies can correctly identify and categorize returned products for disposition, an area that offers many opportunities for additional revenue. The science of reverse logistics includes return policy administration, product recall protocols, repairs processing, product repackaging, parts management, recycling, product disposition management, maximizing liquidation values and much more. The focus of this project is to develop a reverse logistics management system/ tools (RLMS). The proposed tools are demonstrated in the following order. First, we identify the risks involved in the reverse supply chain. Survey tool is used to collect data and information required for analysis. The methodologies that are used to identify key risks are the six sigma tools, namely Define, Measure, Analyse, Improve and Control (DMAIC), SWOT analysis, cause and effect, and Risk Mapping. An improved decision-making method using fuzzy set theory for converting linguistic data into numeric risk ratings has been attempted. In this study, the concept of 'Left and Right dominance approach'(Chen and Liu, 2001) and Method of 'In center of centroids' (Thoran et al., 2012a,b) for generalized trapezoidal fuzzy numbers has been used to quantify the 'degree of risk' in terms of crisp ratings. After the analysis, the key risks are identified are categorized, and an action requirement plan suggested for providing guidelines for the managers to manage the risk successfully in the context of reverse logistics.

Next, from risk assessment findings, information technology risk presents the highest risk impact on the performance of the reverse logistics, especially lack of use of a decision support system (DSS). We propose a novel multi-attribute decision (MADM) support tool that can categorizes return products and make the best alternative selection of recovery and disposal option using carefully considered criteria using MADM decision making methodologies such as fuzzy MOORA and VIKOR. The project can be applied to all types of industries. Once the returned products are collected and categorized at the retailers/ Points of return (PoR), an optimized network is required to determine the number of reprocessing centres to be opened and the optimized optimum material flow

between retailers, reprocessing, recycling and disposal centers at minimum costs. The research develops a mixed integer linear programming model for two scenarios, namely considering direct shipping from retailer/ PoR to the respective reprocessing centers and considering the use of centralized return centers (CRC). The models are solved using LINGO 15 software and excel solver tools respectively.

The advantage of the implementation of our solution is that it will help improve performance and reduce time. This benefits the company by having a reduction in their cost due to uncertainties and also contributes to better customer satisfaction. Implementation of these tools at ABZ computer distributing company demonstrates how the reverse logistics management tools can used in order to be beneficial to the organization. The tool is designed to be easily implemented at minimal cost and serves as a valuable tool for personnel faced with significant and costly decisions regarding risk assessment, decision making and network optimization in the reverse supply chain practices.

To my Mother and Father….all that I am, you have made me.

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CERTIFICATE

This is to certify that thesis entitled, “A DECISION SUPPORT SYSTEM FOR MANAGING REVERSE SUPPLY CHAINS” submitted by Mr. OMOSA B. MICHAEL GEOFFREY in partial fulfilment of the requirements for the award of Master of Technology in Mechanical Engineering with “Production Engineering” Specialization during session 2013-2014 in the Department of Mechanical Engineering National Institute of Technology, Rourkela.

It is an authentic work carried out by him under my supervision and guidance. To the best of my knowledge, the matter embodied in this thesis has not been submitted to any other University/Institute for award of any Degree or Diploma.

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Chapter 1: Introduction

1.1 Introduction

Reverse logistics (RL) is the process of planning, implementing and controlling effective inbound flow and storage of secondary goods and related information opposite to the traditional supply chain direction for the purpose of recovering value or proper disposal. It is also called closed loop supply chain and can be seen as part of sustainable development. The products are returned or discarded because either they do not function any more properly or because their services are no longer needed. According to the original returns, reverse logistics can be categorized into end-of-use returns, commercial return, warranty returns, production scrap, by-products and packaging return. Used products that are taken back from customers are disassembled and the quality of parts is checked. Then, these elements may be used as spare parts or reused for another life cycle after some re-manufacturing activities or components can be used together with other state-of-the-art technologies in the assembly of new products. In addition to the economic advantage obtained through sourcing materials from used products, environmental impact of used products can be minimized through reduction of the requirements to dispose. Used products can be used for landfill and minimized the need to consume new resources. Although RL practices have been evolved from green logistics, the two differ significantly. Green logistics consider the environmental aspects of all logistics activities and concentrates specifically on forward logistics operations rather than reverse channels (DeBrito et al., 2002). Similarly, Rogers and Tibben-Limbke, (2001) describe green logistics as the efforts to minimize the environmental impact of logistics activities while reverse logistics is the reversed supply chain for the flow of products or materials going “the wrong way on a one-way street”. Figure 1.1 highlights the differences and similarities between green and reverse logistics.

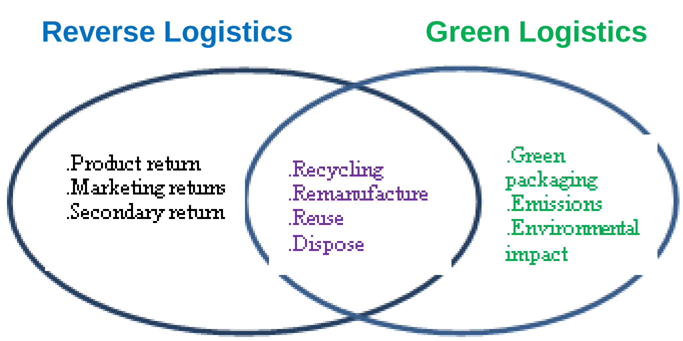


Fig. 1.1: Comparison of Reverse Logistics and Green Logistics (Rogers and Tibben-Lembke, 2001)

Products, components, materials, equipment and even complete technical systems may go backwards in the supply chain. Return products can be taken back from either end user/customers or another member of the distribution channel such as a retailer or distribution center and the material in the reverse flow can be a product or a packaging material which are disassembled and the quality of parts is checked. Then, these parts can be used as spare parts, be reused for another life cycle after some re-manufacturing activities or components can be used together with other state-of-the-art technologies in the assembly of new products. Manufacturing returns occurs on the production floor where the products with unsatisfactory quality are reworked. After the products enter the forward supply chain, those that are found to be defective are pulled back from the supply chain (product recalls). Afterwards, many more actors/ partners are involved within the reverse logistics network at various stages to facilitate the many commercial agreements that may be in place such as stock out returns, end of season product returns etc. (B2B commercial returns). In addition, instances occur when goods are to be returned at the consumer end due to quality issues, performance dissatisfaction, defects, repairs and warranty in the business-to-consumer scenario (B2C commercial returns). Ultimately, all these collected products are to be reprocessed appropriately either by remanufacturing, recycling or disposal (end-of-use and end-of-life returns).

Eventually, even after use or product life, collected products are to be remanufactured, recycled or incinerated (end-of-use and end-of-life returns). At this point, both material hazard and environmental impact have to be taken into account (the latter especially in EU countries). Applications in reverse logistics range from remanufacturing of copiers, re-use of refillable containers and toner cartridges for copiers and printers, spare parts for computers and cars, recovery of by-products and solvents in the chemical industry. Reverse Logistics plays a significant role in six strategic areas, namely competitive reasons, cleaning of supply chain, environmental issues, recapturing of value, asset recovery and protection of market margins (Rodgers and Tibbens-Lembke, 1999).

1.2 Background and Motivation

From the literature in the last decade, the research work in reverse logistics can be classified into seven main categories namely: Risks associated with RL, Recovery and disposal strategies to deal with returned goods/ products, RL relationships, Inventory management of RL products, RL network structures, RL planning and control and ICT for reverse logistics (DeBrito et al., 2002). With regard to RL risk management, it has been found out that most of the companies do not consider the probability of occurrence of uncertain risks involved in RL. This ignorance affects the company's potential of maximizing the collection, distribution, recovery and disposal of secondary products that can be returned from end users/ or supply chain partners. Eventually, this can affect the overall performance in various areas such as finances, management, legal, environmental and customer relationship etc. A risk is a potential future loss or undesirable outcome that may arise from some present action. Risk factors are defined as a source that can pose a serious threat to the outcome. On the contrary, risk assessment is the determination of the quantitative/ qualitative value of risk related to a concrete situation and a well-recognized threat. Although a number of performance measures appropriate for traditional forward supply chains have been developed and a supply network risk tool developed, these existing measures and tools are inadequate for use in the reverse supply chain (Beamon, 1999). Risk analysis in the reverse supply chain has not been adequately measured and there has been no much previous research done regarding the management of such.

Further, recovery and disposal decision management is a critical research issue because it determines the documentation of returns (Inventory), processing of transactions, disposition cycle time, minimization of return inventories and credit refund processing for the returned products in reverse logistics. The location of the testing and grading operations in the network has a substantial impact on the arising goods flows (Thiery et al., 1995). It is only after this stage that individual products can be assigned to an appropriate recovery alternative and hence to a geographical destination. By passing a judgment on the perceived depreciation, quality and suitability of the return product based on the source, reasons for return and perceived depreciation (i.e. physical depreciation level, time depreciation, performance depreciation and market depreciation, environmental impact and legislation requirements (Chang and Lin, 2013)), suitable recovery and disposal alternative can be decided remotely at the points of return/ retailers. This will provide a real-time decision-making on the suitable reprocessing alternatives for the collected products early as they enter in the reverse supply chain; thus may minimize the total reprocessing cycle time as well as offer quick transportation decision-making on the probable reprocessing destination of the return products i.e. can be sent directly to their best recovery alternative.

Consequently, a reverse supply chain refers to the flow of material through different facilities, starting with products from end user or supply chain partner and ending with the products delivered to final reprocessing facilities such as repair and servicing, cannibalizing and re-manufacturing, repackaging and reselling, recycling centers and disposal centers (Rodgers and Tibben-Lembke, 1998). Many activities are included in reverse logistics concept such as the reuse of used products, disassembly and processing of excess inventory of products, parts, and/or materials (Daugherty et al., 2005). Product returns have become a significant management issue and an unavoidable cost for a business. This situation has made firms consider the possibility of managing product returns in a more cost-efficient way whereas increasing the revenue opportunities for these returned products. Typically, a product return involves the collection of returned products at designated regional distribution centers or retail outlets, the transfer and consolidation of returned products at centralized return centers (CRCs), the asset recovery of returned products through repairs, refurbishing and re-manufacturing and the disposal of returned products with no commercial value (Min et al., 2006a). For the last decade, increasing concerns over environmental degradation and increased opportunities for cost savings or revenues from returned products have prompted some researchers to formulate more effective reverse logistics strategies using mathematical models.

All the above background issues on RL provides an opportunity for further research in reverse logistics with regard to risk identification and mitigation, RL system planning, material flow and inventory control, RL network design and optimization. There is a need for a comprehensive decision support tool for managing returned goods in reverse supply chain. These RL management tools shall allow the users to quantify and locate all risks, make decisions on the alternative needed to be taken when a certain risk occurs based on the action plans, make decisions on the best reprocessing alternative and optimize the supply chain networks. These features allow the user to achieve the overlying goal of managing the reverse logistics and developing alternatives quickly and efficiently in the least amount of time. Since the tools may be used for different organizations, many different factors affect the parameters that lie in the reverse network of the organization. Therefore, the effectiveness of these tools will vary among different companies.

1.3 Research Objectives

The following objectives have been set for the proposed research work:

[1] To assess the degree of various reverse logistics risks that impact on the collection, distribution, recovery and disposal of return products. Risk ranking using fuzzy ranking methods is performed so as to identify the impact level of various risk influencing factors under each risk categories. Further, action requirement plans to be implemented to optimize and effect the sustainability of an effective RL system are suggested.

[2] To develop a decision support tool based on fuzzy multi-attribute decision making (MADM) approach for categorization of returned materials based on the product quality and usability to enable selection of suitable reprocessing alternatives that gains value.

[3] To formulate RL network optimization models which can further be optimized using methodologies based on mixed integer linear programing techniques for controlling flow of returned goods and minimize the costs involved.

1.4 Methodology to be adopted

The study will undertake a broad-based cross-sectional questionnaire survey and the responses will be analyzed statistically so that various risk factors of reverse logistics in different categories of Industrial settings can be assessed. Managerial perception on various issues related to risks in reverse logistics and their awareness level can be highlighted so that effective strategies can be evolved for RL systems. Next, a multi-attribute decision-making methodology based on methods like MOORA and VIKOR and their fuzzy variants will be tried for classification of returned materials with utmost emphasis on the type of products. Further, mixed integer linear programming models for reverse logistics will be developed and solved using both conventional operations research methods and evolutionary algorithms and comparison will be made based on selected performance measures.

1.5 Summary

This chapter introduced the scope and reasons for reverse logistics, presented the research and investigative objectives and provided a summary of the methodologies used in this study. Chapter II presents an in-depth review of the existing literature on the subjects of reverse logistics and resource-based theory. Chapter III introduces the various reverse supply chain risks and presents risk analysis models. Once the key risks are identified, they are mapped and categorized, and an action requirement plan is suggested for providing guidelines for the managers to manage the risk successfully in the context of reverse logistics. Chapter IV further presents the modelling and analysis of multi-attribute decision-making approach for categorization of recovered materials based on their quality and usability and selection of reprocessing alternatives that gains value. Chapter V presents the adopted RL networks optimization models based on mixed integer linear programing techniques (MILP) for controlling the flow of returned goods and minimize the costs of reverse supply chains. Chapter VI highlights the research implementation by demonstrating the proposed reverse logistics management system and finally Chapter VII provides conclusions and offers areas for further research.

Chapter 2:
Literature Review

2.1 Introduction

The literature review begins with a discussion of the activities of reverse logistics (RL), strategic use of reverse logistics, highlights the differences between forward logistics (FL) and reverse logistics (RL) and identify the key factors that tend to impact RL program performance. Next, the topic on performance and sustainability of reverse logistics systems will be introduced with specific relevance to risk assessment and management with applications to reverse logistics.

Reverse logistics defined

Reverse Logistics has many definitions. According to the Council of Supply Chain Management Professionals (CSCMP), logistics management is that part of supply chain management that plans, implements and controls the efficient, effective forward **and reverse** flow and storage of goods, services and related information between the point of origin and the point of consumption in order to meet customers' requirements. (CSCMP, 2003). Based on the CSCMP definition of logistics management, Rogers and Tibben-Lembke (2001) define RL as:

"The process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods, and related information from the point of consumption to the point of origin for the purpose of recapturing or creating value or proper disposal".

2.2 Reverse Logistics trends: A brief review

During the last decade, reverse logistics has obtained recognition both as a research field and a practice. During the early nineties, Stock (1992) recognized the field of reverse logistics as being relevant for business and society in general. Later Kopicki et al. (1993) paid attention to the discipline and practice of reverse logistics, pointing out opportunities on reuse and recycling. In the late nineties, several other studies on reverse logistics appeared. Kostecki, (1998) discusses the marketing aspects of reuse and extended product life. Stock (1998) reports in detail how to set up and carry out reverse logistics programs. Rogers and Tibben-Lembke (1999) presented a broad collection of reverse logistics business practices, giving special attention to the US experience where the authors carried out a comprehensive questionnaire survey. In the past, many articles dedicated to the optimization and management of reverse logistics have been appeared, for example Guide et al. (2000) on the characteristics of reverse logistics for remanufacturing systems.

Extensive review of literature suggests that reverse logistics research work can be classified into seven main categories namely: Risks associated with RL, Recovery and disposal strategies to deal with returned goods/products, RL relationships, Inventory management of RL products, RL network structures, RL planning and control and ICT for reverse logistics (DeBrito et al., 2002). These are briefly discussed as follows:

2.2.1 Reverse Logistics Risk assessment

In practice, there is significant and growing need to measure and benchmark the overall sustainability of entire reverse supply chains rather than single processes or firms (Seuring and Müeller, 2008). Therefore, the decision to carry out risk analysis in the reverse logistics functions has been proved beneficial towards gaining increasing advantage in the global market today (Abdullah and Verner, 2012). Few research works has been conducted to ascertain the various risks associated with RL and establish their impact on the overall performance of an RL system. Risk management is an organized/ structured approach to identifying, mitigating and assessing/evaluating risks of reduced losses incurred due to lack of risk management (Tohamy, 2008).

2.2.2 Recovery and disposal strategies

Recovery is only one of the processes in the reverse logistics chain. The other processes include: administrative processes, transportation, inspection and testing, sorting, reprocessing and disposal (Dullaert et al., 2007). There are several recovery options for products and materials being returned (DeBrito and Dekker, 2004): Direct recovery (re-selling and re-distribution), product recovery (repair, refurbishing, remanufacturing), recycling (materials recovery), proper disposal and write-off. Recovery and disposal strategies therefore seek to establish the best way to deal with return goods so as to maximize on their value as well as mitigate environmental effects through proper disposal. The various research in this area focus on how to structure recovery from return flows (degree of disassembly recovery option to be used, the location and capacity levels of the RD centres etc.) (Krikke, 1998; Thiery et al., 1995; Dale et al., 2002).

2.2.3 Reverse logistics relationships

To stimulate the collection of goods and certain behaviour of their partners, parties in the reverse chain may use various incentives. Thereby, there are two types of incentives that have been studied so far namely; i) incentives that may be used to influence the supply of goods to a company in the context of product recovery and ii) incentives that may be used to influence others to accept the goods a company wants to get rid of. (DeBrito et al., 2002). The incentives found in literature can be subdivided into (direct) economical (e.g. deposit fee, buy back option, reduced price 'new', fees, take back with/or without cost for supplier) and non-economic incentives (e.g. new for old, lease contract, legislation, environmental consciousness, charity consciousness etc.) (DeBrito et al., 2002). All these incentives can also be used to stimulate others to accept goods for recovery. The incentives found in literature concern commercial returns, product recalls, end-of-use returns and end-of-life returns.

2.2.4 Inventory management

As an important issue, inventory management is a key research issue because the product being used by the customer is a main part of the inventory in reverse logistics. Traditional inventory control models do not take into consideration that manufactured products, which leave the inventory of serviceable due to customer demands, may be returned by the end-users after a particular time span and recovered by the manufacturer. When the returns of goods and re-manufacturing options have to be taken into consideration in inventory control situations, two additional sources of complexity appear in the traditional approaches of optimizing stochastic inventory control. First, due to uncertainty of returns, an additional stochastic impact has to be regarded. Second, with re-manufacturing a second mode of supply of serviceable goods is given so that coordination with the regular mode of procurement becomes necessary. The inventory control of such a system is complex compared to a traditional one because:

- Demand can be met through manufacturing and/or re-manufacturing
- The inventory level does not decrease over time because of demand, but it may increase with the incoming re-manufactured products.
- In the traditional inventory system, the average cost increases as the lead time for manufacturing increases.

2.2.5 Reverse Logistics Network Structures

Most of the current research on reverse logistics focusses on various issues such as network design, vehicle routing and product distribution. A main activity in reverse logistics is the collection of the products to be recovered and the redistribution of the processed goods. Network structures can be classified according to two dimensions. The first is the type of recovery, i.e. re-use, remanufacturing and recycling, which was also used in Fleischmann et al., (1999). The second dimension concerns the initiative, being either public or private (DeBrito et al,. 2002).

2.2.6 Planning and control of recovery activities

This category deals with the planning and control of the recovery activities i.e. the actual decision where should when how much of what be collected, disassembled or processed. It assumes that the potential recovery options are given. Part of the planning and control of product recovery concerns the planning and control of supply of goods to be recovered in which context incentives play an important role. Therefore, it is strongly related to inventory management. Planning and control of product recovery has been divided to those dealing with disassembly planning, the separate collection of (parts of) products for recovery, the separate processing of (parts of) products for reuse (or disposal) as well as with the combined planning and control of collection and distribution and processing and production (DeBrito et al,. 2002).

2.2.7 Information technology in reverse logistics.

Information and communication technology (ICT) is used to support reverse logistics during different stages of a flow-path of a product. Implementation of ICT tools help in developing alternatives for the product life cycle tracking/ tracing, secondary markets demand forecasting, new parts requirements for remanufacturing inventories and so on. Further, IT (information technology) provides a link from the customer (through the marketing persons) to the factory (several plants) through reverse logistics on to process planning, material flow, inventory control and cost estimates. Online technology provides a low-cost, extremely efficient way to display merchandise, attract customers and handle purchase orders and customer complaints and returns. This is a very high level analytical process that may be time consuming, costly, and company specific. It may be beneficial in situations to have a model that more accurately reflects the decisions needed to be made in time of product returns.

2.3 Reverse Logistics activities

In simple terms, reverse logistics is an organization's management of material resources obtained from its customers. Companies deploy reverse logistics to collect used, damaged, unwanted (stock balancing returns), or outdated products, as well as packaging and shipping materials from the end-user or supply chain partner (Rodgers and Tibben-Lembke, 1998). Products and packaging can be in the reverse flow for many different reasons. Consumers often return items because the item is defective or unwanted while suppliers and retailers may return items to manage better inventories or recapture value. Packaging flows back because it is reusable (e.g., pallets or plastic totes), or due to disposal concerns (e.g., corrugated cardboard) (Rogers and Tibben-

Limbke, 2001). Table 1.2 summarizes the most common reasons why a product or packaging enters the reverse channel.

Table 1.2: Characterization of Items in Reverse Flow by Type and Origin

	Supply chain partners	End users
Products	Stock Balancing Returns Marketing Returns End of Life/Season Transit Damage	Defective/unwanted products Warranty returns Recalls Environmental disposal issues
Packaging	Reusable totes Multi-trip packaging Disposal requirements	Reuse Recycling Disposal Restrictions

2.4 Strategic importance of reverse logistics

Reverse logistics are becoming more and more important in the overall Industry area because of the environment and business factors. Planning and implementing a suitable reverse logistics network could bring more profit, customer satisfaction, and an excellent social picture for companies. The implementation of reverse logistics includes return policy administration, product recall protocols, repairs processing, product repackaging, parts management, recycling, product disposition management, maximizing liquidation values and much more. These RL business elements can have a long-term bottom line impact. Reverse logistics can play a big strategic role in ensuring customer satisfaction thus increased market competitiveness, cleaning of old inventories, keep fresh inventories downstream, environmental protection and improve bottom-line profits through recapturing of value and asset recovery. In summary, RL can be utilized in a strategic manner in order to play the following roles as presented in Table 2.2 below

Table 2.2: Strategic Role of Returns (*Rogers and Tibben-Lembke, 2001*)

Role	Percentage
Competitive reasons	65.2%
Cleaning supply channels	33.4%
Environmental disposal issues	28.9%
Recapture value	27.5%
Asset recovery	26.5%
Protecting margins	18.4%

2.5 Comparison between Forward and Reverse Logistics

It is often assumed that reverse logistics programs can be successfully implemented and maintained by simply reversing the forward supply lines (Gooley, 1998). On the contrary, reverse logistics activities have very different and often more complex issues that affect system performance. Table 2.3, developed by Ronald Tibben-Lembke and Dale Rogers, 2002, details the essential differences between forward and reverse logistics operations. Although the table focusses on the retail sales environment, many of these differences exist equally in other RL applications.

Table 3.2: Differences between Forward and Reverse Logistics

Forward	Reverse
Forecasting relatively straightforward	Forecasting much more difficult
One-to-many transportation	Many-to-one transportation
Product quality uniform	Product quality not uniform
Product packaging uniform	Product packaging often damaged
Destination and routing clear	Destination and routing unclear
Standardized channels	Exception driven channels
Disposition options clear	Disposition not clear
Pricing relatively uniform	Pricing dependent on many factors
Importance of speed recognized	Speed often not considered a priority
Forward distribution costs closely monitored	Reverse costs less visible
Inventory management consistent	Inventory management not consistent
Product life-cycle manageable	Product life-cycle issues more complex
Negotiations between parties straightforward	Negotiations complicated by additional factors
Marketing methods well known	Marketing complicated by many factors
Real-time tracking information available	Visibility often less transparent

2.6 Comparison of Forward and Reverse Logistics Costs

Unlike in forward logistics where the costs are well-defined and well-known, reverse logistics is less visible and sometimes unknown/ or difficult to forecast. Like most complex business operations, reverse logistics requires a wide range of resources, including manpower, information systems, assets, and infrastructure. This can make RL operations much more resource demanding to implement and maintain (Tibben-Lembke and Rogers, 2002). Some of the increased costs associated with RL are illustrated in Table 4.2 below:

Table 4.2: Comparison of Forward and Reverse Logistics Costs

Cost category	Comparison to forward logistics
Transportation	Greater: lower-volume channels
Inventory holding costs	Lower: lower-value items
Shrinkage (theft)	Much lower: limited use without repair
Obsolescence	Obsolescence: may be higher due to delays
Collection	Much higher: less standardized
Sorting, quality diagnosis	Much greater: item-by-item
Handling	Much higher: nonstandard sizes and quantities
Refurbishment	Significant for RL, non-existent for forward
Change from book value	Significant for RL, non-existent for forward

2.7 Factors Impacting on Reverse Logistics Program Performance

There exist very real internal and external factors that can affect and make it difficult to execute reverse logistics successfully. In recent years, considerable research has been conducted on the subject of establishing effective RL programs. An extensive review of the literature has identified numerous reoccurring factors that tend to impact RL program performance. Rodgers and Tibben-Lembke, (2001) identified the following categories: importance of reverse logistics relative to other issues, company policies, lack of systems, competitive issues, management inattention, financial resources, personnel resources, and legal issues as the most impacting factors. The barriers and percentage impacts on reverse logistics are listed below in Table 5.2.

Table 2.5: Barriers to Reverse Logistics

Barrier	Percentage
Importance of reverse logistics relative to other issues	39.2%
Company policies	35.0%
Lack of systems	34.3%
Competitive issues	33.7%
Management inattention	26.8%
Financial resources	19.0%
Personnel resources	19.0%
Legal issues	14.1%

However, there exist many more factors that have been found to influence the performance and efficiency of a reverse logistics system. In Chapter III, we examine and consider these impacting factors further as risk drivers that affect the various key players/ departments of a reverse logistics system (RLS) and documenting those risks and their distinctiveness/ characteristics. Risk identification is a critical step that leads on to further assessing of the stability of the RLS. It is important to identify the main potential risk areas and the risk drivers. Risk driver is an observable phenomenon which is likely to drive up the possibility of some risked consequence whose future occurrence depends, in part at least, on the existence of this event (Berkeley et al., 1991). The type of risks, location and definition, may vary in different organizations. Therefore, it is important for each team to identify the significant risks and locate each risk in order to understand the impact a risk can have on the reverse network as a whole.

Chapter 3:
Reverse logistics risk assessment and analysis

3.1 Background

The reverse supply chain has gained a lot of attention in recent years. Most of the companies do not consider the probability of occurrence of uncertain risks. This ignorance affects the company's performance in various areas such as finances and unsatisfied customers. Companies are not aware of the losses faced by them due to lack of risk management strategies. This research is focused on identifying those risks that have a higher level of impact on the company and find ways to mitigate and control those risks in the reverse supply chain. This study provides methods of reducing key risks that would help businesses minimize losses both in terms of customer satisfaction and finances. Recently, many original equipment manufacturers (OEM) have been facing daunting challenges in terms of efficient and lean reverse logistics (RL) strategy due to the existence of inherent risks. These risks must be recognized and properly managed towards the successful establishment of efficient RL systems. In this research, a hierarchical reverse logistics risk structure representation has been developed so as to explore a formal model for qualitative risk assessment. The various parameters for defining risks have been presented. Further, the metrics for measuring likelihood and impact that aid to achieve consistent assessment have been studied extensively. An improved decision-making method using fuzzy set theory for converting linguistic data into numeric risk ratings has been attempted. In this study, the concept of 'Left and Right dominance approach'(Chen and Liu, 2001) and Method of 'In center of centroids' (Thoran et al., 2012a,b) for generalized trapezoidal fuzzy numbers has been used to quantify the 'degree of risk' in terms of crisp ratings. Finally, a framework for categorizing different risk factors has been proposed on the basis of a distinguished range of risk ratings (crisp). Consequently, an action requirement plan has been suggested for providing guidelines for the managers to manage the risk successfully in the context of reverse logistics.

3.2 Introduction

Risk management plays a significant role in overall revenue of the company and thus net income in reverse supply chains. It has become significant and hence logical analysis of the impact and occurrence of risks involved in the reverse logistics supply chain activities needed. In today's business sector, the tremendous change in business strategy results in increasing competition towards achieving a competitive advantage over lower costs and the ability to meet customer satisfaction through the use of reverse logistics. Companies are experiencing growing pressure from advocacy groups and non-governmental organizations and some customer related to their supply chains (Vachon and Klassen, 2006). Stakeholders demand corporate sustainability, non-financial accounting and reporting, procurement, supplier relations, (Nijhof 2002; Waddock and Bodwell 2004; Teuscher et al, 2006). Companies are increasingly expected to deliver a simultaneous balance of economic, environmental and social society and also result in long-term economic benefits. Organizations must look at improving and sustaining their Reverse logistics systems in order to remain competitive in a cost effective way as well as cope up with this unpredictable business situation. Therefore, the decision to carry out risk analysis in the reverse logistics functions has been proved beneficial towards gaining increasing advantage in the global market today (Abdullah & Verner, 2012).

A risk is a potential future loss or undesirable outcome that may arise from some present action. Risk factors are defined as a source that can pose a serious threat to the outcome. On the contrary, risk assessment is the determination of the quantitative/ qualitative value of risk related to a concrete situation and a well-recognized threat. Although some of the individual risk factors more significant than others, the reverse logistics success usually depends on the effective management all types risks, response strategies used to assess risks and an organization’s ability overcome them. Therefore, it is indeed necessary to develop a unified risk understanding model containing perceived risks in relation to RL system and factors that affect the manageability of these risks. Exhaustive literature review reveals that limited studies have been reported so far highlighting important sources of risks and associated risk influencing factors in the reverse supply chain (RSC). Moreover, it has been found out that limited attempts have been made to establish a comprehensive approach to analyzing various issues like risk assessment, mitigation, and devolvement of best practices in the perspective of RSC. Kou and Lu, 2013, have pointed out that individual knowledge; experience and intuitive judgement, provide a better assessment of risk than probabilistic approach. Hence, the authors have highlighted the applicability of fuzzy set theory for risk assessment in capturing the individual intuitive assessment. The aim this research is to develop a unified hierarchical risk model that can be used to estimate the degree risk extent efficiently and propose risk assessment procedure using fuzzy knowledge representation theory to support risk analysis. Furthermore, all perceived risks have been classified into different categories based on their quantifying value of risk ratings and also an action requirement plan recommended which could provide a guideline towards efficient management of RL risk. Our aim is not only finding the key risk, but also suggests the best possible solution to that particular risk. Hence, a step by step implementation of our solution, organizations will get benefits in terms of reverse supply chain activity improvement and thus reducing costs that may occur due to uncertainties in their overall supply chain activities.

3.3 Problem statement

The reverse supply chain has gained a lot of attention in recent years. Most of the companies do not consider the probability of occurrence of uncertain risks. This ignorance affects the company's performance in various areas such as finances and unsatisfied customers. Companies are not aware of the losses faced by them due to lack of risk management strategies. Although a number of performance measures appropriate for traditional supply chains have been developed, and a supply network risk tool has been developed, these existing measures and tools are inadequate for use in the reverse supply chain (Beamon, 1999). Risk analysis in the reverse supply chain has not been measured, and there has been no much previous research done regarding the management of such. There is room for improvement to minimize cost and create an efficient reverse network. In order to improve the reverse supply chain and minimize costs, a thorough analysis of risk minimization must be performed. The reverse supply chain requires the establishment and implementation of new performance measurement systems and risk analysis model. This research section is triggered in identifying those risks that have a higher level of impact on the company and find ways to mitigate and control those risks in the reverse supply chain.

3.4 Study objectives

This study aims at develop a formal model for qualitative risk assessment. The basic parameters for defining risks have been presented including the metrics for measuring likelihood and impact that aid to achieve consistent assessment. The study will also include the following two elements:

- Categorizing different risk factors on the basis of distinguished ranges of risk ratings
- Provide action requirement plan

The specific objectives of this study may be summarized as follows:

- Provide a network diagram and hierarchy of all potential risks.
- Develop a reverse supply chain network risk analysis model for risk rating.
- Develop, test, and validate a working model for risk analysis.

- Develop a framework for categorizing different risk factors and a guideline action requirement plan.

3.5 Sustainability and Reverse supply management

The concept of sustainability of a reverse logistics system is an increasingly important one. The management of companies are usually under immense pressure both from external (from customers and policy makers) and internal (from their company's objectives and values). Therefore, in practice there is significant and growing need to measure and benchmark the overall sustainability of entire reverse supply chains rather than single processes or firms (Seuring and Müeller 2008). One way to ensure a sustainable RL system is by understanding what are the risks involved in all aspects and key players of a reverse supply chain that can hinder a successful and efficient reverse supply chain system. In order to develop and sustain an effective RL system, companies must carry out an evaluation of financial, inventory, and responsive performance of the reverse supply chains and their subsystems. Even though some early efforts by incorporating the three dimensions of sustainability (economic, social and environmental) into supply chain analysis have occurred (New 1997; Kärnä and Heiskanen 1998; Sarkis 2001a), frameworks for analysis of sustainability parameters in a supply chain usually cover economic and environmental dimensions and to a much lesser extent embrace all three dimensions of sustainability (Seuring and Müller 2008).

Despite this increased interest and various efforts to measure sustainability within organizations and across the supply chain, no method has yet emerged which can effectively incorporate all the dimensions of sustainability and measure and benchmark sustainability across all stages in the reverse supply chain. The absence of such a method has implications for practice. Specifically, how can managers determine if their efforts to improve and sustain their RL systems are effective or even moving things in the right direction? How can they identify which are the risks involved and their impact on the reverse supply chain? The lack of a measure also has implications for theory and research development: how can researchers test hypotheses about the mechanisms of sustainability without a method to measure it? This study fills this void by developing a method to evaluate and analyse various risks involved in the reverse supply chain system and sub-systems, and demonstrating how the method is used by applying it to data from reverse supply chains by utilizing various expert opinions.

3.6 Risk management in reverse supply chain

Risk management is an organized/ structured approach to identifying, mitigating and assessing/ evaluating risks of reduced losses incurred due to lack of risk management (Tohamy, 2008). It includes four steps, namely risk classification, risk identification, risk assessment and risk response (Berkeley et al., 1991). Reverse supply chain systems consist of a lot of risks in various stages, e.g. collecting and transporting of return products from customers and other supply chain partners, determining the quality of return products, timeliness, etc. Further, RL risks can be categorized into process /strategic (internal) risks and external (Diaz et al., 2011). Internal risks are risks associated with physical supply chain (e.g., planning and forecasting, procurement, manufacturing, transportation, inventory management, distribution and warehousing, Financial, management and customer service) and the external risks are the ones where the system interacts with external environment such as customer risk, laws and regulation risk, etc. Fig. 1.3 shows a framework for the remainder of our discussion, represents a systems model Risk identification and analysis. The discussion begins with the major boundaries associated with managing this system, including “external risks” and “internal risks”. The next set of elements discussed, critical inputs to the system, includes various “Risk identification, metrics and measures”, as well as the design of a Reverse supply chain (RSC). To aid the RSC risk management, “risk analysis tools” are also identified. The expected results representing outcomes of such a system are also discussed.

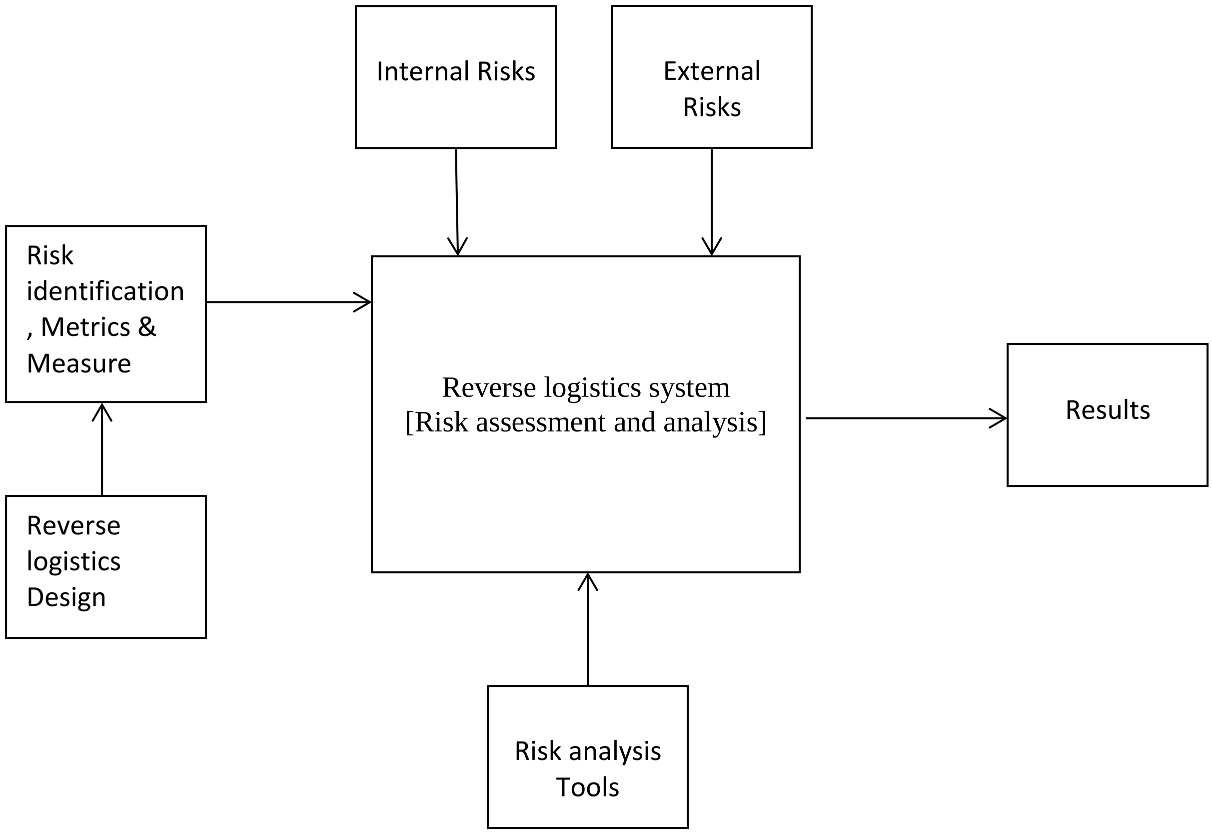


Fig. 1.3: Risk Management Framework

3.6.1 Reverse logistics design

A diagrammatic representation of the supply network helps the company understand the RL process and is beneficial in mapping the flow of all returned materials from one or several locations. Mapping this reverse supply system involves the understanding of the key roles and responsibility in the various stages and steps of the network as well as the different key players involved. There are three primary steps in creating an efficient and accurate reverse supply network diagram (Banisalam, 2008): identification of different functional departments; identification of locations and processes; and processes involved and mapping of returned material process flow.

i. Identification of various departments: Reverse Logistics (RL) activities involve more than on department or organization. They include Sales, production, information Technology, customer services, etc. Proper identification of all the departments involved in the RL will help to create an organized layout of the reverse network, which will also clarify the responsibilities in the occurrence of certain events.

ii. Identification of Locations and processes: In every department involved in RL, there are specific locations and processes within that handles the flow of returned materials/products. Areas such as warehouses, distribution centres, and service centres may be involved in the flow of recovered materials. Each of these locations requires specific systems and procedures to perform and facilitate the process of returned product, as well as the outcome each product. By identifying these precise locations and processes, management will be able to allocate the responsibilities and tasks to them and create an organized layout of the reverse network.

iii. Mapping of RL process flow: More often than not, products are returned due to several reasons, i.e. good returns, customer returns, marketing returns, product recalls, environmental returns, etc. (Thierry et al., 1995; Rodgers et al., 2001). It is important to layout the process of returned materials and the outcome of each product, which typically includes the product being reused, refurbished, resold, or recycled. The multiple streams in a reverse supply chain network make it difficult to isolate different risks that may occur in the network. Therefore, mapping the entire reverse supply chain process, including all the internal and external locations, will assist organizations in managing the different streams and the risks that may associate with the flow of materials being returned.

3.6.2 Risk identification, metrics and measurement

Risk identification is a process that aims at finding risks factors that affect the various key players/ departments of a reverse logistics system (RLS) and documenting those risks and their distinctiveness/ characteristics. Risk identification is a crucial step that leads on to further assessing of the stability of the RLS. It is important to identify the main potential risk areas and the risk drivers. A risk driver is an observable phenomenon which is likely to drive up the possibility of some risked consequence whose future occurrence depends, in part at least, on the occurrence of this phenomenon (Berkeley, Humphreys & Thomas, 1991). The type of risks, location and definition, may vary in different organizations. Therefore, it is important for each organization to identify the significant risks and locate each risk in order to understand the impact a risk can have on the reverse network as a whole. This process encompasses three primary steps:

i. *Identifying the risk types:* - There are a number of internal and external risks that may interfere with the network and cause delays and disruptions. Internal risks arise from within the organization where the organization has direct control over. Examples of internal risks include managerial risks, demand risks, financial risks, inventory and warehousing risks, system risks, etc. External risks arise from the interactions between the organization and its environment, where the organization has no direct control over. Examples of external risks include environmental risk, transportation risks, Legal risks, economic risks, etc. Further, these risks be classified into three core risk elements (Gunasekaran et al., 2001) based on the measures and metrics for performance measurement of supply chain namely; Strategic uncertainty, operational risks and tactical risks. Strategic uncertainty includes risks with a source of uncertainty such a return chain side, reprocessing-side, and asset value risk. Operational catastrophes consist of risks that stem from sources such as terrorism, natural disasters, or bankruptcies. Operational accidents such as delays, disruptions, and accidents include everything from minor everyday occurrences to major malfunctions such as the breakdown of a computer system. By identifying all the major and minor risks, as well as the internal and external risks, organizations can identify the variety of potential threats before they occur, minimizing the element of surprise.

ii. Identifying risk factors: - Once a list of all risks has been created, the next step is to examine each risk and define the specific risk factors that influence the outcome, i.e. incorporated in the definition of each risk should be the following: Risk drivers; risk location and risk effect. The risk drivers are the possible sources that cause the risk occurrence for each risk. Risk location is the process of exploring and searching all the potential areas of the reverse supply chain that might harbour risk. However, locating risks is a complicated process since many risks may occur in multiple locations, or may even affect the entire network as a whole especially if both external and internal risks are involved.

iii. Identifying potential loss: - The occurrence of a risk leads to some problem. The problem often leads to some loss affecting the reverse logistics (RL). After the effect of each risk identified as previously discuss, the potential loss becomes comprehensible to the RL. Losses can be quantified and related to resulting damages caused by a variety of risks. Situations can give rise to different types of loss. Some losses are relatively minor, and others can be catastrophic in their level. The following are categories of loss organizations may experience due to risk occurrence in the reverse supply chain: Customer satisfaction loss, reverse logistics costs, time loss, sales, resource under-utilization, etc.

Table 1.3 below shows the hierarchical structure of the risk system of reverse logistics for the various risks that have been identified in this research (Chopra and Meindl, 2002; Harland et al. 2003; Grewal et al., 2009):

Table 1.3: The risks and risks hierarchy of a reverse logistics system

Target Level	First Level	Second Level	Description
	Managerial risk (R_1)	Management inattention to reverse logistics ($F_{1,1}$)	Affects business strategy implementation as well as the firm's internal ability to coordinate and implement reverse logistics.
		Poor company return policies($F_{2,1}$)	
		Lack of understanding of the strategic importance of reverse logistics($F_{3,1}$)	
		Lack of conflict management ($F_{4,1}$)	
		Unclear decision making process($F_{5,1}$)	
		No standardized process and procedures($F_{6,1}$)	
	Collection and Transport risk, R_2	Disruptions of collection and transportation of materials($F_{1,2}$)	Adversely affects inward flow of returned products to enable subsequent operations to take place thus affecting operations; also termed 'input risk'.
		Transportation and delivery delays($F_{2,2}$)	
		Unidentified and unauthorized returns($F_{3,2}$)	
		Risk of hazardous material ($F_{4,2}$)	
		Inability to satisfy return volumes ($F_{5,2}$)	
		Customers loss of confidence on return process ($F_{6,2}$)	
		Lack of use of decision support systems ($F_{7,2}$)	
		Disagreement over the condition, status and value of return material ($F_{,82}$)	

	IT systems risk, R_3	IT infrastructure breakdown ($F_{1,3}$)	Affects decision making process, flow of information, analysis and execution.
		Task complexity due to extent of networking and data requirements ($F_{2,3}$)	
		Lack of use of IT ($F_{3,3}$)	
		System incompatibility to new IT solutions ($F_{4,3}$)	
		Loss of key IT technical personnel ($F_{5,3}$)	
		Technological discontinuity or obsolescence ($F_{6,3}$)	
		Unable to fulfil customer needs due incorrect/ insufficient data ($F_{,73}$)	
		Customer information/data loss ($F_{8,3}$)	
		Lack of updated customer information in the database ($F_{9,3}$)	
	Inventory risk, R_4	Lack of capacity to handle return volumes ($F_{1,4}$)	Affects likelihood of customers placing return orders; grouped with factors such as product obsolescence/loss of value in 'product/market risk'.
		Loss/damage of materials in storage ($F_{2,4}$)	
		Poor returns rate forecasts ($F_{3,4}$)	
		Unknown total costs of inventory ($F_{4,4}$)	
		Lengthy reprocessing & disposal cycle time ($F_{5,4}$)	
		Damages or loss during transportation ($F_{6,4}$)	
	Financial risks, R_5	Unknown total costs of reverse logistics ($F_{1,5}$)	Exposes a firm to potential loss through changes cost of sustaining RL; can also occur when specific costs are not taken care of in the planning stage.
		Lack of proper planning & budgeting for RL ($F_{2,5}$)	
		Hidden costs ($F_{3,5}$)	
		Financial constraints of the company ($F_{4,5}$)	

		Increased costs of services (labour, facilities) $(F_{5,5})$	
		High cost of repair & delivery back to the customers $(F_{6,5})$	
		High costs of recycling/or disposal $(F_{7,5})$	
	Environmental risk, R_6	Measurement problems $(F_{1,6})$	Exposes the firm with changes in regulations affecting the firm's business, such as environmental regulation.
		Social-corporate responsibility $(F_{2,6})$	
		Lack of adequate environmental guidelines (F_{36})	
		Noncompliance with governmental/legal guidelines (F_{46})	
		Resistance from local community (F_{56})	
		Risk of hazardous material (F_{66})	
		Lack of expertise and/or experience (F_{76})	
	Relationships risk, R_7	Inadequate terms & ambiguous contracts between RL partners (F_{17})	Erodes value of whole business due to loss of confidence.
		RL partners poor service quality (F_{27})	
		Lack of transparent information sharing (F_{37})	
		Disagreement over conditions and value of returns/warranties (F_{47})	
		Timeliness of response amongst partners (F_{57})	
		Loss of confidence amongst RL partners (F_{67})	
		Customers/partners demands too high (F_{77})	
	Outsourcing risk, R_8	Inadequate terms and conditions of contract (F_{18})	
		3PLs/4PLs poor service quality (F_{28})	

		Lack of experience & expertise (F_{38})	Exposes the firm to potential losses of business, high costs of RL and unsatisfied customers.
		Unknown hidden costs (F_{48})	
		Loss of privacy & intellectual property (F_{58})	
		Inflexibility of partners toward changes (F_{68})	
		Lack of transparency and information sharing (F_{78})	
		Lack of financial stability to deliver services (F_{88})	
	Legal risk, R_9	Different global rules and regulations in handling & reprocessing of product returns (F_{19})	Exposes the firm to litigations with action arising from customers, suppliers, shareholders or employees
		Uncertainty about legal environment (F_{29})	
		Loss of privacy & intellectual property (F_{39})	
		Risk of hazardous materials (F_{49})	
		Cost of legal expertise (F_{59})	
		Changing company/ partners policies (F_{69})	
	Time management risk, R_{10}	No proper follow ups ($F_{1,10}$)	Causes delays in collection, distribution, processing and credit refunds
		Not paying attention to details at the starting stages ($F_{2,10}$)	
		Deadlines not met ($F_{3,10}$)	
		Transport delays ($F_{4,10}$)	
		Less manpower ($F_{5,10}$)	
		Return order processing delays ($F_{6,10}$)	
		Sorting delays ($F_{7,10}$)	
	Product risk, R_{11}	Longer time for replacement ($F_{1,11}$)	Exposes the OEM to low customer confidence.
		Unavailability of replacement component(s) ($F_{2,11}$)	
		Short product life cycle ($F_{3,11}$)	

		Unable to provide repair services ($F_{4,11}$)	
		Maintenance of return product/material ($F_{5,11}$)	
	Culture risk, R_{12}	Resistance to apply technology ($F_{1,12}$)	Exposes the firm to lack of continous improvements and competitive edge.
		Language barriers ($F_{2,12}$)	
		Different customs and culture ($F_{3,12}$)	
		Resistance to change ($F_{4,12}$)	

3.6.3 Risk Assessment

Risk can be assessed in terms of their potential severity of loss (impact) and to the probability of occurrence. There are two main ways in which risk probability can be assessed: subjective judgement, and objective analysis (Zhi, 1995). Subjective assessment means directly estimating the likelihood of a risk factor. It is easy and practical, but it needs experience and scrutiny. Direct subjective judgement can assign some risks in reverse logistics, which appear quite often and for which there are many comparable experiences, a probability. Objective analysis is another approach used very widely for assessing the likelihood of a risk factor. There are many researchers who have used objective analysis in quantifying the risk impact (Banisalam, 2008). Choi et al., (2008) investigated the issues of channel coordination in a supply chain when the individual supply chain decision makers take mean-variance (MV) objectives. They proposed an MV formulation to quantify difference risk concerns of the retailer and the supply chain coordinator in a vertically integrated two-echelon supply chain under a stochastic demand environment. Ahluwalia and Nema, (2006) created a multi-objective, multi-step reverse logistics formulation for integrated solid waste management for computer waste management. The model is based on an integer linear programming method with the objectives of minimizing environmental risk as well as reducing cost. Horvath et al. (2007) offer a Markov chain approach to modelling the expectations, risks, and potential shocks associated with the cash flows stemming from retail reverse logistics activities. The Markov chain allowed the retailer to assess liquidity issues as a unit of product moves from one return state to another. Wang et al. (2007) proposed a new integrated AHP-DEA methodology to evaluate the risks of hundreds or thousands of bridge structures. The proposed methodology used analytic hierarchy process (AHP) to determine the weights of criteria; linguistic terms (e.g. High, Medium, Low, and None) to assess bridge risks under each criterion; the data envelopment analysis (DEA) method to determine the values of the linguistic terms, and the simple additive weighting (SAW) method to aggregate bridge risks under different criteria into and overall risk score for each bridge structure. Shyur, (2008) proposed a new quantitative methodology for the assessment of risk in civil aviation. The spline method is used to present the baseline hazard function. This approach allows finding the fundamental cause of human error related accidents through the analysis of operational safety data. The model takes into account the relationships among relevant aviation risk factors such as human, technical, environmental, and organizational factors that affect safety and system performance. However, the above methods are difficult to implement and involves a lot of computations. Besides, some historical data is required. Sometimes, this makes the application of the method impractical in practice, especially for reverse supply because most returned products lack accurate data/information concerning their value, quality, time, etc.

However, in this research, the use of the fuzzy set approach method to assess the impact of risk factors is suggested. This study focuses on subjective judgement process for assessing both the likelihood of occurrence, as well as the impact of each risk influencing factor. The subjectivity of parameters mentioned above has been tackled by means of fuzzy logic and risk has been estimated from the fuzzy point of view rather than probabilistic conceptualizing. Determining the rate of risk occurrence is the fundamental challenge in risk assessment since statistical information is not available on all kinds of past incidents. Furthermore, evaluating the severity of the risk impact is often quite difficult for immaterial assets. Assuming statistics is not available, opinions of experts are the primary source of information. Several criteria are used in judging whether the level of risk is high or low, such as the probability of an undesirable occurrence, the degree of seriousness, and the subsequent impact if it does occur. When people talk about risk, one or more such risk criteria may be involved. Williams, 1993, suggested a multi-criteria structure for risk identification, i.e. the risk concept is broken down into two main criteria: (a) the probability, which is the possibility of an undesirable occurrence, such as a cost overrun, and (b) the impact, which is the degree of seriousness and the scale of the impact on other activities if the undesirable thing occurs. Using a mathematical description (Zhe, 1995; Mitchell, 1995), a risk can be described as follows:

$$R = PxI \tag{1}$$

Where *R* is the degree of risk, within [0, 1]; *P* is the probability of the risk occurring, within [0, 1]; and *I* is the degree of impact of the risk, which is defined as being within [0, 1], (the more serious the impact is, the greater the figure). From the above risk Eq.1, it can be seen that the degree of risk is near 0 if a risk factor has either little impact or little probability of occurrence. In contrast, if a risk factor has a high impact and a high probability of occurrence, its degree of risk is very high, near 1.

3.7 Fuzzy sets approach

Usually most of the qualitative decisions in situations where it is not possible to quantify the value using the available data on considered criteria, are made using human judgment in a multi-criteria decision process. However, to overcome the vagueness, ambiguity and subjectivity of the human thought, Fuzzy set theory are introduced and used (Zadeh, 1965). The decisions are expressed in terms of linguistic scale, i.e., a grade of the membership function ranging from zero to one. In any decision-making situation, candidate risks are evaluated based on qualitative as well as quantitative risk drivers. Conventional tools and techniques can easily assess quantitative factors. However, the difficulty arises in dealing with subjective (qualitative) evaluation indices. As most of the risk characterizing factors are subjective in nature, its assessment relies on the decision-makers' linguistic judgment. In the absence of complete and exact data about the returned products in reverse logistics, use of fuzzy linguistic variables provides a powerful mathematical tool for decision modeling. Their role is significant when applied to complex phenomena not easily described by traditional mathematical methods, specifically where the objective is to find a good approximate solution. Fuzzy set theory has been contributing to the capability of reflecting the real world while providing a more widely frame than classic or crisp set theory. Modeling using fuzzy sets has proven to be an effective way of formulating decision problems where the information available is subjective and imprecise. Linguistic variables are variables whose values are words or sentences in a natural or artificial language. The concept of a linguistic variable provides a means of approximate characterization of phenomena that are too complicated or too ill-defined to be amenable to a description in conventional quantitative terms (Zadeh L. A. 1975a).

A fuzzy number is a fuzzy subset of the universe of discourse X that is both convex and normal. Various types of fuzzy numbers such as triangular, trapezoidal, bell-shaped numbers are used in decision making processes, Chen & Chen, 2009; Chen, Lin, & Huang 2006; Xia, Li, Zhou, & Wang, 2006; Yang & Hung, 2007, (Chitrasen et al., 2014). However, trapezoidal numbers are widely used due to simple mathematical representation and easy computation. A trapezoidal fuzzy number form (a, b, c, d) is the most generic class of fuzzy numbers with linear membership function (Kaufmann & Gupta, 1991). Due to the generic property of this class of fuzzy numbers, it found application in modeling linear uncertainty in scientific and applied engineering problems rather than triangular fuzzy numbers. Ranking of fuzzy numbers plays a significant role in approximate reasoning, optimization, forecasting, decision making, scheduling and risk-based analysis practices In this research, the concepts of ranking fuzzy numbers based on 'Left-Right Dominance' (Chen & Lu, 2001) and Method of 'In center of centroids' (Thoran et al., 2012a, b) for generalized trapezoidal fuzzy numbers has been used to quantify the 'degree of risk' in terms of crisp ratings.

3.7.1 Concept of generalized trapezoidal fuzzy numbers

A generalized trapezoidal fuzzy number can be defined as $\bar{A} = (a, b, c, d; w_A)$ (Chen, 1985) as shown in Fig. 2.3 below:

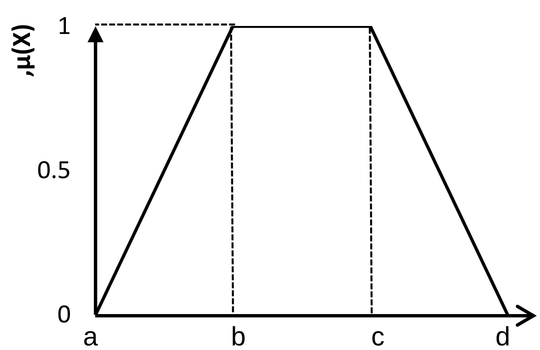


Fig. 2.3: Trapezoidal fuzzy number $\bar{A}$

And the membership function $\mu_A(x): R \rightarrow [0,1]$ is defined as:

$$\mu_{\tilde{A}}(A) = \begin{cases} \frac{x-a}{b-a} \times w_{\tilde{A}}, & x \in (a,b) \\ w_{\tilde{A}}, & x \in (b,c) \\ \frac{x-d}{c-d} \times w_{\tilde{A}}, & x \in (c,d) \\ 0, x \in (-\infty, a) \cup (d, \infty) \end{cases} \quad (2)$$

Where, $a \leq b \leq c \leq d \; and \; w_{\tilde{A}} \in [0,1]$. The elements of the generalized trapezoidal fuzzy numbers $x \in R$ are real numbers, and its membership function $\mu_A(x)$ is the regular and the continuous convex function, i.e. it shows that the membership degree to the fuzzy sets. If $w_{\tilde{A}}$=1, then $\bar{A} = (a, b, c, d; 1)$ is a normalized trapezoidal fuzzy number and $\bar{A}$ is a generalized or non normal trapezoidal fuzzy number if $0 < w < 1$. The image of $\bar{A} = (a, b, c, d; w)$ is given by$-\bar{A} = (-a, -b, -c, -d; w)$. As a particular case if $b = c$, the trapezoidal fuzzy number is reduced to a triangular fuzzy number given by $\bar{A} = (a, b, d; w)$ .The value of '*b*' corresponds with the mode or core and [*a, d*] with the support. If $w = 1$, then $\bar{A} = (a, b, d)$ is a normalized triangular fuzzy number $\bar{A}$ is a generalized or non-normal triangular fuzzy number if 0 < *w* < 1.

3.7.2 Fuzzy operational rules for generalized trapezoidal fuzzy numbers

There are various operations on generalized trapezoidal fuzzy numbers. But here, only important operations used in this study are illustrated. If we define, two generalized trapezoidal fuzzy numbers $\bar{A} = (a_1, a_2, a_3, a_4; w_{\tilde{A}})$ and $\bar{B} = (b_1, b_2, b_3, b_4; w_{\tilde{B}})$ (Chen & Chen, 2007; Chen, 1985) then:

$$\tilde{A} + \tilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4); \min(w_{\tilde{A}}, w_{\tilde{B}})) \quad (3)$$

$$\tilde{A} - \tilde{B} = (a_1 + b_4, a_2 + b_3, a_3 + b_2, a_4 + b_1); min(w_{\tilde{A}}, w_{\tilde{B}})) \quad (4)$$

$$\tilde{A}\text{x}\tilde{B} = (k, l, m, n; \min(w_{\tilde{A}}, w_{\tilde{B}})) \quad (5)$$

Where,

k= $\min(a_1\text{x}b_1, a_1\text{x}b_4, a_4\text{x}b_1, a_4\text{x}b_4)$

$l = \min(a_2xb_2, a_2xb_3, a_3xb_2, a_3xb_3)$

$m = \max(a_2xb_2, a_2xb_3, a_3xb_2, a_3xb_3)$

$n = \max(a_1xb_1, a_1xb_4, a_4xb_1, a_4xb_4)$

If $a_1, a_2, a_3, a_4, b_1, b_2, b_3, b_4$ are real numbers, then

$$\tilde{A}\text{x}\tilde{B} = (a_1xb_1, a_2xb_2, a_3xb_3, a_4xb_4; \text{Min}(w_{\tilde{A}}, w_{\tilde{B}}))$$

$$\tilde{A} \div \tilde{B} = \{\frac{a_1}{b_4}, \frac{a_2}{b_3}, \frac{a_3}{b_2}, \frac{a_4}{b_1}; \min(w_{\tilde{A}}, w_{\tilde{B}})\} \quad (6)$$

3.8 RL Risk rating and ranking

Ranking fuzzy numbers is an important tool in decision-making. In fuzzy decision analysis, fuzzy quantities are used to describe the performance of alternatives in modelling a real-world problem. In order to rank fuzzy quantities, each fuzzy quantity is converted into a real number (crisp) and compared by defining a ranking function from the set of fuzzy numbers to a set of real numbers which assigns a real number to each fuzzy number where a natural order exists (Thoran et al., 2012). Usually by reducing the whole of any analysis to a single number, much of the information is lost and hence an attempt is to be made to minimize this loss. Various ranking procedures have been developed since 1976 when the theory of fuzzy sets was first introduced by Zadeh, (1965). Ranking fuzzy numbers was first proposed by Jain, 1976, for decision making in fuzzy situations by representing the ill-defined quantity as a fuzzy set. Since then, various procedures to rank fuzzy quantities are proposed by various researchers. Wang and Kerre, 2001a, b classified these different methods into three classes. The first class consists of those based on fuzzy mean and spread; the second class consists of ranking procedures based on fuzzy scoring and lastly, consists of methods based on preference relations (Thoran et al., 2012).

The ordering procedures associated with the first class were found to be relatively reasonable for the ordering of fuzzy numbers especially the ranking procedure that satisfies all the logical properties for the ordering of fuzzy quantities. The methods presented in the second class are not doing well, and the methods that belong to class three are reasonable. Then, ranking of fuzzy numbers by the preference ratio (Modarres and Nezhad, 2001), left and right dominance (Chen & Lu, 2001), the area between the centroid point and the original point (Chu and Tsao, 2002), sign distance (Abbasbandy & Asady, 2006), method of in centre of centroids (Thorani et al., 2012a, b) and distance minimization (Asady and Zendehnam, 2007) have been proposed (Chitrasen et al., 2014). Some of the existing approaches are difficult to understand and have suffered from different plights, e.g., the lack of discrimination, producing counterintuitive orderings, and ultimately resulting in inconsistent orders if a new fuzzy number is added; high complexity and cumbersome computational efforts are also characteristic (Chen and Lu, 2001). Nearly all approaches should acquire membership functions of fuzzy numbers before the ranking is performed; however, this may be infeasible in real applications. Furthermore, accuracy and efficiency should be of priority concern in the ranking process if ranking a lot of fuzzy numbers. In this research, the concept of Left and Right dominance method (Chen & Lu, 2001) and 'In centre of centroids method' (Thorani et al., 2012a, b) for generalized trapezoidal fuzzy numbers have been used to quantify the 'degree of risk' in terms of crisp ratings in order to validate the proposed reverse supply chain risk assessment procedures.

3.8.1 Method of Left and Right dominance

Chen and Lu, (2001) illustrated a ranking method for ordering fuzzy numbers using Left and Right dominance method, which follows the concept of area measurement. This concept is utilized to rank a set of fuzzy numbers with the help of a computed crisp score. This concept of crisp evaluation has been explored in this research towards the development of an efficient risk assessment module. The mathematical basis of this concept has been reproduced below. The proposed approximate approach only uses α-cuts and performs simple arithmetic operations for the ranking purpose. Initially, the left (right) dominance is determined by summing the difference between the left (right) spreads at each α-level to denote the degree to which one fuzzy number dominates the other on the left (right)-hand side as shown in Fig. 3. Accordingly, the left (right) dominance approximates the area difference of two fuzzy numbers from the membership axis to the left (right) membership function when the number of $\alpha \rightarrow \infty$. Moreover, to reflect the decision maker's optimistic or pessimistic perspectives, a convex combination of the left and right dominance using an index of optimism is employed to rank the fuzzy numbers (Kim and Park, 1990).

A real fuzzy number can be defined as a fuzzy subset of the real line R which is convex and normal (Chen and Lu, 2001). That is, for a fuzzy number $A \rightarrow R$ defined by the membership function $\mu_A(x); x \in R$ the following expressions exists:

$$max_x \mu_A(x) = 1, \tag{7}$$

$$\mu_A[\tau x_1 - (1-\tau)x_2] \geq \min[\mu_A(x_1), \mu_A(x_2)], \tag{8}$$

Where, $x_1, x_2 \in R, \forall \tau \in [0,1]$.

If we define a generalized trapezoidal fuzzy numbers $\bar{A} = (a, b, c, d)$ with membership function$\mu_A(x); x \in R$, then:

$$\mu_{\bar{A}}(A) = \begin{cases} \mu_A^L & a \leq x \leq b, \\ 1, & b \leq x \leq c, \\ \mu_A^R & c \leq x \leq d, \\ 0, & Otherwise, \end{cases} \tag{9}$$

Where μ_A^L is the left membership function that is an increasing function and $\mu_A^L: [a, b] \rightarrow [0,1]$.

Likewise, μ_A^R is the right membership function that is a decreasing function and $\mu_A^R: [c, d] \rightarrow [0,1]$. If $b = c$, the trapezoidal fuzzy is converted to triangular fuzzy number, i.e $\bar{A} = (a, b, d)$ assuming that every fuzzy number is bounded, i.e $-\infty < a, d < \infty$.

For a fuzzy number, $\bar{A}$, the $\alpha - cuts$ (level sets) $\bar{A}_\alpha = \{x \in R | \mu_A(x) \geq \alpha\}, \alpha \in [0,1]$, are convex subsets of *R.* The lower and upper limits of the k^{th} $\alpha - \mathrm{cut}$ for the fuzzy number can then be defined as:

$$l_{i,k} = \mathrm{Inf}_{x \in R}\{x | \mu_A(x) \alpha_k\}, \tag{10}$$

$$r_{i,k} = \mathrm{Sup}_{x \in R}\{x | \mu_A(x) \alpha_k\}, \tag{11}$$

Respectively, where $l_{i,k}$and $r_{i,k}$ are left and right spreads respectively (Chen and Lu, 2001).

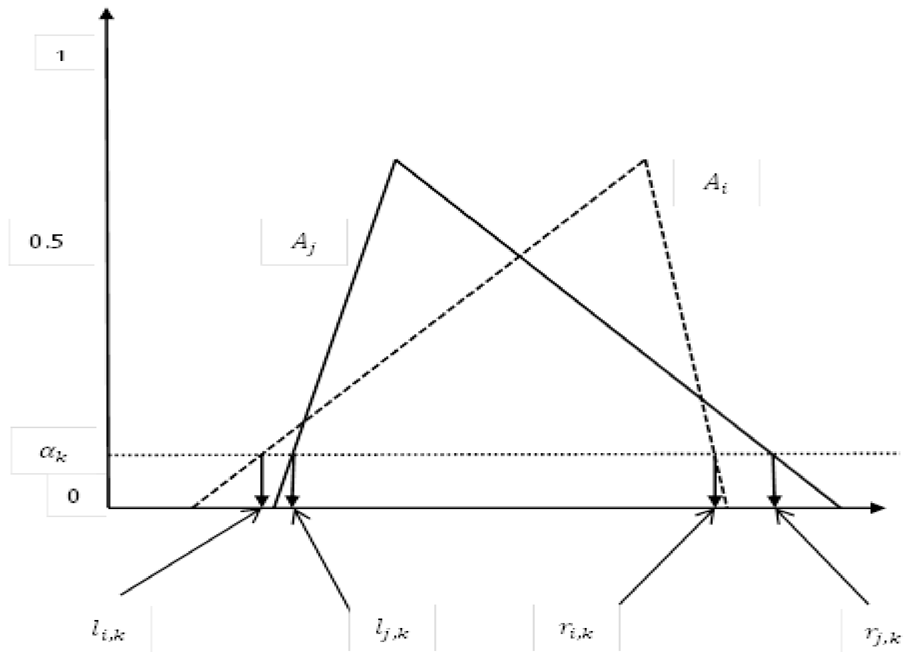


Fig. 3.3: The left and right spreads of fuzzy numbers A_i and A_j (Chen and Lu, 2001)

At some $\alpha-\mathrm{Level}$, the left (right) dominance $D_{i,j}^{L}(D_{i,j}^{R})$ of A_i over A_j is defined as the average difference of the left (right) spread. This can be formulated as:

$$D_{i,j}^{L}=\frac{1}{n+1}\sum_{k=0}^{n}(l_{i,k}-l_{j,k}) \qquad (12a)$$

And

$$D_{i,j}^{R}=\frac{1}{n+1}\sum_{k=0}^{n}(r_{i,k}-r_{j,k}) \qquad (12b)$$

Where, $n+1\ \alpha-\mathrm{cuts}$ are used to calculate the dominance. In particular, the total dominance of A_i over A_j with the index of optimism $\beta\in[0,1]$ can be defined as a convex combination of $D_{i,j}^{L}$ and $D_{i,j}^{R}$ (Chen and Lu, 2001) by:

$$D_{i,j}(\beta)=\beta D_{i,j}^{R}+(1-\beta)D_{i,j}^{L}) \qquad (13a)$$

$$=\beta\left[\frac{1}{n+1}\sum_{k=0}^{n}(r_{i,k}-r_{j,k})\right]+(1-\beta)\left[\frac{1}{n+1}\sum_{k=0}^{n}(l_{i,k}-l_{j,k})\right] \qquad (13b)$$

$$=\frac{1}{n+1}\left\{\left[\beta\sum_{k=0}^{n}r_{i,k}+(1-\beta)\sum_{k=0}^{n}l_{i,k})\right]-\left[\beta\sum_{k=0}^{n}r_{j,k}+(1-\beta)\sum_{k=0}^{n}(l_{j,k}\right]\right\} \qquad (13c)$$

From the above Eq. 13c, it can be shown that the larger the index of optimism f~ implies that the right dominance is more important. Herein, the index of optimism is used to reflect a decision maker's degree of optimism. A more optimistic decision maker generally takes a larger value of the index, for example, a situation in which $\beta=1\ (or\ 0)$

represents an optimistic (pessimistic) decision maker's perspectives, and only right (left) dominance is considered.

The pair of fuzzy numbers can therefore be ranked based on the following conditions:

1. If $D_{i,j}(\beta) > 0$, then $A_i > A_j$;
2. If $D_{i,j}(\beta) = 0$, then $A_i = A_j$; and
3. If $D_{i,j}(\beta) < 0$, then $A_i < A_j$.

i. Some important properties

Some valuable properties are described in the following, which are useful in ranking a large quantity of fuzzy numbers simultaneously. Assume that there are *m* different bounded fuzzy numbers, A_1, A_2,..., A_m, to be ranked. Let A_i, A_j & A_k, be any three arbitrary fuzzy numbers, where $i \neq j \neq k \; and \; 1 \leq i, j, k \leq m$, then:

(1) The total dominance of a fuzzy number over itself is null; i.e.,

$D_{i,i}(\beta) = 0$ for any *i* and β. (14)

(2) The total dominance of $A_i \; over \; A_j$ is opposite to that of $A_j \; over \; A_i$; i.e.,

$D_{i,j}(\beta) = -D_{j,i}(\beta), \forall \; i, j \text{ and } \beta.$ (15)

(3) For A_i, A_j & A_k, the transitivity property for the total dominance exists between them; i.e.,

If $D_{i,j}(\beta) > 0$ and $D_{jk}(\beta) > 0$, the $D_{i,k}(\beta) > 0$. (16)

Therefore if $A_i > A_j$ and$A_k > A_k$ are known, we can infer that $A_i > A_k$ with the order obtained on the basis of sign of $D_{i,j}(\beta)$ and $D_{jk}(\beta)$.

(4) More than two fuzzy numbers can be ranked by comparing with the benchmark fuzzy number. Let A_j be the benchmark, and $D_{i,j}(\beta) = a$ and $D_{k,j}(\beta) = b$. By using the previous two properties, obviously$D_{i,k}(\beta) = D_{i,j}(\beta) - D_{k,j}(\beta) = a - b$. Therefore, if $a > b$, then $D_{i,k}(\beta) > 0$; i.e $A_i > A_k$.

(5) The ranking of more than two fuzzy numbers has the robustness property (Fortemps and Roubens, 1996); i.e.,

If $D_{i,j}(\beta) < \varepsilon$, then $\left|D_{i,k}(\beta) - D_{jk}(\beta)\right| < \varepsilon$. (17)

This equation suggests that the total dominance difference between one fuzzy number and the other two fuzzy numbers is insignificant, if the two fuzzy numbers are close to each other. This is true since

$$D_{i,k}(\beta) - D_{jk}(\beta) = D_{i,j}(\beta). \quad (18)$$

For ranking *m* fuzzy numbers, only *m* - 1 comparisons to the benchmark fuzzy number are necessary when using the above properties, instead of *m(m*- 1)/2 or *m* comparisons (Tseng and Klein, 1989; Chen and Klein, 1997), i.e. if A_j is the benchmark, then only *m*-1values of total dominance, $D_{1,j}(\beta), D_{2,j}(\beta), \ldots\ldots, D_{j-1,j}(\beta), D_{j+1,j}(\beta)$, are necessary to determine. Once these values are known, natural orderings easily determine the rankings.

ii. Proposed methodology

The concepts of hierarchical structure towards reverse logistics (RL) risk assessment with two distinct levels are used in this research. First level is to evaluate the fuzzy risk extent of several risk influencing factors and the second level is to evaluate the degree of risk extent of individual risk sources affecting to the reverse logistics system (RLS). A more general representation of multi-criteria decision making scenario has been introduced. The scenario comprises a committee of *k* decision makers (DM_1, DM_2, . . . , DM_k), who are responsible for assessing the appropriateness of *m* RL risks (R_1, R_2, . . . , R_m), under each of *n* risk influencing factors (F_1, F_2, . . . , F_n). Risks of each influencing factors can be quantified based on two evaluating factors such as likelihood of occurrence and its impact. The following procedural steps have been proposed for calculating fuzzy risk ratings as well as managing the risks:

Step1.Identification of RL risks and their influencing factors which have been used to develop a hierarchical risk assessment model.

Step2.Selection of fuzzy linguistic classification scale for expressing both likelihood of occurrence and impact of risks, and, also choosing suitable membership functions for each variable.

Step3.Linguistic data (in relation to the likelihood of occurrence and impact of risk) for each risk factor have been collected from the experts. Thereafter, linguistic data have been translated into appropriate fuzzy numbers.

Step4. Combined preferences (aggregated decision-making opinion) have been computed using fuzzy aggregation operators. Fuzzy risk ratings of each influencing factor have been calculated by multiplying fuzzy likelihood of occurrence and fuzzy risk impact (Eq. 1).

Step5. Crisp risk rating corresponding to each risk influencing factor has been calculated using ‘Left and right dominance’ method (Chen & Lu, 2001), applicable for generalized trapezoidal fuzzy numbers in fuzzy logic theory.

Step6. Categorization of risks has been carried out based on individual crisp risk ratings.

Step7. An action requirement plan has been formulated with reference to different risk categories.

In summary, the proposed methodology steps for RL risk analysis using *Left and Right dominance method* are as shown in Fig 4.3:

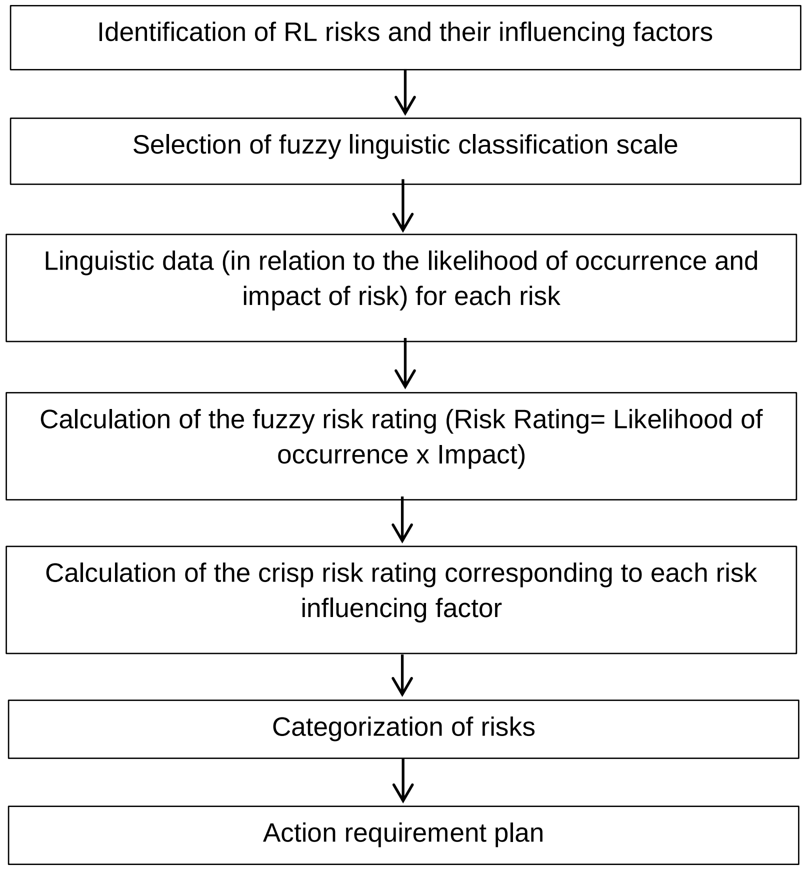


Fig. 4.3: Risk assessment steps

3.8.2 Method of 'In centre of centroids'

Thorani et al., (2012a, b) illustrated a ranking method for ordering fuzzy numbers using orthocentre of centroid method. They provided a formulation towards computing equivalent crisp score against a particular fuzzy number. This concept is utilized to rank a set of fuzzy numbers with the help of computed crisp score. The centroid of a trapezoid is considered as the balancing point of the trapezoid (Fig. 5.3). Divide the trapezoid into three plane figures. These three plane figures are a triangle (AFB), a rectangle (BCEF), and a triangle (CDE), respectively. Let the centroids of the three plane figures be G_1,G_2 and G_3 , respectively. The In-center of these Centroids G_1,G_2 and G_3 is taken as the point of reference to define the crisp value of generalized trapezoidal fuzzy numbers. The reason for selecting this point as a point of reference is that each centroid point are balancing points of each plane figure, and the In-centre of these centroid points is a much more balancing point for a generalized trapezoidal fuzzy number. Therefore, this point would be a better reference point than the centroid point of the trapezoid.

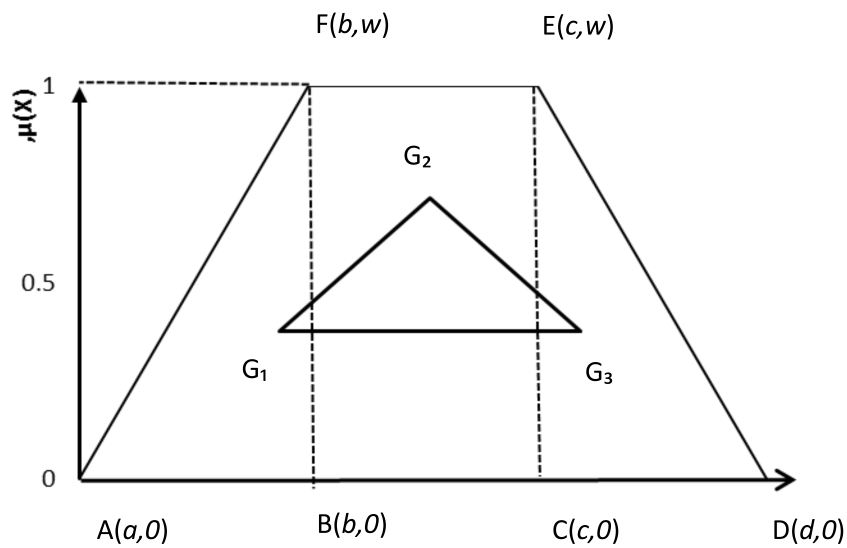


Fig. 5.3: In-centre of centroid fuzzy numbers (Thorani et al., 2012b).

Consider a generalized trapezoidal fuzzy number $\tilde{A} = (a, b, c, d; w_A)$ (Chen, 1985). The centroids of the three plane figures are
$G_1 = \left(\frac{a+2b}{3}, \ \frac{w}{3}\right)$, $G_2 = \left(\frac{b+c}{2}, \ \frac{w}{2}\right)$ and $G_3 = \left(\frac{2c+d}{3}, \ \frac{w}{3}\right)$ respectively (Thorani et al., 2012).
Equation of the line $\overline{G_1G_3}$ is $y = \frac{w}{3}$ and G_2 does not lie on the line $\overline{G_1G_3}$. Therefore, G_1, G_2 and G_3 are non-linear and they form a triangle. We define the In-centre $I_{\tilde{A}}(\bar{x}_o, \bar{y}_o)$ of the triangle with vertices G_1, G_2 and G_3 of the generalized trapezoidal fuzzy number $\tilde{A} = (a, b, c, d; w_A)$ as:

$$I_{\tilde{A}}(\bar{x}_o, \bar{y}_o) = \left(\frac{\alpha\left(\frac{a+2b}{3}\right) + \beta\left(\frac{b+c}{2}\right) + \gamma\left(\frac{2c+d}{3}\right)}{\alpha+\beta+\gamma}, \frac{\alpha\left(\frac{w}{3}\right) + \beta\left(\frac{w}{2}\right) + \gamma\left(\frac{w}{3}\right)}{\alpha+\beta+\gamma} \right) \tag{19}$$

Here

$$\alpha = \frac{\sqrt{(c-3b+2d)^2 + w^2}}{6}$$

$$\beta = \frac{\sqrt{(2c+d-a-2b)^2}}{3}$$

$$\gamma = \frac{\sqrt{(3c-2a-b)^2 + w^2}}{6}$$

As a special case, for triangular fuzzy number, $\tilde{A} = (a, b, c, d; w_A)$, i.e. $c = b$ the in centre of Centroids is given by

$$I_{\tilde{A}}(\bar{x}_o, \bar{y}_o) = \left(\frac{x\left(\frac{a+2b}{3}\right) + yb + z\left(\frac{2b+d}{3}\right)}{x+y+z}, \frac{x\left(\frac{w}{3}\right) + y\left(\frac{w}{2}\right) + z\left(\frac{w}{3}\right)}{x+y+z} \right) \quad (20)$$

Where,

$$x = \frac{\sqrt{(2d-2b)^2 + w^2}}{6}$$

$$y = \frac{\sqrt{(d-a)^2}}{3}$$

$$z = \frac{\sqrt{(2b-2a)^2 + w^2}}{6}$$

The ranking function of the generalized trapezoidal fuzzy number $\bar{A} = (a, b, c, d; w_{\bar{A}})$, which maps the set of all fuzzy numbers to a set of real numbers is defined as,

$$R(\bar{A}) = x_o \times y_o = \left(\frac{x\left(\frac{a+2b}{3}\right) + yb + z\left(\frac{2b+d}{3}\right)}{x+y+z} \times \frac{x\left(\frac{w}{3}\right) + y\left(\frac{w}{2}\right) + z\left(\frac{w}{3}\right)}{x+y+z} \right) \quad (21)$$

This is the area between the in-center of the centroids $I_{\tilde{A}}(\bar{x}_o, \bar{y}_o)$ as defined in Eq. 20 and the original point

3.9 Survey data results and Analysis

3.9.1 Survey brief

In order to validate the proposed risk assessment procedure, a survey study has been conducted seeking expert opinions from various industry players involved in reverse logistics in different parts of India and outside. A focused group survey has been carried out among supply chain executives and managers who were actively associated in reverse supply chain management in their companies. The group constitutes seven RL personnel's (or experts) with more than ten years' experience in the supply chain who were selected to participate in the survey. Due to anonymity reasons, expert identities have not been exposed and, therefore, they have been referred to as DM1, DM2, DM3, DM4, DM5, DM6, and DM7. The experts have been requested to express their opinion in a detailed questionnaire following a linguistic scale. Also, they have been suggested to mention any other objectives (if applicable) and risk assessment factors that have not been specified in the said questionnaire. All the participants in this survey (experts) have been involved in reverse supply chain, and their experience helped enormously in pursuit of this research.

3.9.2 Risk identification:

According to the definition of risk, as discussed in Section 3.6.2, undesirable outcomes may arise due to the existence of various risk factors. In this research, a total of twelve different sources of RL risks and their corresponding influencing factors have been identified from the literature. It has been decided to focus specifically on those risks that are reasonably frequent, relevant and sensitive to RL practices. Table 1 presents a hierarchical risk assessment model that outlines numerous RL risks and their influencing factors. Each influencing factor has been structured to be preceded by the corresponding risk.

3.9.3 *Selection of fuzzy linguistic scale*

Many researchers have used various types of linguistic scales to carry out subjective assessments in a variety of fuzzy based decision-making problems. But, the type of the membership function corresponding to a fuzzy number representing a particular linguistic variable has to be selected in accordance with user needs. A commonly used, trapezoidal membership function has been found satisfactory for this application (Xia et al., 2006). Table 2.3 presents the set of linguistic variables and corresponding fuzzy number representations that has been used for assessing all of the risk sources under consideration. During this risk assessment process, a five-member fuzzy linguistic scale has been adopted from the work by Xia et al., (2006). As discussed earlier, a risk is a function of two parameters such as the likelihood of occurrence, and impact of risk. Thus, linguistic variables such as Very Rare (VR), Rare (R), Often (O), Frequent (F), and Very Frequent (VF) have been used to rate the likelihood of occurrence (of risk). Similarly; Very Low (VL), Low (L), Moderate (M), Serious (S), and Critical (C) have been utilized to rate the impact of risk.

Table 2.3: Linguistic classification of risk factors grades.

Likelihood of occurrence	The Impact of risk	Trapezoidal fuzzy numbers (TrFNs)
Very Rare (VR)	Very Low(VL)	(0,0.1,0.2,0.3)
Rare (R)	Low (L)	(0.1,0.2,0.3,0.4)
Often (O)	Moderate (M)	(0.3,0.4,0.5,0.6)
Frequent (F)	Serious (S)	(0.5,0.6,0.7,0.8)
Very Frequent (VF)	Critical (C)	(0.7,0.8,0.9,1.0)

Source: Xia et al., (2006)

3.9.2 Data collection

The Survey is powerful tools that can help reach out to a larger group of people. In this research, survey plays a significant role in data collection, which is further analyzed, and results are obtained. The form was designed with the aim of collecting information on risks faced by different industries in the reverse supply chain area. While framing survey question, close attention was given to details on the reverse supply chain and possible risks. The survey form is designed in a way that it is easy to understand and can be filled with no difficulty (See Appendix II). Two sets of linguistic data have been collected from the expert group on assessment of the likelihood of occurrence and impact of risk for each of the risk influencing factors. Experts or Decision-Makers (DMs) have been provided their judgment in linguistic terms. Both the data sets have been separately collected from the group of decision makers. Table 3.3 present the likelihood of occurrence of various risk influencing factors assigned by DMs. Also, risk impact of corresponding influencing risk factors has been shown in Table. 4.3. Then, this linguistic information has been transformed into appropriate trapezoidal fuzzy numbers referring to the linguistic scale (Table 2.3). Apart from collecting information concerning the likelihood of occurrence and impact of risk for each influencing factors, the survey also sought the expert or decision makers' opinion on various parameters and statistics in the reverse supply chain area on which the responses obtained were analysed and presented as well. Some of the statistical information included in the survey included:

- The sector of the industry the respondent is working.
- The respondents' industry experience.
- Respondents' opinion of which sector of industry has integrated reverse logistics most.
- The respondents' opinion of the industry understanding of the role of reverse logistics.
- Do most companies implement risk management for identifying/Assessing/controlling/monitoring risks in reverse supply chain?
- How much do they think the application of risk management in reverse supply chain will affect sales, RL costs, customer satisfaction and reprocessing cycle efficiency?
- What are Reverse Supply Chain activities in many companies that are taken care of most once product returns?

Table 3.3: Likelihood of occurrence *(L)* of various risk factors assigned by the DMs in linguistic terms.

Risk Factor	Decision makers						
	DM1	DM2	DM3	DM4	DM5	DM6	DM7
F1,1	O	O	O	F	O	O	R
F21	O	O	O	O	O	O	R
F31	F	F	O	VF	O	O	R
F41	O	O	O	O	O	R	R
F51	F	O	O	F	F	R	O
F61	F	R	O	O	O	R	R
F12	O	O	O	O	O	O	R
F22	F	R	O	O	O	F	R
F32	O	R	R	R	R	O	R
F42	O	O	O	O	O	O	O
F52	O	R	R	R	R	O	R
F62	O	R	R	R	R	O	R
F72	O	O	R	O	O	O	R
F13	O	O	O	R	O	O	R
F23	O	O	F	F	O	O	R
F33	F	VF	VF	VF	O	F	O
F43	O	F	O	VF	O	O	R
F53	O	F	O	F	O	O	R
F63	F	O	O	F	O	F	O
F73	O	O	O	F	O	O	R
F83	F	R	R	R	R	F	R
F93	O	O	O	R	O	R	R
F14	O	O	O	O	O	O	R
F24	O	O	O	O	O	O	R
F34	O	O	O	F	O	O	R
F44	O	O	O	O	O	R	R

F54	F	VF	VF	VF	O	F	O
F64	O	R	R	R	R	R	O
F15	O	O	O	O	O	O	R
F25	R	R	O	O	F	R	F
F35	R	F	O	O	O	R	F
F45	F	F	R	O	O	F	R
F55	F	O	O	R	O	F	R
F65	O	O	O	F	O	R	O
F75	O	R	O	R	O	O	R
F16	O	F	O	O	O	R	R
F26	O	O	O	O	O	R	O
F36	F	F	O	R	R	R	O
F46	O	F	R	R	O	O	O
F56	O	VR	VR	R	O	O	O
F66	O	O	O	O	O	R	O
F76	F	F	O	R	R	R	O
F17	O	O	O	O	O	O	O
F27	O	O	O	O	O	O	R
F37	R	O	R	O	R	R	R
F47	O	F	O	F	O	O	R
F57	O	O	O	O	O	R	R
F67	O	O	O	O	O	F	R
F77	O	O	O	O	O	O	R
F18	O	R	O	R	O	O	R
F28	O	O	O	R	F	O	R
F38	O	O	O	O	O	F	O
F48	O	O	R	R	O	O	O
F58	O	R	R	R	O	O	O
F68	VR	O	O	F	O	R	VR
F78	O	O	R	R	O	O	O
F88	O	F	O	F	O	F	R

F98	O	F	O	O	O	R	F
F19	R	O	O	O	O	R	R
F29	O	R	R	R	O	O	O
F39	O	O	R	R	R	R	R
F49	O	O	O	O	O	O	R
F59	O	O	R	R	R	R	R
F69	F	O	O	O	O	O	R
F1,10	O	O	O	O	O	O	R
F2,10	R	O	R	R	O	R	R
F3,10	O	O	R	R	O	O	O
F4,10	O	O	R	R	R	R	R
F5,10	O	O	O	O	O	R	R
F6,10	O	O	O	O	O	O	R
F7,10	O	O	O	O	O	F	R
F1,11	O	VR	VR	R	VR	O	VR
F2,11	O	O	R	O	O	O	R
F3,11	O	O	R	O	R	O	R
F4,11	O	O	O	O	O	O	R
F5,11	O	O	R	R	R	O	R
F1,12	VR	R	R	O	VR	O	O
F2,12	R	O	O	R	R	O	O
F3,12	R	R	R	O	O	O	O
F4,12	R	O	O	O	R	O	R

Table 4.3: Impact of risk (I) of various risk factors assigned by DMs in linguistic terms.

Risk Factor	Decision makers						
	DM1	DM2	DM3	DM4	DM5	DM6	DM7
F1,1	S	S	C	C	C	C	S
F21	C	C	C	S	C	C	S
F31	C	C	C	C	C	S	S
F41	C	C	C	S	C	C	S

F51	C	S	C	S	C	S	S
F61	M	M	C	C	S	S	C
F12	C	C	C	C	C	S	S
F22	C	C	S	C	C	S	S
F32	S	C	C	C	C	S	S
F42	S	S	C	S	C	C	S
F52	C	S	C	S	C	C	S
F62	C	S	C	S	C	C	S
F72	C	C	C	C	C	S	S
F13	C	C	C	C	C	S	S
F23	C	C	C	C	C	S	S
F33	S	S	S	S	S	S	S
F43	S	C	C	C	C	S	S
F53	S	C	C	C	C	S	S
F63	S	C	S	C	C	S	S
F73	C	C	S	C	C	C	S
F83	C	S	S	S	C	C	S
F93	S	C	C	C	C	S	S
F14	C	C	C	C	C	C	M
F24	C	S	C	S	C	C	S
F34	S	S	S	S	C	C	S
F44	S	S	S	S	C	S	S
F54	S	S	S	S	S	S	S
F64	C	S	M	M	C	C	S
F15	C	C	C	C	C	S	S
F25	S	C	S	C	C	S	S
F35	S	C	S	C	C	S	S
F45	C	C	S	C	C	S	S
F55	C	C	S	S	C	S	S
F65	S	C	C	C	C	S	S
F75	C	C	C	C	C	M	S

F16	C	C	C	S	S	S	M
F26	C	C	S	S	S	S	S
F36	S	S	M	M	M	S	C
F46	S	C	C	C	C	C	C
F56	C	C	C	C	C	M	M
F66	S	S	M	M	M	S	C
F76	S	C	C	C	C	C	C
F17	C	S	C	C	C	S	S
F27	C	S	C	S	C	C	S
F37	C	S	S	S	S	S	S
F47	C	S	C	S	C	C	S
F57	C	M	C	M	C	S	S
F67	C	C	C	C	C	C	S
F77	S	C	C	C	C	C	S
F18	C	C	C	C	C	C	S
F28	C	C	C	C	C	S	M
F38	C	C	C	C	C	C	C
F48	C	C	S	C	C	S	S
F58	C	S	S	C	C	S	S
F68	S	C	C	C	C	S	S
F78	C	C	S	C	C	S	S
F88	C	C	C	C	C	C	S
F98	C	C	C	C	C	C	S
F19	S	M	M	M	C	S	S
F29	C	C	C	C	C	C	S
F39	S	S	S	S	S	S	S
F49	C	C	C	C	C	C	S
F59	C	C	S	C	S	C	S
F69	S	S	C	M	C	C	S
F1,10	S	C	C	C	C	S	M
F2,10	S	C	C	C	C	S	S

F3,10	C	S	S	C	C	S	S
F4,10	C	C	S	C	C	S	M
F5,10	C	C	C	C	C	S	S
F6,10	C	C	C	C	S	C	M
F7,10	C	C	C	S	C	C	S
F1,11	C	S	S	S	C	S	S
F2,11	C	C	S	C	C	S	S
F3,11	C	C	S	C	S	S	S
F4,11	C	C	C	C	C	S	S
F5,11	C	C	C	C	C	C	S
F1,12	M	M	M	M	M	M	M
F2,12	S	M	S	S	S	C	M
F3,12	M	M	M	S	S	S	S
F4,12	M	S	S	S	M	S	M

3.9.3 Risk rating and analysis using 'Left and Right dominance method'

During the risk assessment process, experts' individual decisions have been translated into combined (aggregated) preference using fuzzy aggregation rules, based on that, associated decision matrices have been prepared. The exploration of the concept of fuzzy arithmetic operations has been found necessary at this stage to form an aggregation rule. Aggregation is the process by which the fuzzy sets are combined to form a single collective preference fuzzy set. Let *k* is the number of decision makers (DM_t, k = 1, . . . , k), who are responsible for assessing *m* RL risks (R_i, *i* = 1,...., *m*), with corresponding *n* influencing factors (F_{ij}, *j* = 1, . . . , *n*). The aggregated fuzzy preferences $\tilde{F}_{ij}$ of each influencing factor in both forms (*L* and *I*) under each risk can be calculated as (Chen, 2000):

$$\tilde{F}_{ij} = \frac{1}{k}\left[F_{ij1} + F_{ij2} + \cdots\cdots + F_{ijk}\right] \quad (22)$$

The following relation has been used for calculating the fuzzy risk rating of each influencing factors, such as:

$$\text{Degree of Risk/Risk rating} = (\tilde{F}_{ij})_L \times (\tilde{F}_{ij})_I \quad (23)$$

Also, the crisp risk rating $R(A_j)$ of each influencing factor has been calculated by using Eq. (13a, b, c) (by Left (Right) dominance method). The rankings of *m* fuzzy numbers are calculated based on the comparisons to the benchmark fuzzy number, A_j. Then, the crisp rating of each RL risk has been calculated by adding the corresponding influencing factors' ratings. The results of aggregated preferences, fuzzy risk ratings and crisp risk ratings have been furnished in Table 5.3.

Table 5.3: Aggregated preferences by seven candidates in terms of fuzzy numbers and their crisp ratings.

Risk (*Ri*)	Risk factors (*Fi*,j)	Likelihood of occurrence (L)	Impact of risk (I)	Degree of risk/risk rating (fuzzy)	Total dominance, $D_{i,j}(\beta)$ (crisp)	Risk rating (crisp) & % contribution
R1	F1,1	(0.30,0.40,0.50,0.60)	(0.61,0.71,0.81,0.91)	(0.18,0.29,0.41,0.55)	0.0655	0.3603
	F2,1	(0.27,0.37,0.47,0.57)	(0.64,0.74,0.84,0.94)	(0.17,0.28,0.40,0.54)	0.0557	
	F3,1	(0.39,0.49,0.59,0.69)	(0.64,0.74,0.84,0.94)	(0.25,0.36,0.49,0.65)	0.1463	
	F4,1	(0.24,0.34,0.44,0.54)	(0.64,0.74,0.84,0.94)	(0.16,0.25,0.37,0.51)	0.0331	
	F5,1	(0.36,0.46,0.56,0.66)	(0.59,0.69,0.79,0.89)	(0.21,0.31,0.44,0.58)	0.0715	
	F6,1	(0.24,0.34,0.44,0.54)	(0.53,0.63,0.73,0.83)	(0.13,0.22,0.32,0.45)	-0.0118	
R2	F1,2	(0.27,0.37,0.47,0.57)	(0.64,0.74,0.84,0.94)	(0.17,0.28,0.40,0.54)	0.0557	0.0759
	F2,2	(0.30,0.40,0.50,0.60)	(0.61,0.71,0.81,0.91)	(0.18,0.29,0.41,0.55)	0.0655	
	F3,2	(0.16,0.26,0.36,0.46)	(0.61,0.71,0.81,0.91)	(0.10,0.18,0.29,0.42)	-0.0437	
	F4,2	(0.30,0.40,0.50,0.60)	(0.59,0.69,0.79,0.89)	(0.18,0.27,0.39,0.53)	0.0527	
	F5,2	(0.16,0.26,0.36,0.46)	(0.61,0.71,0.81,0.91)	(0.10,0.18,0.29,0.42)	-0.0437	
	F6,2	(0.16,0.26,0.36,0.46)	(0.61,0.71,0.81,0.91)	(0.10,0.18,0.29,0.42)	-0.0437	
	F7,2	(0.24,0.34,0.44,0.54)	(0.64,0.74,0.84,0.94)	(0.16,0.25,0.37,0.51)	0.0331	
R3	F1,3	(0.24,0.34,0.44,0.54)	(0.64,0.74,0.84,0.94)	(0.16,0.25,0.37,0.51)	0.0331	0.5268
	F2,3	(0.39,0.49,0.59,0.69)	(0.64,0.74,0.84,0.94)	(0.25,0.36,0.49,0.65)	0.1463	
	F3,3	(0.17,0.27,0.37,0.47)	(0.61,0.71,0.81,0.91)	(0.11,0.19,0.30,0.43)	-0.0328	
	F4,3	(0.36,0.46,0.56,0.66)	(0.61,0.71,0.81,0.91)	(0.22,0.33,0.45,0.60)	0.1092	
	F5,3	(0.33,0.43,0.53,0.63)	(0.61,0.71,0.81,0.91)	(0.20,0.31,0.43,0.57)	0.0873	
	F6,3	(0.39,0.49,0.59,0.69)	(0.59,0.69,0.79,0.89)	(0.23,0.33,0.46,0.61)	0.1157	
	F7,3	(0.30,0.40,0.50,0.60)	(0.64,0.74,0.84,0.94)	(0.19,0.30,0.42,0.57)	0.0784	
	F8,3	(0.21,0.31,0.41,0.51)	(0.59,0.69,0.79,0.89)	(0.13,0.22,0.33,0.46)	-0.0104	

	F9,3	(0.21,0.31,0.41,0.51)	(0.61,0.71,0.81,0.91)	(0.13,0.22,0.34,0.47)	0.0000	
R4	F1,4	(0.27,0.37,0.47,0.57)	(0.64,0.74,0.84,0.94)	(0.17,0.28,0.40,0.54)	0.0557	0.2588
	F2,4	(0.27,0.37,0.47,0.57)	(0.61,0.71,0.81,0.91)	(0.17,0.27,0.38,0.52)	0.0437	
	F3,4	(0.30,0.40,0.50,0.60)	(0.56,0.66,0.76,0.86)	(0.17,0.26,0.38,0.51)	0.0398	
	F4,4	(0.24,0.34,0.44,0.54)	(0.53,0.63,0.73,0.83)	(0.13,0.22,0.32,0.45)	-0.0118	
	F5,4	(0.53,0.63,0.73,0.83)	(0.50,0.60,0.70,0.80)	(0.26,0.38,0.51,0.66)	0.1627	
	F6,4	(0.21,0.31,0.41,0.51)	(0.53,0.63,0.73,0.83)	(0.11,0.20,0.30,0.43)	-0.0312	
R5	F1,5	(0.27,0.37,0.47,0.57)	(0.64,0.74,0.84,0.94)	(0.17,0.28,0.40,0.54)	0.0557	0.3455
	F2,5	(0.27,0.37,0.47,0.57)	(0.59,0.69,0.79,0.89)	(0.16,0.25,0.37,0.51)	0.0316	
	F3,5	(0.30,0.40,0.50,0.60)	(0.59,0.69,0.79,0.89)	(0.18,0.27,0.39,0.53)	0.0527	
	F4,5	(0.33,0.43,0.53,0.63)	(0.61,0.71,0.81,0.91)	(0.20,0.31,0.43,0.57)	0.0873	
	F5,5	(0.30,0.40,0.50,0.60)	(0.59,0.69,0.79,0.89)	(0.18,0.27,0.39,0.53)	0.0527	
	F6,5	(0.30,0.40,0.50,0.60)	(0.61,0.71,0.81,0.91)	(0.18,0.29,0.41,0.55)	0.0655	
	F7,5	(0.21,0.31,0.41,0.51)	(0.61,0.71,0.81,0.91)	(0.13,0.22,0.34,0.47)	0.0000	
R6	F1,6	(0.27,0.37,0.47,0.57)	(0.56,0.66,0.76,0.86)	(0.15,0.24,0.36,0.49)	0.0196	0.0861
	F2,6	(0.27,0.37,0.47,0.57)	(0.56,0.66,0.76,0.86)	(0.15,0.24,0.36,0.49)	0.0196	
	F3,6	(0.27,0.37,0.47,0.57)	(0.44,0.54,0.64,0.74)	(0.12,0.20,0.30,0.42)	-0.0286	
	F4,6	(0.27,0.37,0.47,0.57)	(0.67,0.77,0.87,0.97)	(0.18,0.29,0.41,0.56)	0.0678	
	F5,6	(0.19,0.29,0.39,0.49)	(0.59,0.69,0.79,0.89)	(0.11,0.20,0.30,0.43)	-0.0314	
	F6,6	(0.27,0.37,0.47,0.57)	(0.44,0.54,0.64,0.74)	(0.12,0.20,0.30,0.42)	-0.0286	
	F7,6	(0.27,0.37,0.47,0.57)	(0.67,0.77,0.87,0.97)	(0.18,0.29,0.41,0.56)	0.0678	
R7	F1,7	(0.30,0.40,0.50,0.60)	(0.61,0.71,0.81,0.91)	(0.18,0.29,0.41,0.55)	0.0655	0.2616
	F2,7	(0.27,0.37,0.47,0.57)	(0.61,0.71,0.81,0.91)	(0.17,0.27,0.38,0.52)	0.0437	
	F3,7	(0.16,0.26,0.36,0.46)	(0.53,0.63,0.73,0.83)	(0.08,0.16,0.26,0.38)	-0.0700	
	F4,7	(0.33,0.43,0.53,0.63)	(0.61,0.71,0.81,0.91)	(0.20,0.31,0.43,0.57)	0.0873	
	F5,7	(0.24,0.34,0.44,0.54)	(0.53,0.63,0.73,0.83)	(0.13,0.22,0.32,0.45)	-0.0118	
	F6,7	(0.30,0.40,0.50,0.60)	(0.67,0.77,0.87,0.97)	(0.20,0.31,0.44,0.58)	0.0912	
	F7,7	(0.27,0.37,0.47,0.57)	(0.64,0.74,0.84,0.94)	(0.17,0.28,0.40,0.54)	0.0557	
R8	F1,8	(0.21,0.31,0.41,0.51)	(0.67,0.77,0.87,0.97)	(0.14,0.24,0.36,0.50)	0.0208	0.4790
	F2,8	(0.27,0.37,0.47,0.57)	(0.61,0.71,0.81,0.91)	(0.17,0.27,0.38,0.52)	0.0437	
	F3,8	(0.33,0.43,0.53,0.63)	(0.70,0.80,0.90,1.00)	(0.23,0.34,0.48,0.63)	0.1284	

	F4,8	(0.24,0.34,0.44,0.54)	(0.61,0.71,0.81,0.91)	(0.15,0.24,0.36,0.50)	0.0218	
	F5,8	(0.21,0.31,0.41,0.51)	(0.59,0.69,0.79,0.89)	(0.13,0.22,0.33,0.46)	-0.0104	
	F6,8	(0.21,0.31,0.41,0.51)	(0.61,0.71,0.81,0.91)	(0.13,0.22,0.34,0.47)	0.0000	
	F7,8	(0.24,0.34,0.44,0.54)	(0.61,0.71,0.81,0.91)	(0.15,0.24,0.36,0.50)	0.0218	
	F8,8	(0.36,0.46,0.56,0.66)	(0.67,0.77,0.87,0.97)	(0.24,0.35,0.49,0.64)	0.1382	
	F9,8	(0.33,0.43,0.53,0.63)	(0.67,0.77,0.87,0.97)	(0.22,0.33,0.46,0.61)	0.1147	
R9	F1,9	(0.21,0.31,0.41,0.51)	(0.44,0.54,0.64,0.74)	(0.09,0.17,0.27,0.38)	-0.0624	0.0565
	F2,9	(0.21,0.31,0.41,0.51)	(0.67,0.77,0.87,0.97)	(0.14,0.24,0.36,0.50)	0.0208	
	F3,9	(0.16,0.26,0.36,0.46)	(0.50,0.60,0.70,0.80)	(0.08,0.15,0.25,0.37)	-0.0788	
	F4,9	(0.27,0.37,0.47,0.57)	(0.67,0.77,0.87,0.97)	(0.18,0.29,0.41,0.56)	0.0678	
	F5,9	(0.16,0.26,0.36,0.46)	(0.61,0.71,0.81,0.91)	(0.10,0.18,0.29,0.42)	-0.0437	
	F6,9	(0.30,0.40,0.50,0.60)	(0.56,0.66,0.76,0.86)	(0.17,0.26,0.38,0.51)	0.0398	
R10	F1,10	(0.27,0.37,0.47,0.57)	(0.59,0.69,0.79,0.89)	(0.16,0.25,0.37,0.51)	0.0316	0.1012
	F2,10	(0.16,0.26,0.36,0.46)	(0.61,0.71,0.81,0.91)	(0.10,0.18,0.29,0.42)	-0.0437	
	F3,10	(0.24,0.34,0.44,0.54)	(0.59,0.69,0.79,0.89)	(0.14,0.24,0.35,0.48)	0.0106	
	F4,10	(0.16,0.26,0.36,0.46)	(0.59,0.69,0.79,0.89)	(0.09,0.18,0.28,0.40)	-0.0524	
	F5,10	(0.24,0.34,0.44,0.54)	(0.64,0.74,0.84,0.94)	(0.16,0.25,0.37,0.51)	0.0331	
	F6,10	(0.27,0.37,0.47,0.57)	(0.61,0.71,0.81,0.91)	(0.17,0.27,0.38,0.52)	0.0437	
	F7,10	(0.30,0.40,0.50,0.60)	(0.64,0.74,0.84,0.94)	(0.19,0.30,0.42,0.57)	0.0784	
R11	F1,11	(0.10,0.20,0.30,0.40)	(0.56,0.66,0.76,0.86)	(0.06,0.13,0.23,0.34)	-0.1016	0.0371
	F2,11	(0.24,0.34,0.44,0.54)	(0.61,0.71,0.81,0.91)	(0.15,0.24,0.36,0.50)	0.0218	
	F3,11	(0.21,0.31,0.41,0.51)	(0.59,0.69,0.79,0.89)	(0.13,0.22,0.33,0.46)	-0.0104	
	F4,11	(0.27,0.37,0.47,0.57)	(0.64,0.74,0.84,0.94)	(0.17,0.28,0.40,0.54)	0.0557	
	F5,11	(0.19,0.29,0.39,0.49)	(0.67,0.77,0.87,0.97)	(0.12,0.22,0.34,0.47)	-0.0027	
R12	F1,12	(0.16,0.26,0.36,0.46)	(0.30,0.40,0.50,0.60)	(0.05,0.10,0.18,0.27)	-0.1402	0.3380
	F2,12	(0.21,0.31,0.41,0.51)	(0.47,0.57,0.67,0.77)	(0.10,0.18,0.28,0.40)	-0.0520	
	F3,12	(0.21,0.31,0.41,0.51)	(0.41,0.51,0.61,0.71)	(0.09,0.16,0.25,0.37)	-0.0729	
	F4,12	(0.21,0.31,0.41,0.51)	(0.41,0.51,0.61,0.71)	(0.09,0.16,0.25,0.37)	-0.0729	

The graphical representation of risk ratings (crisp scores) in relation to various risk influencing factors has been illustrated in Fig. 6.3.

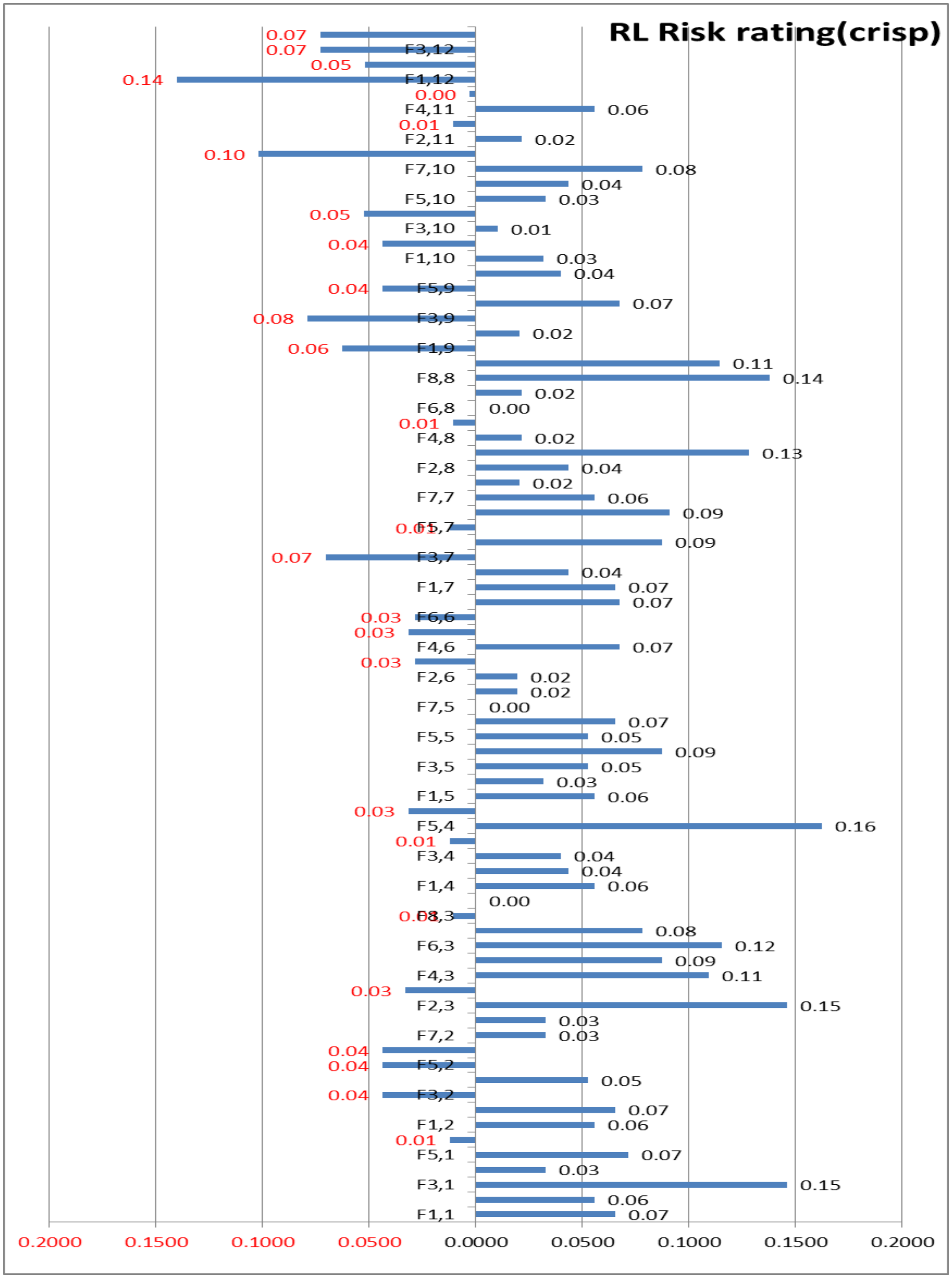


Fig. 6.3: Risk ratings (crisp) corresponding to various risk influencing factors in relation to RL.

It has been observed that the factors like underestimation of the strategic importance of reverse logistics(F3,1), Task complexity due to extent of networking & data requirements (F2,3), systems incompatibility to new IT solutions (F4,3), Lengthy reprocessing and disposal cycle time (F5,4), technological discontinuity or obsolescence (F6,3), system incompatibility to new IT solutions (F4,3), Lack of expertise and experienced personnel with outsourcing companies (F3,8) and Lack of financial stability to deliver service on the part of outsourcing companies (F8,8) impose amplified adverse impact to the performance of reverse supply chain systems. The factors other than aforementioned also have reasonable (or) less negative impact on performance but highly influence to the certain areas of risks. Therefore, the risk rating of each identified risk source can be computed by the summation of their corresponding risk ratings of influencing factors. Moreover, the overall risk extent can be determined by adding all influencing factors' risk ratings. The above results have been shown in Table 5.3 and it can also be observed that IT systems risk has the highest crisp rating (0.5268) which can impose highest impact on overall RL performance. Moreover, its percentage of contribution is about 25.53% to the overall RL performance risk. The percentage of contribution of all individual perceived risks can be clearly understood by Fig. 7.3. The risk with high contribution value is the major source that necessitates managing their influencing factors.

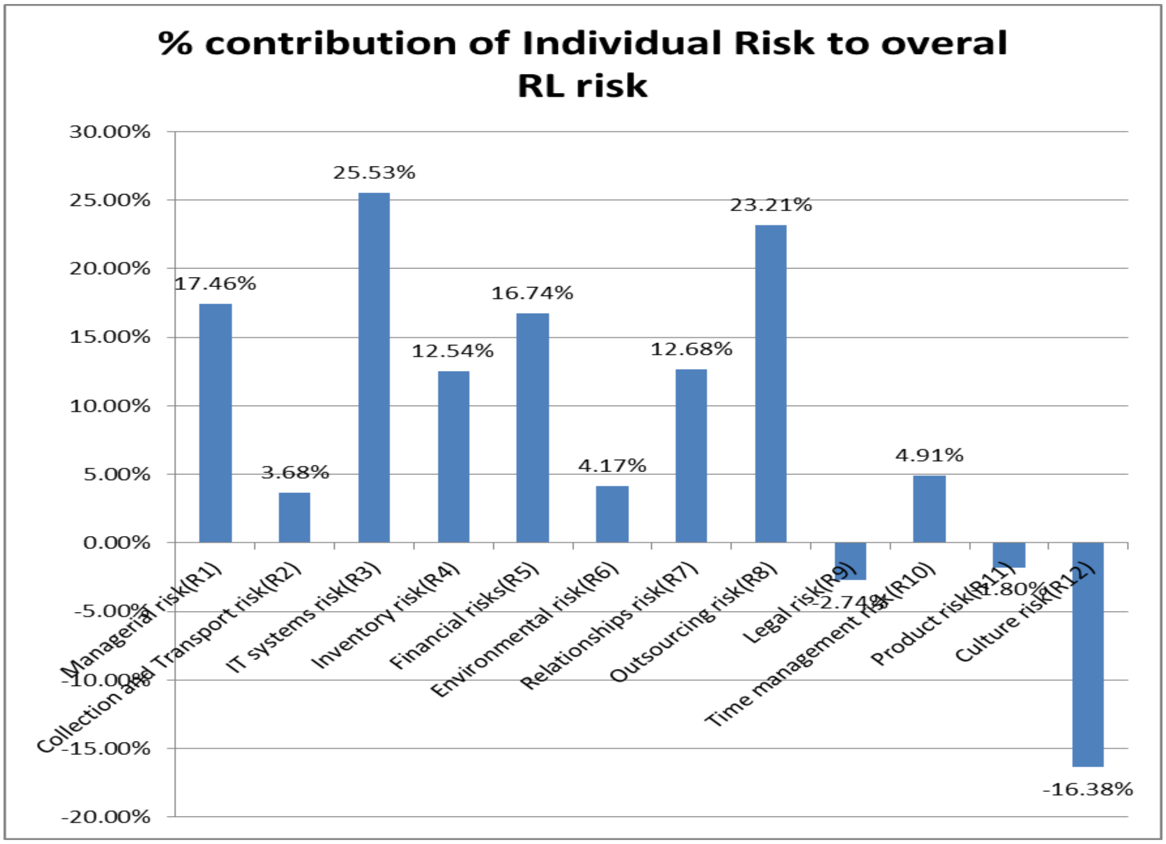


Fig.7.3: Percentage of contribution (approx.) of individual risks to the overall RL risk.

3.9.6 Risk rating and analysis using 'Incenter centroid method'

Also, the crisp risk rating $R(A_j)$ of each influencing factor has been calculated by using Eq. 21 (by Incenter of centroids method). The rankings of *m* fuzzy numbers are calculated based on the comparisons to the benchmark fuzzy number, A_j. Then, the crisp rating of each RL risk has been calculated by adding the corresponding influencing factors ratings. The results of aggregated preferences, fuzzy risk ratings and crisp risk ratings have been furnished in Table 6.3.

Table 6.3: Aggregated preferences by seven candidates in terms of fuzzy numbers and their crisp ratings.

Risk (*Ri*)	Risk factors (*Fi*,j)	Likelihood of occurrence (L)	Impact of risk (I)	Degree of risk/risk rating (fuzzy)	Risk rating (crisp)	Risk rating (crisp)
R1	F1,1	(0.30,0.40,0.50,0.60;1)	(0.61,0.71,0.81,0.91;1)	(0.18,0.29,0.41,0.55;1)	0.1140	0.6809
	F2,1	(0.27,0.37,0.47,0.57;1)	(0.64,0.74,0.84,0.94;1)	(0.17,0.28,0.40,0.54;1)	0.1103	
	F3,1	(0.39,0.49,0.59,0.69;1)	(0.64,0.74,0.84,0.94;1)	(0.25,0.36,0.49,0.65;1)	0.1433	
	F4,1	(0.24,0.34,0.44,0.54;1)	(0.64,0.74,0.84,0.94;1)	(0.16,0.25,0.37,0.51;1)	0.1021	
	F5,1	(0.36,0.46,0.56,0.66;1)	(0.59,0.69,0.79,0.89;1)	(0.21,0.31,0.44,0.58;1)	0.1247	
	F6,1	(0.24,0.34,0.44,0.54;1)	(0.53,0.63,0.73,0.83;1)	(0.13,0.22,0.32,0.45;1)	0.0866	
R2	F1,2	(0.27,0.37,0.47,0.57;1)	(0.64,0.74,0.84,0.94;1)	(0.17,0.28,0.40,0.54;1)	0.1103	0.6599
	F2,2	(0.30,0.40,0.50,0.60;1)	(0.61,0.71,0.81,0.91;1)	(0.18,0.29,0.41,0.55;1)	0.1140	
	F3,2	(0.16,0.26,0.36,0.46;1)	(0.61,0.71,0.81,0.91;1)	(0.10,0.18,0.29,0.42;1)	0.0747	
	F4,2	(0.30,0.40,0.50,0.60;1)	(0.59,0.69,0.79,0.89;1)	(0.18,0.27,0.39,0.53;1)	0.1094	
	F5,2	(0.16,0.26,0.36,0.46;1)	(0.61,0.71,0.81,0.91;1)	(0.10,0.18,0.29,0.42;1)	0.0747	
	F6,2	(0.16,0.26,0.36,0.46;1)	(0.61,0.71,0.81,0.91;1)	(0.10,0.18,0.29,0.42;1)	0.0747	
	F7,2	(0.24,0.34,0.44,0.54;1)	(0.64,0.74,0.84,0.94;1)	(0.16,0.25,0.37,0.51;1)	0.1021	
R3	F1,3	(0.24,0.34,0.44,0.54;1)	(0.64,0.74,0.84,0.94;1)	(0.16,0.25,0.37,0.51;1)	0.1021	1.0036
	F2,3	(0.39,0.49,0.59,0.69;1)	(0.64,0.74,0.84,0.94;1)	(0.25,0.36,0.49,0.65;1)	0.1433	
	F3,3	(0.17,0.27,0.37,0.47;1)	(0.61,0.71,0.81,0.91;1)	(0.11,0.19,0.30,0.43;1)	0.0786	
	F4,3	(0.36,0.46,0.56,0.66;1)	(0.61,0.71,0.81,0.91;1)	(0.22,0.33,0.45,0.60;1)	0.1298	
	F5,3	(0.33,0.43,0.53,0.63;1)	(0.61,0.71,0.81,0.91;1)	(0.20,0.31,0.43,0.57;1)	0.1219	
	F6,3	(0.39,0.49,0.59,0.69;1)	(0.59,0.69,0.79,0.89;1)	(0.23,0.33,0.46,0.61;1)	0.1323	
	F7,3	(0.30,0.40,0.50,0.60;1)	(0.64,0.74,0.84,0.94;1)	(0.19,0.30,0.42,0.57;1)	0.1185	
	F8,3	(0.21,0.31,0.41,0.51;1)	(0.59,0.69,0.79,0.89;1)	(0.13,0.22,0.33,0.46;1)	0.0868	
	F9,3	(0.21,0.31,0.41,0.51;1)	(0.61,0.71,0.81,0.91;1)	(0.13,0.22,0.34,0.47;1)	0.0903	
R4	F1,4	(0.27,0.37,0.47,0.57;1)	(0.64,0.74,0.84,0.94;1)	(0.17,0.28,0.40,0.54;1)	0.1103	0.6370
	F2,4	(0.27,0.37,0.47,0.57;1)	(0.61,0.71,0.81,0.91;1)	(0.17,0.27,0.38,0.52;1)	0.1061	
	F3,4	(0.30,0.40,0.50,0.60;1)	(0.56,0.66,0.76,0.86;1)	(0.17,0.26,0.38,0.51;1)	0.1049	
	F4,4	(0.24,0.34,0.44,0.54;1)	(0.53,0.63,0.73,0.83;1)	(0.13,0.22,0.32,0.45;1)	0.0866	
	F5,4	(0.53,0.63,0.73,0.83;1)	(0.50,0.60,0.70,0.80;1)	(0.26,0.38,0.51,0.66;1)	0.1495	

	F6,4	(0.21,0.31,0.41,0.51;1)	(0.53,0.63,0.73,0.83;1)	(0.11,0.20,0.30,0.43;1)	0.0797	
R5	F1,5	(0.27,0.37,0.47,0.57;1)	(0.64,0.74,0.84,0.94;1)	(0.17,0.28,0.40,0.54;1)	0.1103	0.7572
	F2,5	(0.27,0.37,0.47,0.57;1)	(0.59,0.69,0.79,0.89;1)	(0.16,0.25,0.37,0.51;1)	0.1019	
	F3,5	(0.30,0.40,0.50,0.60;1)	(0.59,0.69,0.79,0.89;1)	(0.18,0.27,0.39,0.53;1)	0.1094	
	F4,5	(0.33,0.43,0.53,0.63;1)	(0.61,0.71,0.81,0.91;1)	(0.20,0.31,0.43,0.57;1)	0.1219	
	F5,5	(0.30,0.40,0.50,0.60;1)	(0.59,0.69,0.79,0.89;1)	(0.18,0.27,0.39,0.53;1)	0.1094	
	F6,5	(0.30,0.40,0.50,0.60;1)	(0.61,0.71,0.81,0.91;1)	(0.18,0.29,0.41,0.55;1)	0.1140	
	F7,5	(0.21,0.31,0.41,0.51;1)	(0.61,0.71,0.81,0.91;1)	(0.13,0.22,0.34,0.47;1)	0.0903	
R6	F1,6	(0.27,0.37,0.47,0.57;1)	(0.56,0.66,0.76,0.86;1)	(0.15,0.24,0.36,0.49;1)	0.0977	0.6655
	F2,6	(0.27,0.37,0.47,0.57;1)	(0.56,0.66,0.76,0.86;1)	(0.15,0.24,0.36,0.49;1)	0.0977	
	F3,6	(0.27,0.37,0.47,0.57;1)	(0.44,0.54,0.64,0.74;1)	(0.12,0.20,0.30,0.42;1)	0.0810	
	F4,6	(0.27,0.37,0.47,0.57;1)	(0.67,0.77,0.87,0.97;1)	(0.18,0.29,0.41,0.56;1)	0.1145	
	F5,6	(0.19,0.29,0.39,0.49;1)	(0.59,0.69,0.79,0.89;1)	(0.11,0.20,0.30,0.43;1)	0.0793	
	F6,6	(0.27,0.37,0.47,0.57;1)	(0.44,0.54,0.64,0.74;1)	(0.12,0.20,0.30,0.42;1)	0.0810	
	F7,6	(0.27,0.37,0.47,0.57;1)	(0.67,0.77,0.87,0.97;1)	(0.18,0.29,0.41,0.56;1)	0.1145	
R7	F1,7	(0.30,0.40,0.50,0.60;1)	(0.61,0.71,0.81,0.91;1)	(0.18,0.29,0.41,0.55;1)	0.1140	0.7278
	F2,7	(0.27,0.37,0.47,0.57;1)	(0.61,0.71,0.81,0.91;1)	(0.17,0.27,0.38,0.52;1)	0.1061	
	F3,7	(0.16,0.26,0.36,0.46;1)	(0.53,0.63,0.73,0.83;1)	(0.08,0.16,0.26,0.38;1)	0.0659	
	F4,7	(0.33,0.43,0.53,0.63;1)	(0.61,0.71,0.81,0.91;1)	(0.20,0.31,0.43,0.57;1)	0.1219	
	F5,7	(0.24,0.34,0.44,0.54;1)	(0.53,0.63,0.73,0.83;1)	(0.13,0.22,0.32,0.45;1)	0.0866	
	F6,7	(0.30,0.40,0.50,0.60;1)	(0.67,0.77,0.87,0.97;1)	(0.20,0.31,0.44,0.58;1)	0.1231	
	F7,7	(0.27,0.37,0.47,0.57;1)	(0.64,0.74,0.84,0.94;1)	(0.17,0.28,0.40,0.54;1)	0.1103	
R8	F1,8	(0.21,0.31,0.41,0.51;1)	(0.67,0.77,0.87,0.97;1)	(0.14,0.24,0.36,0.50;1)	0.0975	0.9854
	F2,8	(0.27,0.37,0.47,0.57;1)	(0.61,0.71,0.81,0.91;1)	(0.17,0.27,0.38,0.52;1)	0.1061	
	F3,8	(0.33,0.43,0.53,0.63;1)	(0.70,0.80,0.90,1.00;1)	(0.23,0.34,0.48,0.63;1)	0.1365	
	F4,8	(0.24,0.34,0.44,0.54;1)	(0.61,0.71,0.81,0.91;1)	(0.15,0.24,0.36,0.50;1)	0.0982	
	F5,8	(0.21,0.31,0.41,0.51;1)	(0.59,0.69,0.79,0.89;1)	(0.13,0.22,0.33,0.46;1)	0.0868	
	F6,8	(0.21,0.31,0.41,0.51;1)	(0.61,0.71,0.81,0.91;1)	(0.13,0.22,0.34,0.47;1)	0.0903	
	F7,8	(0.24,0.34,0.44,0.54;1)	(0.61,0.71,0.81,0.91;1)	(0.15,0.24,0.36,0.50;1)	0.0982	
	F8,8	(0.36,0.46,0.56,0.66;1)	(0.67,0.77,0.87,0.97;1)	(0.24,0.35,0.49,0.64;1)	0.1402	
	F9,8	(0.33,0.43,0.53,0.63;1)	(0.67,0.77,0.87,0.97;1)	(0.22,0.33,0.46,0.61;1)	0.1316	

R9	F1,9	(0.21,0.31,0.41,0.51;1)	(0.44,0.54,0.64,0.74;1)	(0.09,0.17,0.27,0.38;1)	0.0690	0.5237
	F2,9	(0.21,0.31,0.41,0.51;1)	(0.67,0.77,0.87,0.97;1)	(0.14,0.24,0.36,0.50;1)	0.0975	
	F3,9	(0.16,0.26,0.36,0.46;1)	(0.50,0.60,0.70,0.80;1)	(0.08,0.15,0.25,0.37;1)	0.0630	
	F4,9	(0.27,0.37,0.47,0.57;1)	(0.67,0.77,0.87,0.97;1)	(0.18,0.29,0.41,0.56;1)	0.1145	
	F5,9	(0.16,0.26,0.36,0.46;1)	(0.61,0.71,0.81,0.91;1)	(0.10,0.18,0.29,0.42;1)	0.0747	
	F6,9	(0.30,0.40,0.50,0.60;1)	(0.56,0.66,0.76,0.86;1)	(0.17,0.26,0.38,0.51;1)	0.1049	
R10	F1,10	(0.27,0.37,0.47,0.57;1)	(0.59,0.69,0.79,0.89;1)	(0.16,0.25,0.37,0.51;1)	0.1019	0.6693
	F2,10	(0.16,0.26,0.36,0.46;1)	(0.61,0.71,0.81,0.91;1)	(0.10,0.18,0.29,0.42;1)	0.0747	
	F3,10	(0.24,0.34,0.44,0.54;1)	(0.59,0.69,0.79,0.89;1)	(0.14,0.24,0.35,0.48;1)	0.0943	
	F4,10	(0.16,0.26,0.36,0.46;1)	(0.59,0.69,0.79,0.89;1)	(0.09,0.18,0.28,0.40;1)	0.0718	
	F5,10	(0.24,0.34,0.44,0.54;1)	(0.64,0.74,0.84,0.94;1)	(0.16,0.25,0.37,0.51;1)	0.1021	
	F6,10	(0.27,0.37,0.47,0.57;1)	(0.61,0.71,0.81,0.91;1)	(0.17,0.27,0.38,0.52;1)	0.1061	
	F7,10	(0.30,0.40,0.50,0.60;1)	(0.64,0.74,0.84,0.94;1)	(0.19,0.30,0.42,0.57;1)	0.1185	
R11	F1,11	(0.10,0.20,0.30,0.40;1)	(0.56,0.66,0.76,0.86;1)	(0.06,0.13,0.23,0.34;1)	0.0546	0.4389
	F2,11	(0.24,0.34,0.44,0.54;1)	(0.61,0.71,0.81,0.91;1)	(0.15,0.24,0.36,0.50;1)	0.0982	
	F3,11	(0.21,0.31,0.41,0.51;1)	(0.59,0.69,0.79,0.89;1)	(0.13,0.22,0.33,0.46;1)	0.0868	
	F4,11	(0.27,0.37,0.47,0.57;1)	(0.64,0.74,0.84,0.94;1)	(0.17,0.28,0.40,0.54;1)	0.1103	
	F5,11	(0.19,0.29,0.39,0.49;1)	(0.67,0.77,0.87,0.97;1)	(0.12,0.22,0.34,0.47;1)	0.0890	
R12	F1,12	(0.16,0.26,0.36,0.46;1)	(0.30,0.40,0.50,0.60;1)	(0.05,0.10,0.18,0.27;1)	0.0428	0.2465
	F2,12	(0.21,0.31,0.41,0.51;1)	(0.47,0.57,0.67,0.77;1)	(0.10,0.18,0.28,0.40;1)	0.0726	
	F3,12	(0.21,0.31,0.41,0.51;1)	(0.41,0.51,0.61,0.71;1)	(0.09,0.16,0.25,0.37;1)	0.0655	
	F4,12	(0.21,0.31,0.41,0.51;1)	(0.41,0.51,0.61,0.71;1)	(0.09,0.16,0.25,0.37;1)	0.0655	

The graphical representation of risk ratings (crisp scores) in relation to various risk influencing factors has been illustrated in Fig. 8.3.

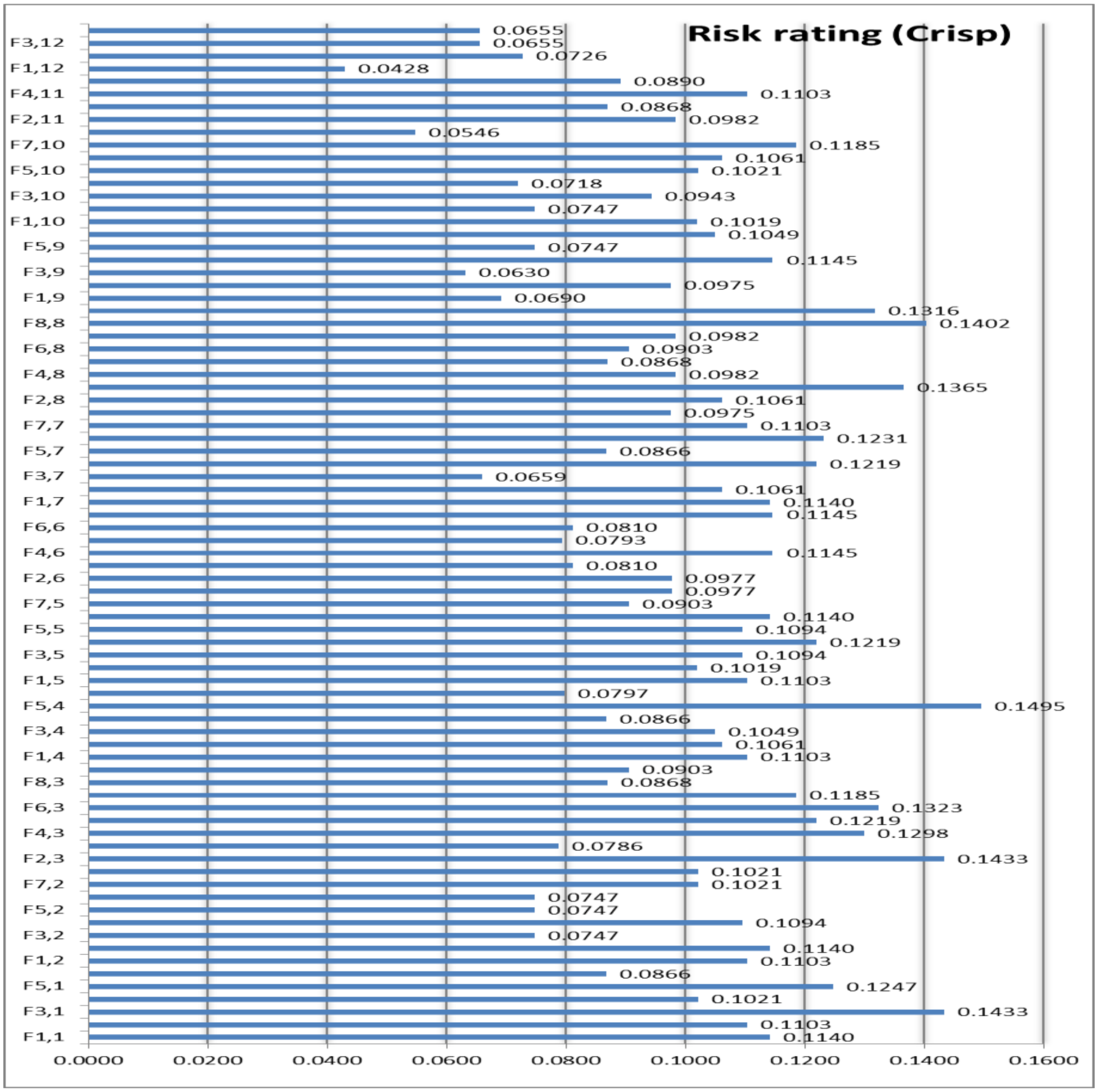


Fig. 8.3: Risk ratings (crisp) corresponding to various risk influencing factors in relation to RL.

By using Incenter of centroid method of ranking, it has also been observed that the factors like underestimation of the strategic importance of reverse logistics(F3,1), Task complexity due to extent of networking & data requirements (F2,3), systems incompatibility to new IT solutions (F4,3), Lengthy reprocessing and disposal cycle time (F5,4), technological discontinuity or obsolescence (F6,3), system incompatibility to new IT solutions (F4,3), Lack of expertise and experienced personnel with outsourcing companies (F3,8) and Lack of financial stability to deliver service on the part of outsourcing companies (F8,8) impose amplified adverse impact to the performance of reverse supply chain systems. The factors other than aforementioned also have reasonable (or) less negative impact on performance but highly influence to the certain areas of risks. Therefore, the risk rating of each identified risk source can be computed by the summation of their corresponding risk ratings of influencing factors. Moreover, the overall risk extent can be determined by adding all influencing factors' risk ratings. The above results have been shown in Table 6.3 and it can also be observed that IT systems risk has the highest crisp rating (1.0036) which can impose highest impact on overall RL performance. Moreover, its percentage of contribution is about 12.55% to the overall RL performance risk. The percentage of contribution of all individual perceived risks can be clearly understood by Fig. 9.3. The risk with high contribution value is the major source that necessitates managing their influencing factors.

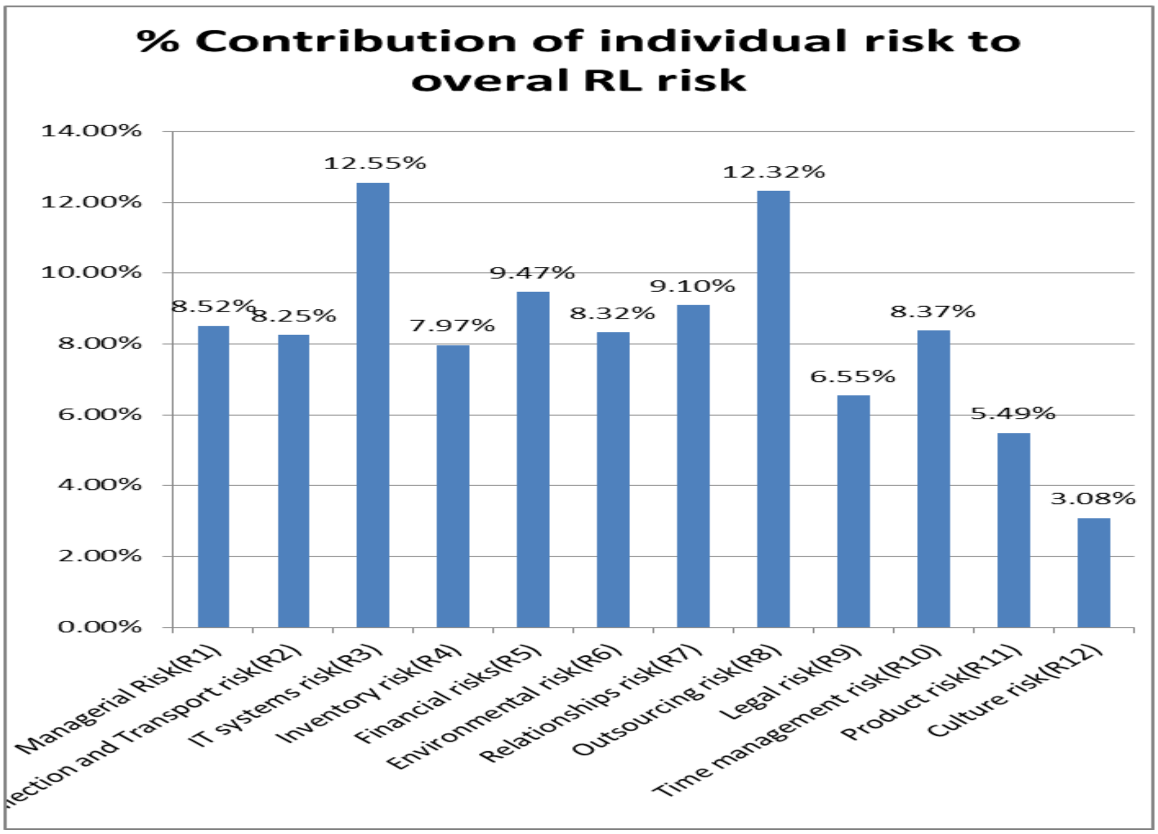


Fig.9.3: Percentage of contribution (approx.) of individual risks to the overall RL risk.

3.10 Risk factor categorization and mapping

The identified reverse logistics' risk influencing factors can be categorized in different risk categories based on the risk rating (crisp) ranges. The maximum range has been decided on the highest risk rating assigned to a risk in linguistic scale (Table 7.3). The likelihood factor (L) has been multiplied by impact factor (I) and the consequence of those two trapezoidal fuzzy numbers in terms of crisp score becomes the risk rating.

Table 6 presents risk rating (crisp) values for linguistic risk parametric scale with reference to Table 2.

Table 7.3: Risk rating (crisp) values for linguistic risk parametric scale.

Likelihood of occurrence	Impact of risk	Fuzzy risk rating (*LxI*)	Risk rating (crisp)
Very Rare (VR)	Very Low(VL)	(0.00, 0.01, 0.04, 0.09;1)	0.0108
Rare (R)	Low (L)	(0.01, 0.04, 0.09, 0.16; 1)	0.0256
Often (O)	Moderate (M)	(0.09, 0.16, 0.25,0.36; 1)	0.0797
Frequent (F)	Serious (S)	(0.25, 0.36, 0.49,0.64; 1)	0.1678
Very Frequent (VF)	Critical (C)	(0.49, 0.64, 0.81,1.00; 1)	0.2900

All five crisp values have been calculated using 'Incenter of Centroids Method 'with 0.2900 being the highest risk rating assigned to a particular risk source. Risks have then been defined in five different risk categories (0–5) corresponding to different risk rating (crisp ranges) within a range of (0–0.2900) as shown in Table 7.3. Fig. 10.3 shows the risk mapping where all the considered risk factors have been mapped into five zones namely: Very Low, Low, Medium Low, Moderate, Serious and Critical. Finally, an action requirement plan has been prescribed on the basis of aforesaid crisp ratings by the Risk Management Team Lead, Risk Owner, Risk Committee, and Decision Team, etc. to successfully identify and manage the risks appeared in different risk categories as shown in Table 8.3.

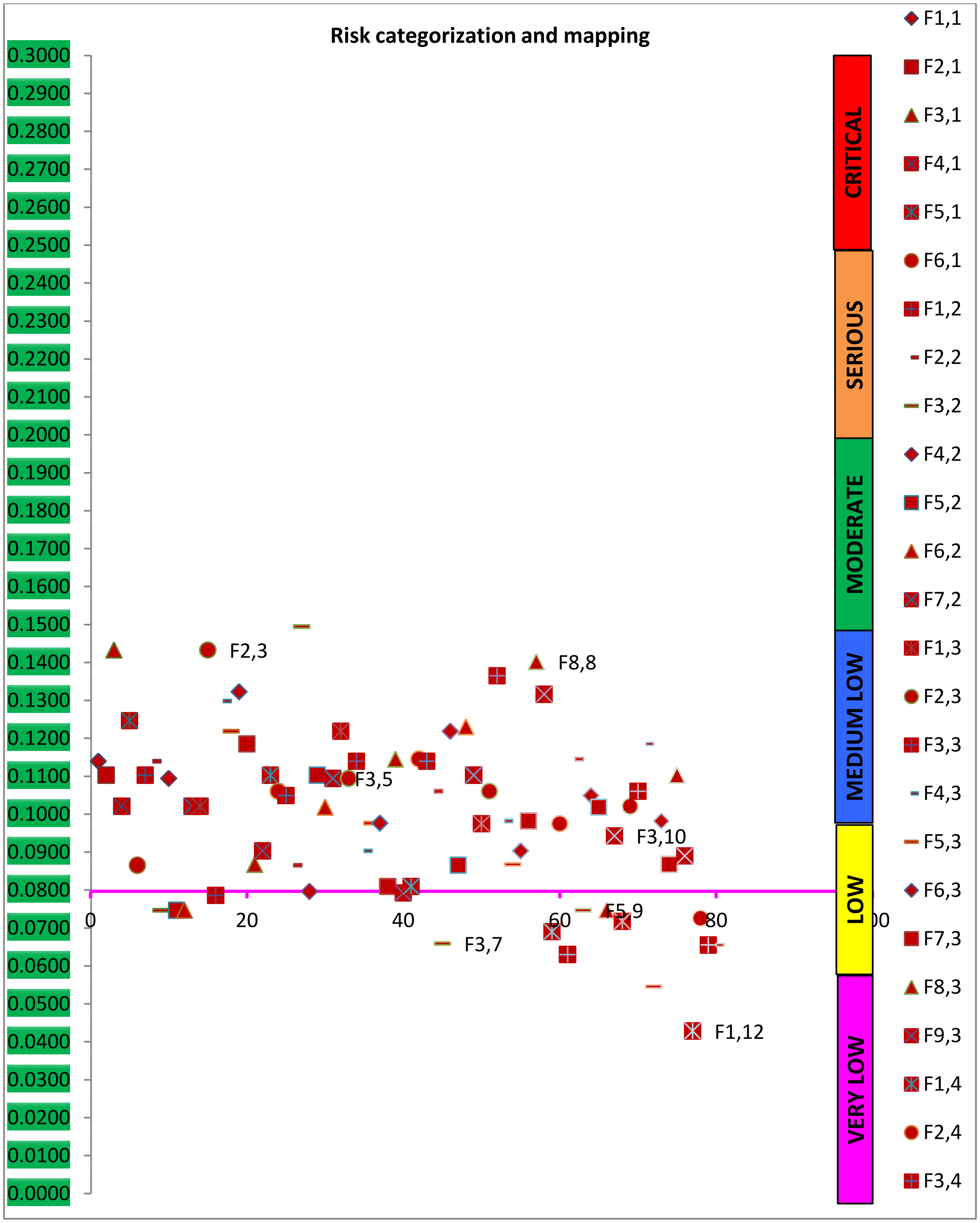


Fig 10.3: Risk categorization and mapping.

The identification of various risk influencing factors under each risk categories and their actions requirement plans has been illustrated in Table 8.3.

Table 8.3: Identification of risk factors belonging in various risk categories and requirement of action to manage the risk.

Risk category/ risk rating (crisp)	Risk influencing factors	Action required
Category 5 Rating 0.2500–0.2900		_Very immediate notification of Risk by Risk Owner to the RM Team Lead (proper documentation created) _ Immediate investigation required by RM Team Lead _ Risk committee convened immediately to review risk _ Decision Team placed on high alert _ Risk committee creates a recommendation to be presented immediately to Decision Team _ Decision Team reviews, approves, and or revises Action Plan _ Risk Owner implements Action Plan _ RM Team Lead tracks Action Plan results _ Risk Committee reviews monthly Action Plan implementation results _ Decision Team reviews monthly Risk Reports
Category 4 Rating 0.2000–0.2499		_ Immediate notification of Risk by Risk Owner to the RM Team Lead (proper documentation created) _ Immediate investigation required by RM Team Lead _ Risk committee convened urgently to review risk _ Decision Team placed on alert _ Risk committee creates a recommendation to be presented to Decision Team at their next scheduled meeting _ Decision Team reviews, approves, and or revises Action Plan _ Risk Owner implements Action Plan _ RM Team Lead tracks Action Plan results _ Risk Committee reviews monthly Action Plan implementation results _ Decision Team reviews monthly Risk Reports
Category 3 Rating 0.1500–0.1999		_ Immediate notification of Risk by Risk Owner to the RM Team Lead (proper documentation created) _ Immediate investigation required by RM Team Lead _ Risk committee convened in a timely manner to review risk _ Risk committee creates a recommendation to be presented to Decision Team at their next scheduled meeting _ Decision Team reviews, approves, and or revises Action Plan _ Risk Owner implements Action Plan _ RM Team Lead tracks Action Plan results _ Risk Committee reviews monthly Action Plan implementation results _ Decision Team reviews monthly Risk Reports
Category 2 Rating 0.1000–0.1499		_ Prompt notification of Risk by Risk Owner to the RM Team Lead (proper documentation created) _ Timely investigation by RM Team Lead _ Reviewed and evaluated at monthly Risk Committee meeting _ Action Plan determined, if required _ Risk Owner implements Action Plan _ RM Team Lead tracks Action Plan results _ Risk Committee reviews monthly Action Plan implementation results _ Decision Team reviews monthly Risk Reports
Category 1 Rating 0.0600–0.0999		_ Timely investigation by RM Team Lead _ Reviewed and evaluated at monthly Risk Committee meeting _ Action Plan defined _ Risk tracked for further possible action if Risk Rating escalates
Category 0 Rating 0–0.0599		_ No action required _ Risk placed on Watch List and reviewed by RiskCommittee _ Risk tracked for further possible action if Risk Rating escalates

3.11 Managerial implications

The study presents an experimental research on important issues of RL risks and subsequent management plan in a long-term entire reverse logistics practices in the context a typical reverse supply chain. The effectiveness of risk management can be achieved by the critical review of the risk management process that includes identifying, assessing and managing risks. A hierarchical framework has been proposed here to facilitate the process of risk identification in RL practices. Twelve potential risks such as managerial risks, collection and transport risks, IT systems risk, financial risk, legal risk, Inventory risk, environmental risk, relationship risk, outsourcing risk, product risk, culture risk and time management risk that have been identified from the review of past reverse logistics literature (Chopra and Meindl, 2002; Harland et al. 2003; Grewal et al., 2009). A significant contribution of this research is that a case study has been conducted considering a total of 80 risk influencing factors that have been identified for the assessment of overall risk extent in the said RL system. In this research, a unique methodology has been proposed that facilitates to quantify the degree of risk and suggests a risk mitigation plan at an early stage of reverse flow of materials/ products. The methodology has been outlined as a fuzzy based multi-criteria decision-making approach, which seems fruitful for the process of assessing and evaluating the identified risks. The fuzzy concepts have been applied for collecting subjective data on the likelihood of occurrence and information regarding the impact of the identified risk factors related to reverse logistics operations. This could increase the willingness of participating experts to provide their perception of information for the qualitative risk assessment process. It has been considered as an advantage that the crisp value of fuzzy numbers can give the sensitivity analysis of a fuzzy linguistic algorithm.

From the risk assessment results, it has been concluded that the risk factors with a high degree of risk should then be carefully monitored, controlled and managed to improve the effectiveness of project success. Therefore, this study has introduced an action requirement plan for identified risk factors in the different particular category that can be successfully monitored, controlled and managed by Risk Management Team Lead, Risk Owner, Risk Committee, and Decision Team. It can also be considered as another contribution of this research. In this study, the proposed methodology has been considered as a generic one. But the presented risk model and developed fuzzy based decision support system have been treated as a company specific. Every company has its risk knowledge and experience with respect to particular risk sources as well as risk influencing factors, and may have different risk attitudes. Therefore, this study could provide the guidance to the managers how the detailed procedure can be utilized in practice rather than a universally accepted solution for risk management in RL. In order to validate this proposed process, ten supply chain executives with more than fifteen years' experience in reverse logistics practice have been interviewed to confirm the validity of proposed process with respect to (a) applicability of the proposed risk assessment process for reverse logistics exercise, (b) benefits of operating the proposed risk assessment steps, (c) completeness of identified risk factors for Reverse logistics systems, and (d) importance to the strategic planning of RL systems. Ninety percent of the interviewed personnel have confirmed positively to the above questions after the precise examination of theory and operational steps.

3.12 Conclusions

Effective RL risk management necessitates a reliable risk assessment as well as risk treatment planning and subsequent implementation. The proposed risk assessment approach has appeared to more practical as well as reliable than traditional statistical methods since it utilizes the experts' risk perceptions in a subjective manner rather than objective way. In this research, fuzzy set theory has been embedded in the risk assessment process that facilitates to quantify risk ratings where both the risk impacts and the likelihood of occurrence have been evaluated by experts' subjective judgements. The developed hierarchical structure can easily model the perceived RL risks and their influencing factors. The proposed methodology not only assesses the overall risk in reverse logistics, its concept and procedure can also be implemented to evaluate risks in different industrial settings. The applicability of the proposed methodology has been tested by conducting a questionnaire survey of supply managers and experts from various established companies. The unique research contribution of the current work relates to the identification of important risk dimensions (effects) and their influencing factors (causes) in relation to reverse logistics. The research presents a unique integrated hierarchical risk assessment module for providing a framework for risk management in the reverse supply chain using fuzzy set theory instead of probabilistic assessment. Use of Left and Right dominance and 'In-centre of Centroid' methods for crisp representation of a fuzzy number improves the reliability of decision making by giving comparative results. Both methods yield same risk ranking for both individual influencing factors and overall risk ratings. Further, systematic and logical categorization of various risk dimensions followed by an action plan for risk mitigation is quite useful for the practicing managers. Exploration of a risk assessment module would help supply chain managers in understanding various risks associated with reverse logistics and their impact on the overall success of the supply chain. Getting a precise knowledge of RL risk dimensions, managers can tactfully deal with risks and finalize risk mitigation plans at the corporate level. These may be helpful for RL system's success. Reduction of RL risk may enhance flexibility as well as the competitiveness of the production company against recent recession (downfall of the financial sector). The study can be extended in several directions. However, few visible directions for future research are presented. Firstly, the present study uses trapezoidal fuzzy numbers for extracting the linguistic representation of risk assessment; the study can be extended to explore the appropriateness of different types of fuzzy numbers for risk estimation. In future, the accurate number of decision makers (DMs) needed for such type of study may be determined to save data collection time. The present study focusses on RL risk identification as well as risk quantification based on companies' supply chain managers and experts' viewpoint. The same may be tested with 'reverse supply chain partners' as well as end users' perspective to compare the risks from different perspectives.

Chapter 4: Selection of Reprocessing Alternatives: A Decision Support Tool Approach

4.1 Introduction

Reverse logistics processes and plans rely heavily on reversing the supply chain so that companies can correctly identify and categorize returned products for disposition, an area that offers many opportunities for additional revenue. The managerial- decisions regarding the most profitable/or suitable reverse disposal alternative is a key strategic consideration of any manufacturer. With some information regarding time, quantity, quality and probable market values as well as environmental impact and existing legislation regarding the returned products available to the decision makers, Fuzzy decision modelling offers an alternative framework of determining a more suitable alternative selection for reprocessing.

As an important issue, recovery and disposal decision management is a critical research issue because it determines the documentation of returns, processing of transactions, disposition cycle time, minimization of return inventories and credit refund processing for the returned products in reverse logistics. The location of the testing and grading operations in the network has a substantial impact on the arising goods flows (Thiery et al., 1995). It is only after this stage that individual products can be assigned to an appropriate recovery alternative and hence to a geographical destination. Real-time decision making on the collected products early as they enter in the reverse supply chain may minimize total reprocessing cycle time as well as offer quick transportation decision-making on the probable reprocessing destination of the return products, I.e can be sent directly to their best recovery alternative. This can aid in the flexible designing, planning, and controlling of logistics and related activities in advance. In particular, unnecessary transportation to the main collection and testing centers can be avoided by separating reusable items from unrecoverable scrap at the points of return in real time. On the other hand, detailed analysis using expensive specialized reprocessing equipment's and the need for skilled labor shall be carried out at the respective reprocessing centers as per requirements.

The study aims to propose a faster, 'localized' and easy-to-use decision-making framework that can be used to hasten categorization and grading of returns at the point of return (POR). The result shall help in achieving a cheaper, reliable and efficient 'remote 'inspection of product returns in the reverse networks. The model proposes the use of fuzzy linguistic process to pass a judgment on the perceived depreciation, quality and suitability of the return product based on the source, reasons for return and perceived depreciation, i.e. physical depreciation level, Time depreciation, Performance depreciation and Market depreciation, environmental impact and legislation requirements (Chang and Lin, 2013) to remotely decide the suitable recovery and disposal alternative. The use of Fuzzy approach is to overcome the vagueness, ambiguity and subjectivity of the human thought due to lack of accurate data about the quality, value etc. of the most returned products.

In this study, we provide an integrated, holistic conceptual framework that makes use of modified Fuzzy MOORA and Fuzzy VIKOR Multi-criteria decision making (MCDM) techniques to develop a group decision support tool that categorize return products and make the best alternative selection of recovery and disposal option using carefully considered criteria. Finally, one example, using product from market/stock out returns and the other using a product from the end of life/ use returns, from the consumer/customer, has been illustrated to highlight the procedural implementation of the proposed modified models and similarity in the results shown. The second case is used to demonstrate the sensitivity analysis of the proposed algorithm to various cases of reasons for product return under consideration. Our findings provide useful insights to various stakeholders and suggest avenues for further research. It specifically provides an efficient way of selecting the best alternatives for the real-world problems using qualitative criteria.

The definitions of various reverse manufacturing (product recovery) reasons for returns and alternatives in Reverse logistics are as follows (Thierry et al., 1995; Rodgers et al., 2001).

Consumer Returns

They form the largest category of returns. These are end user returns due to buyer remorse or defects or customer dissatisfaction. Many companies have a liberal return policy that allows their customers to return products so as to increase their customer loyalty and revenues.

Marketing Returns

Marketing returns consists of products returned from a supply chain partner due to slow sales, quality issues or repositioning of inventory. Other examples of marketing return include; closeout returns, which are first quality products which the retailer has decided not to carry; Buy- outs or ‘Lifts’, which are competitors’ products in the retailers’ supply bought by the new manufacturer; Job-outs, first quality, seasonal holiday merchandise; Non-defective defectives, which are products thought incorrectly to be defective.

Asset Returns

It consists of the recapture and repositioning of assets i.e. items that the management wants to see returned, e.g. shipping containers, reusable, collapsible packages, Tots etc.

Product Recalls

This is voluntary or mandated returns by a government agency due to safety or quality issues.

Environmental Returns

Environmental returns include the collection and disposal of hazardous materials/or products or abiding by the environmental regulations.

Processing error returns

These are those products that are returned by the end user/or supply chain partner due to error during processing and dispatch. This error includes; wrong orders, over quantities, missing parts/or components etc.

Repair & Servicing

The purpose of repair is to return the used product to its 'working order'. It only involves fixing and/or replacing of broken part(s) only, whereas other parts are not affected.

Repackaging & Reselling

Over-ordered, wrong order and other first quality products such as closeout returns, job-out returns and non-defective- defects from supply chain partners can be repackaged and resold to other demand areas. They are still in their perfect first quality, hence they are ready for reselling to other markets as they are i.e. 'sell as it is'.

Refurbishing

This is defined as the disassembly of used product into modules where they are inspected and fixed or replaced by approved modules to bring the reassembled product up to specified quality level. Refurbishing significantly improves their quality standards and extends their service life; however, it is less rigorous than that of new product.

Cannibalization & Remanufacturing

In cannibalization, only a limited set of reusable parts from used product or component is recovered. These recovered parts with strictly high quality standards are then reused in the Remanufacture of other new products/ components. Others with lesser quality standards can be reused in the repair or refurbishing of other product that require similar parts

Recycling

Recycling is defined as the reusing of the materials from used product/components in the production of original parts if the quality of material is high, or else in the production of other products. The identity and functionality of original returned products/components are lost.

4.2 Literature Review

Reverse logistics refers to the collection and distribution activities of product returns so as to achieve source reduction/conservation, recycling, substitution, reuse, disposal, refurbishment, repair and Remanufacturing (Stock, 1992). Despite its differences, reverse logistics have drawn little attention from researchers and practitioners alike until recent years. Over time, increasing concerns over environmental degradation and increased opportunities for cost savings or revenues for returning products has prompted some researchers to formulate more effective reverse logistics strategies. However, their research used mathematical modeling in arriving at decision-making, such as the location of reprocessing centers, allocation of site users and capacities in many real-world problems. Caruso et al. (1993) proposed a multi-objective mixed-integer model and a heuristic solution procedure for solving the location-allocation of waste service users, processing plants, and sanitary landfills with capacity constraints. Kroon and Vrijens, (1995) studied the applicable application of reverse logistics in the reuse of returnable containers by use of quantitative models. In their study, both the product and information flow were considered as important in the design of RL systems. Considering multiple recovery options, Thierry et al., (1995) defined the five product recovery system; Remanufacturing, repairing, Refurbishment, cannibalization, and recycling. Their study included a comprehensive discussion of the product design approach for recovery, the preparation of customer for green products and environmental legislative issues for recovery systems. Barros et al., (1996) proposed a mixed-integer model to determine the locations of regional depots for receiving the flow of sieved sand in an effort to recycle waste sand. Similarly, Krikke et al., (1999) developed a mixed-integer program to determine the locations for the recovery and disposal of used automobiles while determining the amount of product flows in the reverse logistics network. Following on his work, Krikke et al., (1999) identified two key areas concerning reverse logistics. First, the product recovery management (PRM) which deals with the collection of returns and processing them with a recovery strategy based on the quality dependent decision rules regarding their degree of disassembly and treatment options. Secondly, the physical network designs of an RL system, i.e. the locations and capacities of processing facilities where optimization of good flow between facilities is determined.

A comprehensive and updated analysis of product recovery network models has been contributed by Fleischmann et al. (2000); Dowlatshahi, (2000) and Fleischmann, (2003). Recently, the evolution of reverse logistics concepts and strategies in the retail industry is dealt by Bernon and Cullen, (2007). More recently, Srivastava, (2007) presented a multi-product-multi-echelon profit maximizing RL and value recovery network model that covered activities from the collection to the first stage of remanufacturing. The model was used to determine the optimal number and locations of remanufacturing facilities in the consumer electronics industry. Rigid constraints are imposed to determine the reprocessing decision on the returns. However, various factors such as the reasons for returns, sources of returns etc., were not considered. Chouinard et al. (2008) studied the quality of return products levels in a stochastic modeling approach. They considered the categorization of the products quality into five levels, i.e. S=0, Unknown, S=1, New, S=2, Good condition, S=3, deteriorated, S=4, Unusable. However, their model gives a category number to the product without considering its characteristics that may result in the ranking of available reprocessing options for the product being evaluated. Bastiaan et al., (2010) developed a theoretically and empirically grounded diagnostic tool for assessing the Consumer Electronics Company's reverse logistics practices and help identify potentials for RL improvement. Lambert et al., (2011) proposed a reverse logistics decision conceptual framework to channel the return flow of product called return policies. They suggested four steps as Gatekeeping (Rodgers& Tibben-Lembke (1999), preliminary grouping of collected products based on the subsequent operation, detailed sorting and choice of disposal. As summarized above, the majority of existing reverse logistics models have, so far, focused on the physical network design aspects (i.e. the location and capacities of reprocessing facilities) and the optimization of goods flows between facilities using a stochastic approach. They have all considered the traditional Centralized collection and Inspection in which the return products are thoroughly tested before deciding the best reprocessing destinations. These kinds of problems are known as facility location problems in OR-literature.

However, recently, many probabilistic MCDM techniques such as Analytical Hierarchy Process (AHP) Saaty, (1980), technique for order preference by similarity to ideal solution (TOPSIS), Hwang and Yoon, (1981) etc. and their fuzzy models have been proposed for selecting the best reprocessing alternatives in the supply chain. Kahraman, et al., (2003), introduced a multi-criteria supplier selection using fuzzy analytical Hierarchical process (FAHP).The supplier criteria, product performance, service performance standards and cost criteria were used to evaluate the best supplier. Chen et al., (2006) developed a fuzzy model for supplier selection using a fuzzy TOPSIS approach. In their approach, benefits criteria were considered, i.e. profitability of the vendor, relationship closeness, technological capability, conformance to quality and conflict resolution. Ravi et al., (2005), analyzed alternative selection in reverse logistics for the end of life computers using ANP and balanced scorecard approach. They considered decision criteria such as economic factors, legislation, corporate citizens and environmental issues related to the recovery options in selecting the suitable alternative. Wadhwa et al., (2007) proposed a flexible decision modeling of reverse logistics system for alternative selections. They claim that the proposed model can help in designing effective and efficient flexible return policy depending on the various criteria. Ertugrul and Karakasoglu, (2007) studied the selection of facility location using Fuzzy AHP and fuzzy TOPSIS decision-making methods. The study focused on making a decision for the new facility or plant location. Sasikumar, et al., (2010) presented an integrated closed loop distribution and 3PRLP selection for the used battery recycling in order to achieve cost efficiency and delivery schedules in reverse logistics. The RL providers were selected using the fuzzy VIKOR approach. Chitrasen et al., (2012) presented a decision-making approach to selecting reverse logistics alternatives using interval-valued fuzzy sets combined with VIKOR. They rated the alternatives against a set of attributes and developed an efficient product recovery policy. Dragisa, (2013) proposed an extension of the MOORA method to use triangular fuzzy numbers (TFN) for solving fuzzy decision-making problems. The approach is applicable and efficient for many real life world problems, especially in alternative selection.

All the above reviewed fuzzy approaches apply in situations where direct rating and ranking of alternatives to a set of criteria, e.g., selection of location, suppliers, etc. However, in many real-life problems, the entities are to be allocated to the best destination/alternative by using a set of criteria. Problems such as supplier selection to the individual industries, personnel selection to departments, software selection for various applications, project selection for different regions and machine selection for various jobs in companies' etc. fall in this category. In reverse logistics (RL) the interest is in judging and rating the actual return product and making a decision on the most suitable reprocessing option/alternative as its final destination using a set of criteria. In order to achieve this, we propose a modification of the proposed fuzzy MOORA and fuzzy VIKOR methods.

Our study will specifically aim to design a fast and easy to use decision-making framework at the Point of Return (POR) in order to hasten categorization and grading of returned products. This model aims at achieving a cheaper, reliable, and efficient information flow reverse networks. Products in the reverse supply chain can be assessed based on a set of criteria/ attributes, e.g., physical depreciation level, time depreciation, performance depreciation, market depreciation, environmental effect and reprocessing legislation requirements (Chang and Lin, 2013) to 'remotely' decide their best reprocessing alternatives. In this research, we seek to present a comprehensive, integrated, holistic conceptual framework of the RL as an enterprise system i.e. Integrated Reverse Enterprise system (RES) Fig.2.4, where the flow of goods and information can be presented logically to achieve the desired decision-making process at various stages of the reverse supply chain system. In our model, two phases of decision making are considered, namely the pre-requisite manual sorting and categorization step based on the product source and reason for return and a fuzzy decision making stage where a fuzzy judgment based on a proposed set of Criteria and performance rating as given by a set of decision makers/experts.

4.3 Fuzzy Sets

Usually most of the qualitative decisions in situations, where it is not possible to quantify the value using the available data on considered criteria, are made using human judgment in a multi-criteria decision process. However, to overcome the vagueness, ambiguity and subjectivity of the human thought, Fuzzy set theory are introduced and used (Zadeh, 1965). The decisions are expressed in terms of linguistic scale, i.e., a grade of the membership function ranging from zero to one. The difference between a fuzzy set and a crisp set is that Crisp sets only allow full membership or non-membership at all, while, on the contrary, fuzzy sets allow partial membership. In other words, an element may partially belong to a fuzzy set (Ertuğrul and Karakaşoğlu, 2007). In the absence of complete and exact data about the returned products in reverse logistics, use of fuzzy linguistic variables provides a powerful mathematical tool for decision modeling. Their role is significant when applied to complex phenomena not easily described by traditional mathematical methods, specifically where the objective is to find a good approximate solution. Fuzzy set theory has been contributing to the capability of reflecting the real world while providing a more widely frame than classic or crisp set theory. Modeling using fuzzy sets has proven to be an effective way of formulating decision problems where the information available is subjective and imprecise (Dragisa, 2013).The Implementation of fuzzy set technique to a real problem requires the following three steps (Wang et al., 2006) namely:- Fuzzification where classical data or crisp data is converted into fuzzy data or membership functions (MFs); Fuzzy Inferencing, which is to assign fuzzy variables and fuzzy numbers to derive the fuzzy output and defuzzification where different methods are used to convert the fuzzy outputs to crisp set for interpretation of the results.

4.3.1 Linguistic Variables: These are variables whose values are words or sentences in a natural or artificial language. The concept of a linguistic variable provides a means of approximate characterization of phenomena that are too complicated or too ill-defined to be amenable to description in conventional quantitative terms (Zadeh L. A. 1975a). In literature, numerous studies have considered the use of various linguistic scales. Like many other approaches; same scale or different scale for assigning significance coefficients and responses of alternatives can be used. The proposed linguistic scale is shown in Table 1.4.

Table 1.4: Linguistic scales for significance coefficients and responses of alternatives

Linguistic Variable	$\mu_{triang}(x)$	TFN support
Very Low(VL)	(0,0,2)	2
Low(L)	(1,2.5,4)	3
Medium (M)	(3,5,7)	4
High(H)	(6,7.5,9)	3
Very High(VH)	(8,10,10)	2

4.3.2 Fuzzy Numbers (Fuzzification): A fuzzy number Ã is a convex of normalized fuzzy set, Ã of the real line R such that (Zimmermann, 1992):

-It exists such that one $X_o \in R$ $with$ $\mu_A \sim (X_o) = 1$ (X_o is called the mean value of Ã)

-$\mu_A \sim (X_o)$ is piecewise continuous, i.e. degree of membership.

In crisp sets, the value of membership function is given as μ_A from X to$\{0,1\}$, i.e.

$$\mu_A(A) = \{ \begin{matrix} 1, & if\ X \in A \\ 0, & otherwise \end{matrix} \quad (1)$$

It's possible to use different fuzzy numbers according to the situation, e.g., Triangular fuzzy numbers, Trapezoidal Fuzzy numbers etc. In application, Triangular fuzzy numbers (TFN) are used because they are easy to utilize in computations and very useful in the presentation and processing of information in a fuzzy environment. In this study, TFNs are adopted for the fuzzy MOORA and fuzzy VIKOR methods.

Triangular fuzzy numbers can be defined in triple format (l, m, u) where l, m, and u represents the lower limit value, the most acceptable value and the largest possible limit respectively that can describe a fuzzy event (Dragisa, 2013). Fig. 1.4 shows a triangular fuzzy number (TFN) representation.

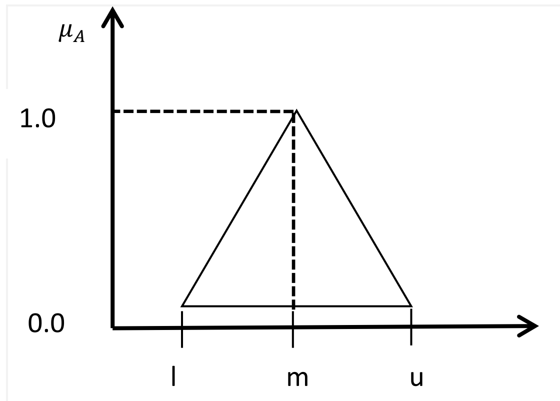


Fig 1.4: Triangular Fuzzy number

As important characteristics of a TFN there can also be specified: mode *m*, support (*u* – *l*), left spread (*m* – *l*) and right spread (*u* – *m*). TFN with equal left and right spread is known as asymmetrical TFN (STFN).

The membership function of the TFN is defined as:

$$\mu_A(A) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & l \leq x \leq m \\ 0, & x > u \end{cases} \quad (2)$$

There are various operations on triangular fuzzy numbers. But here, only important operations used in this study are illustrated. If we define, two positive triangular fuzzy numbers Ã (l_1, m_1, u_1) and $\tilde{B}$ (l_2, m_2, u_2) then Dragisa, 2013:

$$\tilde{A} + \tilde{B} = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (3)$$

$$\tilde{A} - \tilde{B} = (l_1 + u_2, m_1 + m_2, u_1 + l_2) \quad (4)$$

$$\tilde{A} \text{x} \tilde{B} = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (5)$$

$$\tilde{A} \div \tilde{B} = \{\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\} \quad (6)$$

$$k \times \tilde{A} = (kl_1, km_1, ku_1) \quad (7)$$

$$\tilde{A}^{-1} = \{\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\} \quad (8)$$

The distance between two triangular fuzzy numbers can be calculated by vertex method (Chen, 2000):

$$d_{vert}(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 \ + ((u_1 - u_2)^2} \quad (9)$$

4.3.3 Defuzzification: Since the operations of obtaining the results are performed on fuzzy numbers, the obtained results are also in fuzzy form. There is need to convert these results into crisp responses so that the alternatives can be ranked in fuzzy environment using MCDM methods.

Different methods have been proposed over time for the defuzzification of fuzzy responses (Dragisa, 2013). They include:-

For mapping of a fuzzy number into the corresponding crisp number Eq. 10 is proposed:

$$\overline{m}(\tilde{A}) = (l + 2m + u)/4 \quad (10)$$

Where $\overline{m}(\tilde{A})$ is the resulting generalized mean of fuzzy number $(\tilde{A})$ i.e crisp number. If two fuzzy numbers have the same value of resulting crisp number, then fuzzy number with the larger mode will be ranked higher. Also, if they have the same mode, the higher-ranked fuzzy number will be the one which has a smaller left spread.

The proposed Interval Value method for ranking fuzzy numbers and for calculating the generalized mean of fuzzy number is suggested by Eq. 11:

$$\overline{m}(\tilde{A}) = \frac{1}{2}[(1 - \lambda)l + m + \lambda u] \quad (11)$$

With **λ** as a coefficient which represents the decision maker risk-taking attitude, also denoted as an index of optimism, and I∈[0,1] .

Chiu and Park (1994) proposed the following equation for mapping a fuzzy number into a corresponding crisp number:

$$\overline{m}(\tilde{A}) = \frac{1}{3}(l + m + u) + \ \lambda m] \quad (12)$$

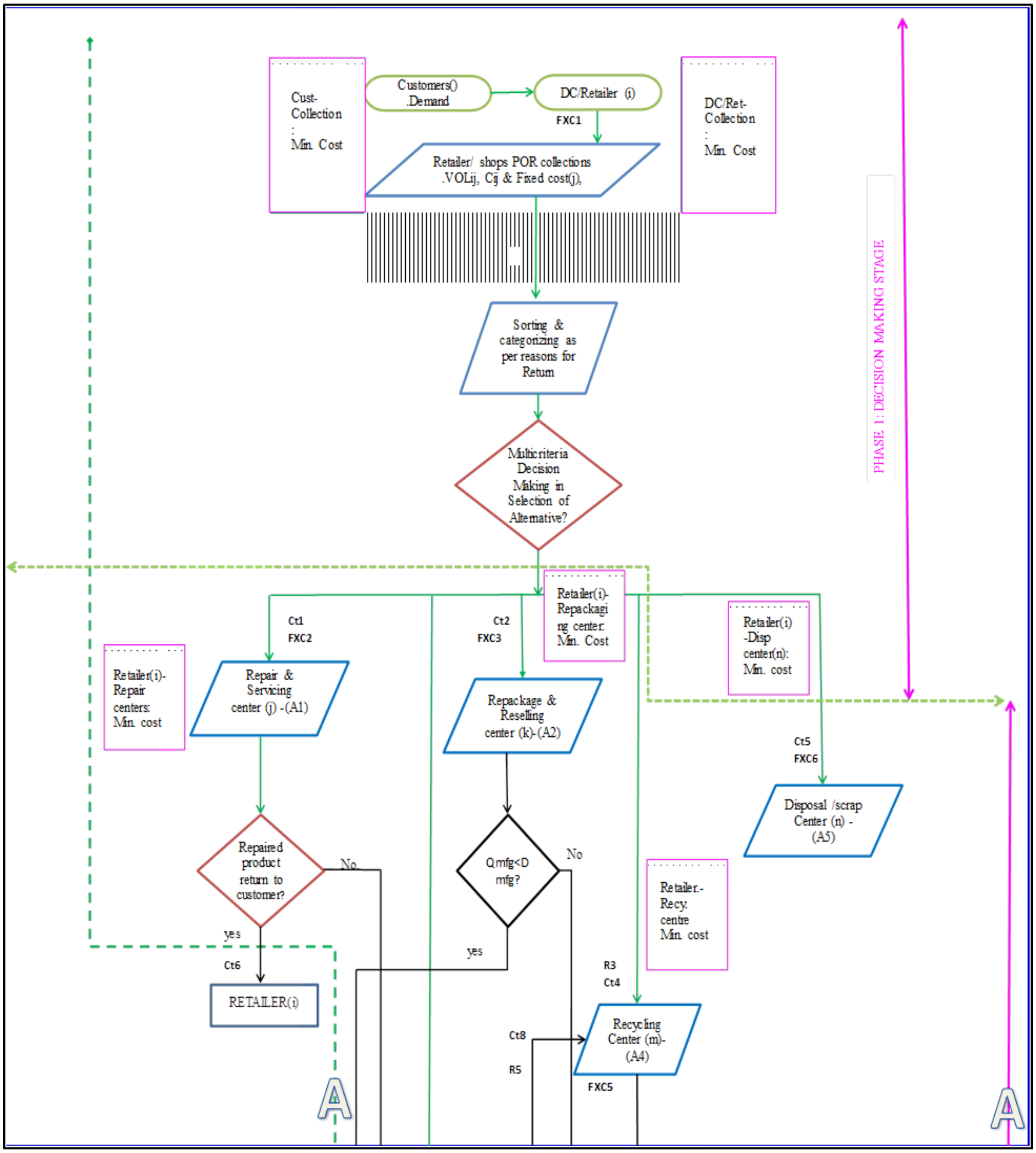
Where λ is a coefficient by which the decision maker can express his opinion about the nature and importance of the TFN mode, and I ≥ 0.

And finally, Opricovic and Tzeng (2004) proposed Eq. 13 for determining the generalized mean of fuzzy numbers:

$$\overline{m}(\tilde{A}) = \left(l + \frac{(m-l)+(u-l)}{3}\right) \quad (13)$$

4.4 Materials and methodology

In this study, we seek to present a comprehensive, integrated, holistic conceptual framework of the RL as an enterprise system i.e. Reverse Enterprise system (RES) Fig. 2.4, where the flow of goods and information can be presented logically to achieve the desired decision-making process at various stages of the reverse supply chain system. In this system framework, goods from customer end are assumed to enter the reverse supply chain at the retailers/ distribution centers, which are considered as points of return (POR) in our study. The goods/ products are sorted and categorized as per reasons for return criteria before final multi-criteria decision making process to select the best reprocessing alternative.



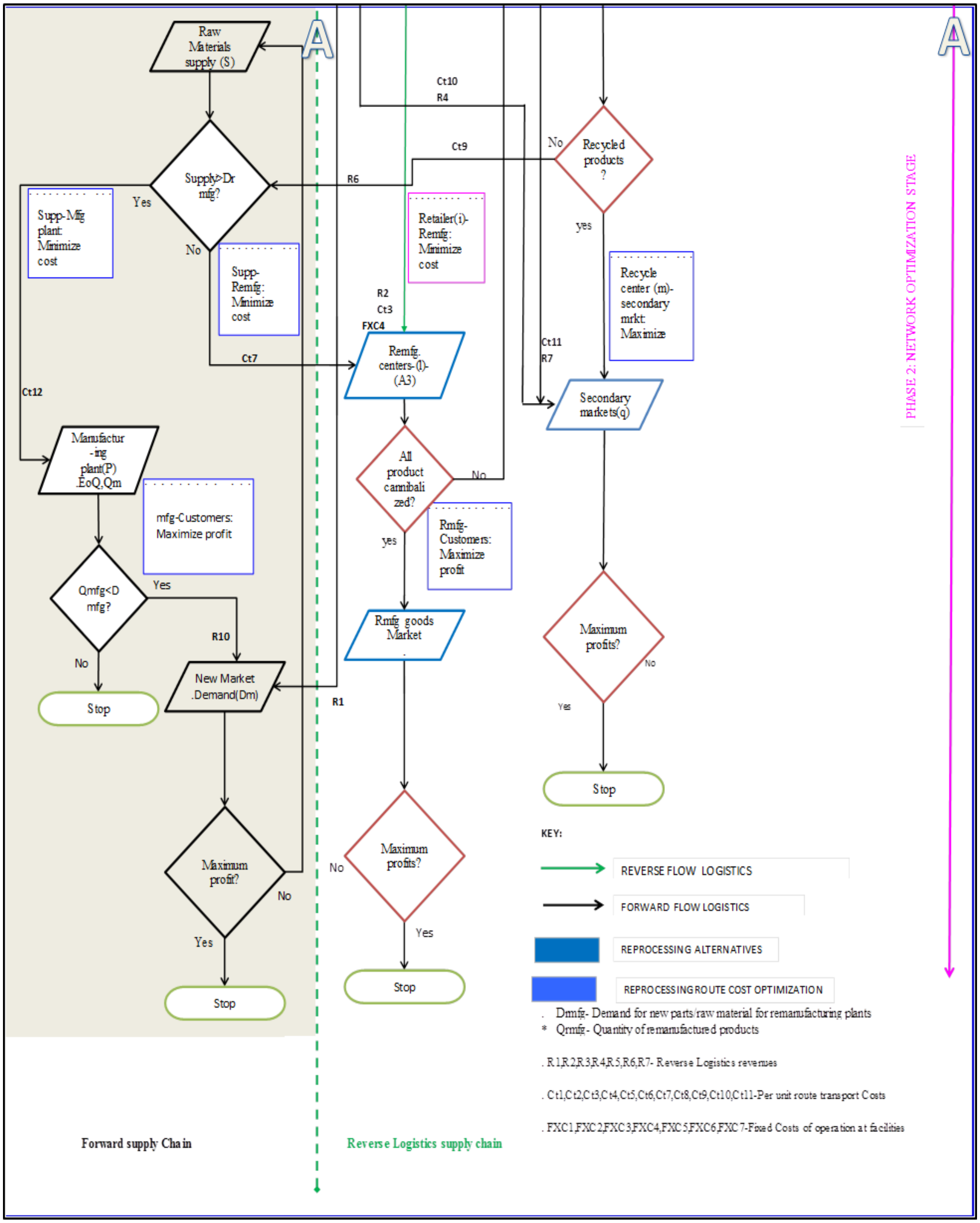


Fig 2.4: Integrated reverse logistics enterprise system

As shown from the reverse logistics system above, our model proposes a two phases of decision making approach, namely the pre-requisite manual sorting and categorization step based on the product source and reason for return and a fuzzy decision making stage where a fuzzy judgment based on a proposed set of Criteria and performance rating as given by a set of decision makers/experts as shown in Fig.3.4

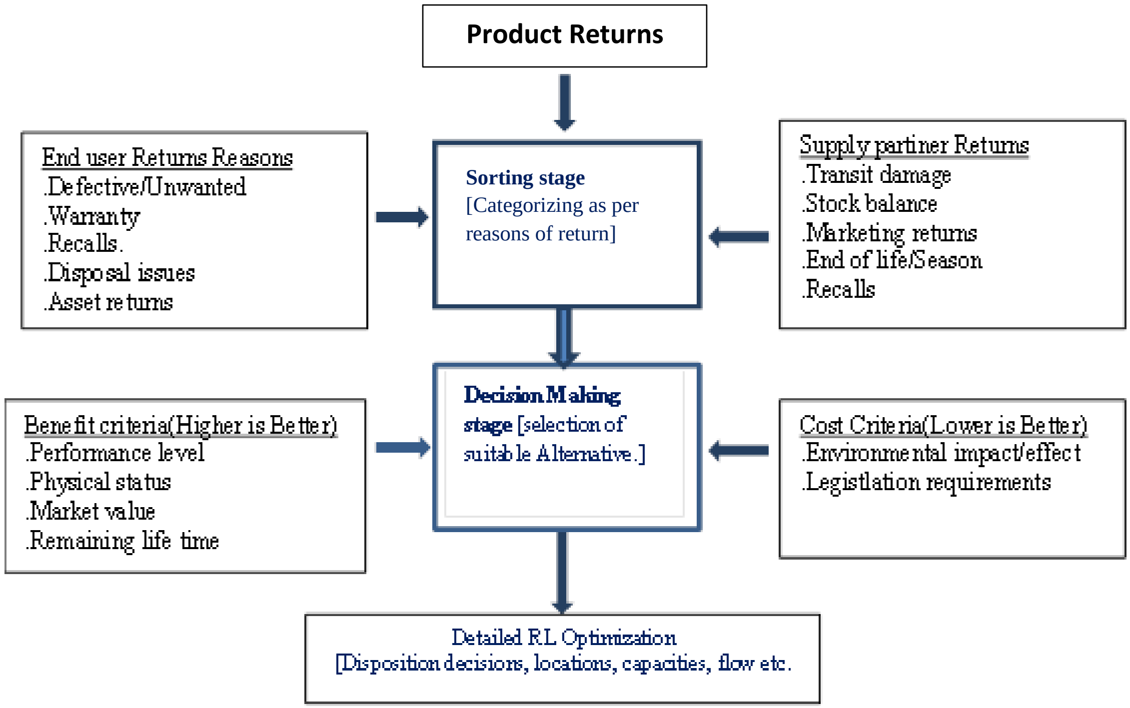


Fig 3.4: Hierarchical Decision making stages.

4.5 Fuzzy MOORA Method

The fuzzy MOORA multi-criteria decision-making method is proposed for analyzing and determining the best alternative selection in this study. Brauers and Zavadskas (2006) introduced the MOORA method based on the previous researches (Brauers 2004a, b). It consists of two components, namely: the Ratio system and reference point approach. Dragisa (2013) proposed an extension to the MOORA method for solving fuzzy decision-making problems. Our study suggests a systematic approach to modifying the extended MOORA ratio system by Dragisa (2013) to solve decision problems in reverse logistics in a fuzzy environment.

4.5.1 The common steps of extended MOORA ratio system approach

The initial steps in solving the MCDM problem are identified as:

- Identify alternatives, which can be used to solve problem; and
- Select objectives, on which basis the evaluation of alternatives will be done.
- Next usually follow the typical steps, such as:
- Determine the responses of alternatives on objectives, and construct a decision matrix;
- Normalize the responses of alternatives.
- Determine the significance of the objectives; and

- Determine fuzzy overall performance index, for each of considered alternatives;
- Defuzzification, i.e. transform a fuzzy into a crisp overall performance index; and
- Select the optimal/most appropriate/most desirable alternative.

In relation to the steps in ordinary MCDM methods, the use of fuzzy numbers and linguistic variables has certain specificities, and these are discussed below.

4.5.2 Determining the responses of alternatives on the criteria and construction of Fuzzy decision matrix

The responses of alternatives on the set of criteria for fuzzy MCDM problem involving m alternatives, *n* criteria and k decision makers, can be expressed in the following matrix form:

$$\widetilde{D}^k = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & . & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & . & \tilde{x}_{2n} \\ \tilde{x}_{m1} & \tilde{x}_{m2} & . & \tilde{x}_{mn} \end{bmatrix} \qquad (14)$$

Where: $\widetilde{D}^k$ Is the fuzzy decision matrix formed by decision maker k; $\tilde{x}_{11}, \tilde{x}_{12}, \dots \tilde{x}_{mn}$,are fuzzy response of alternative *j* on criteria *i* for all alternative m and criteria n given by decision maker k using linguistic variables in table 1; i=1,2,…, n as criteria; j=1,2,3,…,m as alternatives; and k=1,2,….,k as decision makers.

As a result, the fuzzy responses of alternative for each criterion based on each criterion for all decision makers are aggregated using Eq. 15:

$$\tilde{x}_{ij} = \frac{1}{k} \sum_{k=1}^{k} \tilde{x}_{ij}{}^{k} \qquad (15)$$

Where $\tilde{x}_{ij}$ is the aggregated fuzzy response of alternative j on objective i.

The resulting fuzzy decision matrix $\widetilde{D}$ is formed i.e;

$$\widetilde{D} = [\tilde{x}_{ij}]_{mxn} \qquad (16)$$

While forming the resulting fuzzy decision matrix, the linguistic variables are also transformed into the corresponding triangular fuzzy numbers.

The next step is to normalize the fuzzy responses and construct a normalized fuzzy decision matrix as follows:

$$\widetilde{D}^* = [\tilde{x}^*{}_{ij}], \qquad (17)$$

Where, $\tilde{x}^*{}_{ij}$,as a normalized fuzzy response of alternative *j* on criteria *i*.

For Normalization, the following Equation is proposed (Dragisa, 2013):

$$\tilde{x}^*{}_{ij} = \left(\frac{x_{ijl}}{x_i^+}, \frac{x_{ijm}}{x_i^+}, \frac{x_{iju}}{x_i^+} \right),$$

Where;

$$x_i^+ = (\textstyle\sum_{j=1}^{m} x_{iju}^2)^{1/2} \qquad (18)$$

4.5.3 Determining the significance of criteria on alternatives

When solving the real-world problems using MCDM methods, decision criteria mainly do not have the same significance weight on alternatives, i.e. some criteria have higher significance in relation to a particular alternative than the others. As a result, to include the different significance of the various criteria, Brauers and Zavadskas, 2009, 2012 introduced the Significance coefficient. They proposed Eq. 19 which adds the significance factors, s_i in the Ratio system approach of the MOORA method during the calculation of overall ranking indices of alternatives:

$$\ddot{y}_j^* = \sum_{i=1}^{g} \; s_i \, \tilde{x}_{ij}{}^* - \sum_{i=g+1}^{i=n} \; s_i \, \tilde{x}_{ij}{}^* \qquad (19)$$

Where: s_i as the normalized significance coefficient of criteria *i*; and $\ddot{y}_j^*$ is the overall ranking of index of alternative j with respect to all criteria and their significance coefficients; $\ddot{y}_j^* \in [-1{,}1]$; *i=1,2…,g* are the criteria to be maximized; *i=g+1,g+2,.., n* are criteria to be minimized; *j=1,2…m* is the alternatives.

This can further be simplified as:

$$y_j^* = y_j^+ - y_j^-; \qquad (20)$$

Where;

$$y_j^+ = \sum_{i \in \Omega_{max}} s_i \, \tilde{x}_{ij}{}^*, \text{ and} \qquad (21)$$

$$\mathrm{y_j^-} = \sum_{\mathrm{i} \in \Omega_{\min}} \mathrm{s_i} \, \tilde{\mathrm{x}}_{\mathrm{ij}}{}^* \qquad (22)$$

Where $y_j^+$is the sum of normalized responses of alternatives j on criteria to be maximized; y_j^- is sum of normalized responses of alternatives j on criteria to be minimized; $\Omega_{max}$is set of objectives/criteria to be maximized; and Ω_{min} is set of criteria to be minimized.

Based on the Ratio system approach of the MOORA method, the optimal alternative A_{RS}^*can be determined using Eq. 23:

$$A_{RS}^* = \left\{ A_j \middle| \max_j y_j^* \right\} \qquad (23)$$

Therefore, to determine the significance coefficient more realistically, often is necessary to take into account the opinions of several experts. In such cases, the use of linguistic variables can be very appropriate. For a decision making-problem which involves *n* criteria and *K* decision makers, the aggregated fuzzy significance coefficient can be calculated using the Eq. 24:

$$\widetilde{s'}_i = \frac{1}{k}\sum_{k=1}^{k} \tilde{s}_i^{\,k} \tag{24}$$

Where : $\widetilde{s'}_i$ are the non-normalized fuzzy significance coefficients of objective/criteria *i*; $\tilde{s}_i^{\,k}$ is the fuzzy significance coefficient *i* given by decision maker *k*; *i*=1,2,…, *n* are the objectives; and *k*=1,2,…*K* as the decision makers/experts.

The fuzzy significance coefficients obtained in Eq. 24 above are non-normalized i.e. $\sum_{k=1}^{k} \widetilde{s'}_i \neq 1$, hence they must be scaled (normalized) using Linear Transformation – Sum Method, which is adapted for use when significance coefficients are expressed by using triangular fuzzy numbers as follow:

Let $\widetilde{s'}_i = (s'_{il}, s'_{im}, s'_{iu})$ Then,

$$\tilde{s}_i = \frac{1}{s_{i\sum m}} \times \widetilde{s'}_i, \tag{25}$$

Where,

$$s_{i\sum m} = \sum_{i=1}^{n} s'_{im} \tag{26}$$

Where: $s_{i\sum m}$ is a sum of modes of non-normalized significance coefficients of criteria *i*.

4.5.4 Determining fuzzy overall performance index for the alternatives.

Next Eq. 27, 28 and 29 are used to determine the overall fuzzy performance index when fuzzy numbers are used:

$$y_j^* = y_j^+ - y_j^-; \tag{27}$$

Where;

$$y_j^+ = \sum_{i\in\Omega_{max}} s_i\, \tilde{x}_{ij}^{\,*}; \text{ and} \tag{28}$$

$$y_j^- = \sum_{i\in\Omega_{min}} s_i\, \tilde{x}_{ij}^{\,*} \tag{29}$$

Where y_j^+ is the sum of normalized responses of alternatives j on criteria to be maximized; y_j^- is sum of normalized responses of alternatives j on criteria to be minimized; Ω_{max} is set of objectives/criteria to be maximized; and Ω_{min} is set of criteria to be minimized.

4.5.5 Defuzzification of fuzzy overall performance index.

Results obtained from Eq. 27 are triangular fuzzy numbers. To enable evaluation and ranking of considered alternatives, they are translated into crisp overall performance indices. This can be achieved by using any of the methods described in subsection 4.3.3. If a decision maker has no risk-taking attitude, then the crisp overall performance indexes can be calculated using the Eq. 10 or Eq.13. In contrast, if a decision maker has a risk-taking attitude then the Eq. 11 or Eq. 12 can be much more appropriate, because it enables the decision maker to assign greater significance to the mean of the fuzzy number.

4.5.6 Selection of the optimal alternative

Finally, based on the results obtained from the previous steps, the overall performance index of alternatives, y_j^*, can be ranked in descending order with the one with the maximum value of y_j^* being the best, as expressed in Eq. 28.

4.6 The proposed modifications of the Fuzzy extended MOORA ratio system approach method

In order to make the selection of the most appropriate alternative based on a ratio system approach of the MOORA method in the industry decision support system application easy, faster and with reduced error of judgment, the following modifications are proposed in this study:

4.6.1 Determining the performance rating of return product based on second level criteria

In the proposed model, the performance rating of the return product is determined based on the selected criteria/objectives, i.e., the decision maker passes a judgment/rating on each criteria/objective for the return product at the point of return. For example, in the given used computer being returned, the decision maker shall directly rate its physical condition level, market value, remaining life level etc., by observing and using available data for that product.

This modification allows the decision making process to be made easier and faster with minimum errors of judgment at the point of returns where limited expertise is available.

4.6.2 Determining the significance of second level criteria on the alternatives

When solving the real-world problem using MCDM methods, the significance of criteria/objectives is not the same to all the alternatives, i.e., each criterion will have different significance weight on the alternatives being compared. As an illustration, in the case of the computer manufacturing company, the market depreciation/value criterion shall carry a higher significance for refurbishing and reselling alternative compared to a lower significance when considering its destination as disposal, i.e., for the returned computer to be considered for refurbishing and reselling, its market value should be from Medium to Very High. On the contrary, it will be deemed as very low/very poor for disposal alternative. In reverse logistics, the decision makers are usually required to pass human judgment on the return product based on the set of criteria. Based on this, the study we propose that the decision makers pre-determine the significance of each criterion on each alternative, and only the performance response of product on a set of criteria be given at the point of return (POR) . The fuzzy judgment of the performance response of the product can be made by a number of decision makers as well. This shall offer the following advantages:

1. Reduce errors of judgment in cases where high number of alternatives and criteria/ objectives are being considered, i.e., allowing decision maker to carry out performance response of each alternative on each criteria/objectives during decision making in cases of large number of criteria and alternatives being considered is prone to systematic human error and lack of consistence especially when applied at the point of return (POR) in reverse logistics. Moreover, since the significance of each criteria on the alternatives can been pre-determined in the proposed modified model by the experts, only the performance rating of criteria/objectives against each product can be carried out easily by the company staff (who are not necessarily experts) at the POR with high accuracy.
2. It makes the decision-making process faster and easier, thus leading to a responsive and efficient RL system: The decision makers at the POR shall only be required to perform rating/response of the return product based on the criteria/objectives at the POR.

Therefore, for a reverse logistics decision-making, problem which involves *g* products, *h* reasons of product returns, *n* criteria, *j* alternatives and *k* decision makers, the aggregated fuzzy response of criteria and fuzzy significance coefficient calculated using the Eq.14-18 and Eqs.20-29 respectively are modified as follows:

$$\tilde{x}_{ghi} = \frac{1}{k} \sum_{k=1}^{k} \tilde{x}_{ghi}{}^{k} \qquad (30)$$

Where $\tilde{x}_{ghi}$ is the aggregated fuzzy response of product g in a group of return products based on reason h based on criteria/ objective i. For example, the responses of a product based on criteria/objectives are determined as in table 2:

The resulting fuzzy decision matrix $\widetilde{D}$ is formed i.e;

$$\widetilde{D} = [\tilde{x}_{ghi}]_{mxn} \qquad (31)$$

For Normalization of the fuzzy responses obtained, Eq.18-19 are modified and used as follows:

$$\tilde{x}^{*}{}_{igh} = \left(\frac{x_{igl}}{x_i^+}, \frac{x_{igm}}{x_i^+}, \frac{x_{igu}}{x_i^+}\right), \qquad (32)$$

Where;

$$x_i^+ = (\sum_{i=1}^{n} x_{igu}^2)^{1/2} \qquad (33)$$

Where $\tilde{x}^{*}{}_{ig}$is the normalized fuzzy response of criteria i on product g from reason of return, *h*.

Similarly, the significance of objectives/criteria, *i* on alternative *j* given by Eq.24 will be modified as:

$$\widetilde{s'}_{ij} = \frac{1}{k}\sum_{k=1}^{k}\tilde{s}_{ij}{}^{k} \qquad (34)$$

The significance of objectives on alternatives shall then be normalized using expressions in Eq. 25 and Eq. 26 modified as below:

$$\tilde{s}_{ij} = \frac{1}{s_{ij\sum m}} \times \widetilde{s'}_{ij}, \qquad (35)$$

Where,

$$s_{ij\sum m} = \sum_{i=1}^{n} s'_{ijm} \qquad (36)$$

Where: $s_{i\sum m}$ is a sum of modes of non-normalized significance coefficients of criteria *i* on alternatives *j*.

4.6.3 determining the performance index based on the second level criteria

Next, the overall fuzzy performance rating for the considered alternatives is determined using the modified Eq. 37 as follows:

$$y_j^{*} = \left|y_j^{+} - y_j^{-}\right|; \qquad (37)$$

where;

$$y_j^{+} = \sum_{i\in\Omega_{max}} s_{ij}\,\tilde{x}_{ghi}{}^{*}; \text{ and} \qquad (38)$$

$$\mathrm{y_j^{-}} = \sum_{\mathrm{i}\in\Omega_{\mathrm{min}}} \mathrm{s_{ij}}\,\tilde{\mathrm{x}}_{\mathrm{ghi}}{}^{*} \qquad (39)$$

Where: s_{ij} is the normalized significance of criteria *i* on alternative *j*; $\tilde{\mathrm{x}}_{\mathrm{ghi}}{}^{*}$ is the performance rating of product *g*, in a set of products in reason for return *h* based on criteria *i*; $y_j^{+}$is the sum of normalized responses of alternatives *j*, on criteria to be maximized; y_j^{-} is sum of normalized responses of alternatives *j*, based on criteria to be minimized; $\Omega_{max}$is set of objectives/criteria to be maximized; Ω_{min} is set of criteria to be minimized; *g=1,2,…G* is the number of products; and *h=1,2,…,H* as reasons for return; *i=1,2,…,n,* number of criteria or objectives; *j=1, 2,….*m as alternatives.

Note that the absolute value of performance rating is considered in Eq. 37 in order to obtain a positive difference between the normalized response of alternatives based on criteria to be maximized and those to be minimized i.e. if the sum of the normalized responses of alternatives based on criteria to be minimized is more than for those to be maximized, then the least valuable alternative is the best i.e. Disposal.

4.6.4 Determining the significance of first level criteria on the alternatives

In our proposed model, the reasons for return, which are considered independently when selecting the alternative, are treated as First level hierarchy level, i.e. the reason for return have different significance weights on each alternative considered. For example, the product returned due to marketing or stock balance reasons shall have different weightage to different alternatives considered, i.e. it shall have Very High weightage on Repackaging & Reselling alternative compared to Very Low on Disposal.

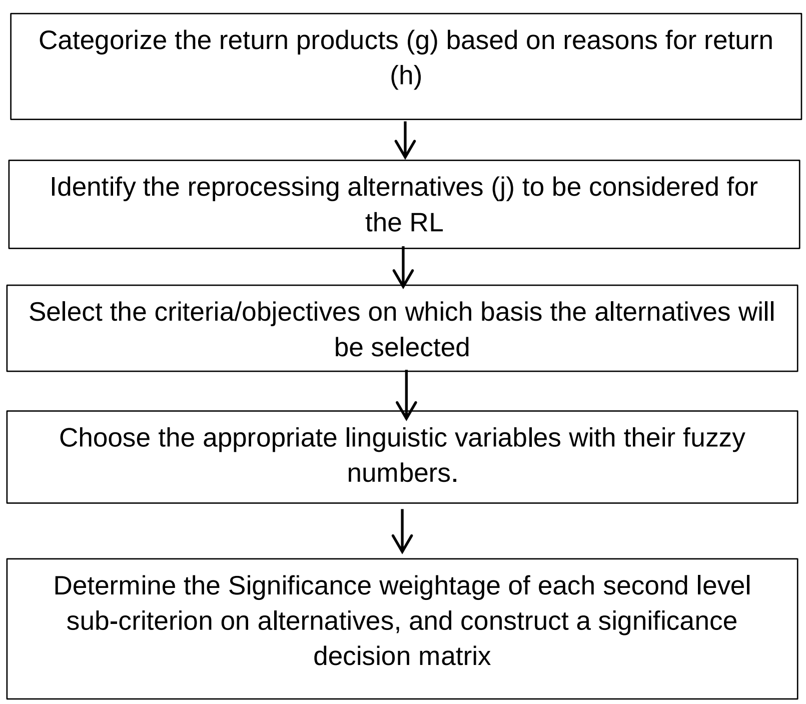
4.6.5 Determining the overall performance index of alternatives: To determine the overall performance index for each considered alternative, Eq. 40 is used:

$$Y_j^O = \widetilde{w}_{hj} \cdot y_j^* \qquad (40)$$

Where; Y_j^O is the overall fuzzy performance Index of alternative j; y_j^* is the fuzzy priority rating of the considered alternatives; $\widetilde{w}_{hj}$ is the significance weights of the 2nd level criteria (i.e. reason for return) *h* on alternative *j; j=1,2,…,m* as the alternatives; and *h=1,2,…,H* as the reasons for returns.

Finally, the procedures for the defuzzification of the overall fuzzy performance index obtained using Eq. 40 into crisp values, the ranking and selection of alternatives remains the same as described in the previous subsections.

In summary, the steps of the proposed methodology for RL alternative selection are shown in Fig 4.4:



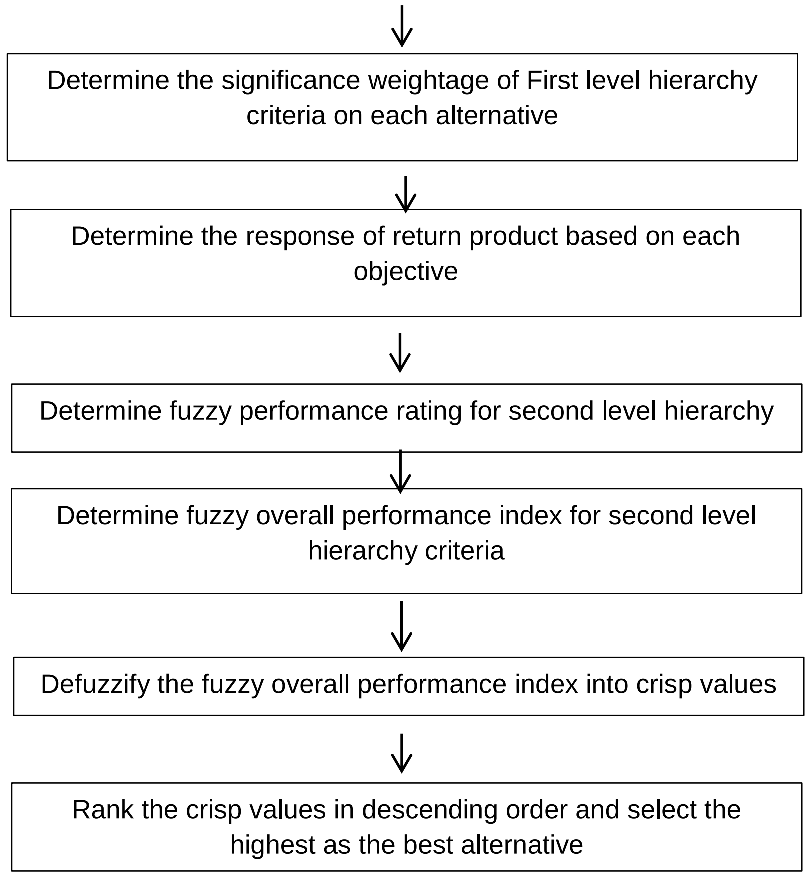


Fig. 4.4: Steps for the proposed modified fuzzy MOORA method.

4.7 Case study and application with modified fuzzy MOORA ratio system approach

Our application is related to the facility selection problem for return products of a Computer Retailing Company ABZ operating within Orissa state in India. This company experienced a growth in the returns for its products due to various reasons both marketing and reprocessing legislative requirements from its retailer shops throughout the country. In order to ensure a responsive and efficient reverse logistics network, they propose that the decision in the selection of the reprocessing alternative shall be made at the points of return (Customer end) so that the products can be are shipped directly. The Company desires to open five reprocessing alternatives (A1, A2, A3, A4 & A5). First of all, a committee of decision makers is formed. There are three decision-makers (DM1, DM2, and DM3) in the committee. Then the evaluation criteria were determined by: Performance/Functional level (C1), Market/ brand value (C3), Physical condition/status level (C3), Quality of product life (C4), Environmental impact level (C5) and

Reprocessing requirements (C6). The hierarchical structure for the selection of the best reprocessing facility is as shown in Fig. 5.4.

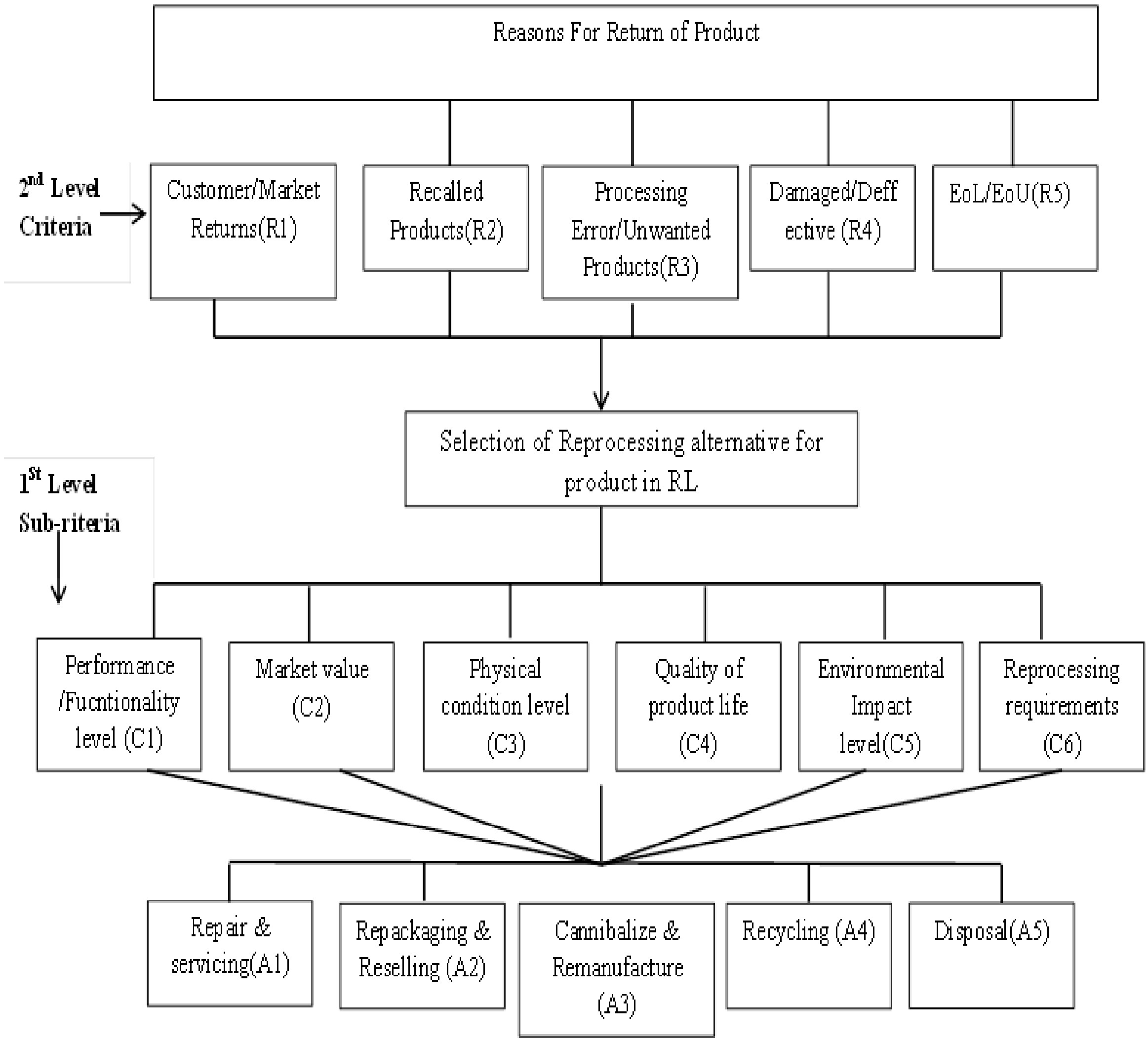


Fig 5.4: Hierarchical structure of RL alternative selection process.

In rating of the performance of return computers against each criteria , its multi-components i.e. their retrievable components that are considered critical (modules, parts or sub-parts etc.) can be presented as a disassembly tree Fig. 6.4 , analogous to Dijkhuizen and Harten, (Krikke,1998) after which, by using their availability and status, the decision maker can determine the performance rating of the parent product using the aforementioned criteria such as the work performance level, physical status, perceived market demand/value, remaining lifetime, etc. to eventually make the recovery of the parent assembly possible since the sub-assemblies are re-attached back to it (Krikke, 1998). These qualitative aspects are modelled using conditional probabilities, i.e.

fuzzy inference such as Low, Medium, High or Very High or as Poor, Fair, Medium, Good & Very Good.

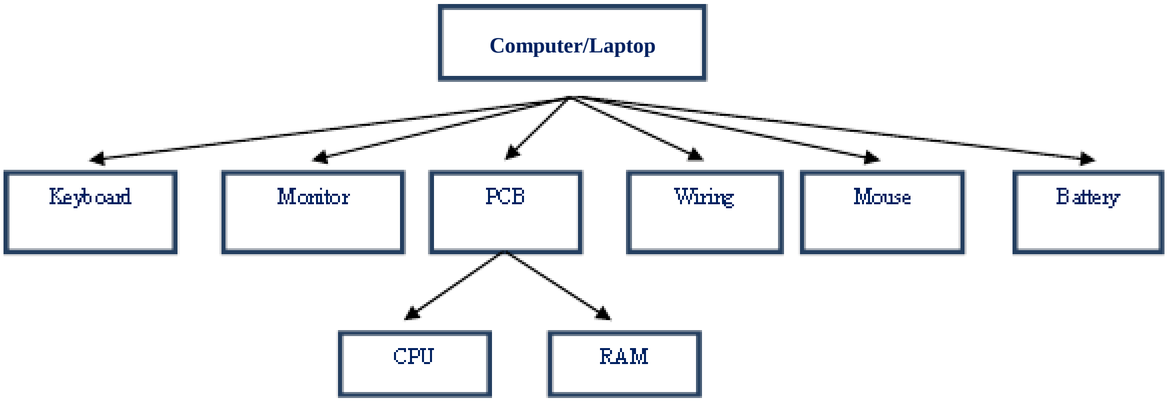


Fig 6.4: Return product disassembly decision tree.

4.7.1 Case 1: Market/stock returns from Customers/supply chain partners

In this section, the modified fuzzy MOORA method is proposed for the reprocessing alternative selection problem for the products returned due to marketing/stock balance reasons for the Computer manufacturing company. Firstly, the three decision-makers evaluated the significance of criteria on alternatives by using the linguistic variables in Table 1.4. The assigned performance/response of the product on each criterion by three decision-makers and the obtained aggregated performance response using Eq. 30 are shown in Table 2.4.

Table 2.4: The aggregated performance response of market/stock balance return product on each criteria/objective

Criteria/objectives	DM1	DM2	DM3	Aggregated ($\tilde{x}_{ghi}$)
C1	VH	H	VH	(7.33,9.17,9.67)
C2	H	VH	VH	(7.33,9.17,9.67)
C3	VH	H	VH	(7.33,9.17,9.67)
C4	M	H	VH	(5.00,6.67,8.33)
C5	VL	VL	L	(0.33,2.67,5.00)
C6	L	L	M	(1.67,3.33,5.00)

The Three decision-makers evaluate the significance of criteria/objectives with respect to each alternative using the linguistic variables shown in Table 1.4. The assigned significance of six criteria on the five alternatives is obtained using Eq.32 and Eq.33 as shown in Table 3.4.

Table 3.4: The significance of sub-criteria on alternatives.

Criteria	Alt.	DM1	DM2	DM3	Aggregated significance ($\widetilde{s'}_{ij}$)			Normalized significance ($\tilde{s}_{ij}$)		
C1	A1	M	H	M	(4.00,	5.83,	7.67)	(0.16	0.23	0.30)
	A2	VH	VH	VH	(8.00,	10.0,	10.0)	(0.31	0.39	0.39)
	A3	H	M	L	(3.33,	5.00,	6.67)	(0.13	0.19	0.26)
	A4	L	M	L	(1.67,	3.33,	5.00)	(0.06	0.13	0.19)
	A5	VL	L	VL	(0.33,	1.50,	2.67)	(0.01	0.06	0.10)
C2	A1	M	M	L	(2.33	4.17	6.00)	(0.10	0.18	0.26)
	A2	VH	H	VH	(7.33	9.17	9.67)	(0.32	0.40	0.42)
	A3	L	M	H	(3.33	5.00	6.67)	(0.14	0.22	0.29)
	A4	L	M	L	(1.67	3.33	5.00)	(0.07	0.14	0.22)
	A5	VL	L	VL	(0.33	1.50	2.67)	(0.01	0.06	0.12)
C3	A1	H	M	L	(3.33	5.00	6.67)	(0.15	0.23	0.30)
	A2	VH	VH	VH	(8.00	10.00	10.0)	(0.36	0.45	0.45)
	A3	M	H	L	(2.33	4.17	6.00)	(0.11	0.19	0.27)
	A4	L	L	VL	(0.67	2.00	3.33)	(0.03	0.09	0.15)
	A5	VL	VL	VL	(0.00	1.00	2.00)	(0.00	0.05	0.09)
C4	A1	H	M	VH	(5.67	7.50	8.67)	(0.26	0.34	0.39)
	A2	VH	H	VH	(7.33	9.17	9.67)	(0.33	0.42	0.44)
	A3	L	VL	M	(1.33	2.83	4.33)	(0.06	0.13	0.20)
	A4	VL	VL	L	(0.33	1.50	2.67)	(0.02	0.07	0.12)
	A5	VL	VL	VL	(0.00	1.00	2.00)	(0.00	0.05	0.09)
C5	A1	L	M	L	(1.67	3.33	5.00)	(0.06	0.13	0.19)
	A2	VL	VL	VL	(0.00	1.00	2.00)	(0.00	0.04	0.08)
	A3	M	L	M	(2.33	4.17	6.00)	(0.09	0.16	0.23)
	A4	H	H	VH	(6.67	8.00	8.67)	(0.25	0.30	0.33)
	A5	VH	VH	VH	(8.00	10.00	10.0)	(0.30	0.38	0.38)
C6	A1	L	M	L	(1.67	3.33	5.00)	(0.06	0.12	0.18)
	A2	VL	VL	VL	(0.00	1.00	2.00)	(0.00	0.04	0.07)
	A3	M	L	H	(3.33	5.00	6.67)	(0.12	0.18	0.23)
	A4	H	VH	VH	(7.33	9.17	9.67)	(0.26	0.32	0.34)
	A5	VH	VH	VH	(8.00	10.00	10.0)	(0.28	0.35	0.35)

The normalization factors, x_i^+, for the responses of objectives/criteria on the product are determined using Eq. 33 and the normalized values using Eq. 32 are shown in table 4.4:

Table 4.4: The normalized fuzzy values for the responses.

	C1	C2	C3	C4	C5	C6
$\tilde{x}^*_{ig}$	(0.37,0.46,0.48)	(0.52,0.46,0.48)	(0.37,0.46,0.48)	(0.25,0.33,0.42)	(0.02,0.13,0.25)	(0.08,0.17,0.25)

Based on the data from table 3 and 4, the normalized fuzzy decision matrix was formed as shown in table 5.4:

Table 5.4: The normalized fuzzy decision matrix.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**
$\tilde{x}^*_{ig}$	(0.37,0.46,0.48)	(0.52,0.46,0.48)	0.370.460.48	0.250.330.42	0.020.130.25	0.080.170.25
Opt.	Max	Max	Max	Max	Min	Min
D1	(0.16,0.23,0.30)	(0.10,0.18,0.26)	(0.15,0.23,0.30)	(0.26,0.34,0.39)	(0.06,0.13,0.19)	(0.06,0.12,0.18)
D2	(0.31,0.39,0.39)	(0.32,0.40,0.42)	(0.36,0.45,0.45)	(0.33,0.42,0.44)	(0.00,0.04,0.08)	(0.00,0.04,0.07)
D3	(0.13,0.19,0.26)	(0.14,0.22,0.29)	(0.11,0.19,0.27)	(0.06,0.13,0.20)	(0.09,0.16,0.23)	(0.12,0.18,0.23)
D4	(0.06,0.13,0.19)	(0.07,0.14,0.22)	(0.03,0.09,0.15)	(0.02,0.07,0.12)	(0.25,0.30,0.33)	(0.26,0.32,0.34)
D5	(0.01,0.06,0.10)	(0.01,0.06,0.12)	(0.00,0.05,0.09)	(0.00,0.05,0.09)	(0.30,0.38,0.38)	(0.28,0.35,0.35)

Next the significance weight is assigned to the reason for return criteria and then normalized using Eq. 35 and Eq. 36 as table 6.4:

Table 6.4: The normalized fuzzy significance weights matrix for main criteria (reasons for Return)

Criteria	Alter.	DM1	DM2	DM3	Aggregated significance ($\tilde{w}_{hj}$)			Normalized significance ($\tilde{w}^*_{hj}$)		
R1	A1	M	L	M	(2.33	4.17	6.00)	(0.08	0.14	0.20)
	A2	VH	VH	H	(7.33	9.17	9.67)	(0.25	0.31	0.33)
	A3	H	H	VH	(6.67	8.33	9.33)	(0.23	0.28	0.32)
	A4	H	M	M	(4.00	5.83	7.67)	(0.14	0.20	0.26)
	A5	L	VL	L	(0.67	2.00	3.33)	(0.02	0.07	0.11)

The Ratio system approach: From data in table 5.4, the fuzzy performance rating of the alternatives on the basis of objectives or criteria to be maximized, $y_j^+$are calculated using Eq. 38 and for the objectives to be minimized, y_j^- was determined using Eq. 39 as shown in column I & II of Table 7.4. The fuzzy performance rating,y_j^* of the considered alternative are then calculated using Eq. 37 as shown in column III.

Table 7.4: The overall performance rating based on sub-criteria.

	Y_i^+			**Y_i^-**			**y_j^***		
	I			**II**			**III**		
D1	(0.23	0.40	0.58)	(0.01	0.04	0.09)	(0.14	0.37	0.57)
D2	(0.50	0.71	0.79)	(0.00	0.01	0.04)	(0.46	0.69	0.79)
D3	(0.18	0.32	0.48)	(0.01	0.05	0.12)	(0.06	0.27	0.47)
D4	(0.08	0.19	0.32)	(0.03	0.09	0.17)	(0.09	0.10	0.30)
D5	(0.01	0.09	0.19)	(0.03	0.11	0.18)	(0.17	0.02	0.16)

Using Eq. 40 and the normalized significance weight given in table 6.4, the overall fuzzy performance Index of considered alternatives is calculated as shown in table 8.4, where Ẍ are the defuzzified overall crisp performance index values.

Finally, by using the Eq. 11, or the Eq. 12, and different values for the parameter, the decision maker can determine the ranking order of alternatives, and select the most appropriate one. Also, by using different values of the coefficient λ, decision makers can consider different scenarios, such as pessimism, moderate and optimistic.

Table 8.4: Ranking results obtained for characteristic values of λ

		Liou & Wang					
Overall Performance Index Y_j^O		λ=0 Ẍ	Rank	λ=0.5 Ẍ	Rank	λ=1 Ẍ	Rank
A1	(0.0109,0.0519,0.1166)	0.0314	3	0.0578	3	0.08	3
A2	(0.114, 0.216,0.2593)	0.1650	1	0.2013	1	0.24	1
A3	(0.014,0.076,0.148)	0.0447	2	0.0781	2	0.11	2
A4	(0.0123,0.019,0.077)	0.0033	4	0.0256	4	0.05	4
A5	(0.0038,0.0011,0.018)	0.0025	5	0.0030	5	0.01	5

The transformation from the fuzzy into crisp overall performance indexes can be made using any of the methods discussed in subsection 4.3.3, as well as many other de-Fuzzification methods, which are not covered in this paper. In this case, all methods have the same ranking order of alternatives. However, many authors warn that different de-Fuzzification methods may give different results. In the considered example, the symmetrical TFNs have been used.

According to the crisp overall performance indices of the Five alternatives, the ranking order of five alternatives is determined as A2>A3>A1>A4>A5. The Repackaging & reselling alternative is identified as the most appropriate reprocessing destination for that evaluated product from the market/stock balance return products.

4.7.2 Case 2: End of Life/Use returns from Customers/ supply chain partners

As a sensitivity analysis of the proposed model, a product returned due to end of life/use (EoL) was evaluated using the modified fuzzy MOORA ratio system approach. The following results were obtained:

Step 1: The aggregated performance response of End of life return product on each criterion was as shown in table 9.4:

Table 9.4: The aggregated performance response of End of life/use returns on each criteria/objective

Criteria/objectives	DM1	DM2	DM3	Aggregated ($\tilde{x}_{ghi}$)
C1	VL	VL	VL	(7.33,9.17,9.67)
C2	VL	VL	VL	(7.33,9.17,9.67)
C3	VL	VL	VL	(7.33,9.17,9.67)
C4	VL	L	VL	(5.00,6.67,8.33)
C5	VH	VH	VH	(0.33,2.67,5.00)
C6	VH	H	H	(1.67,3.33,5.00)

Step 2: The significance of criteria/objectives with respect to each alternative remains unchanged as given in Table. 3.4.

Step 4: Next the significance weight is assigned to the reason for return criteria and then normalized using Eq. 35 and 36 as table 10.4:

Table 10.4: The normalized fuzzy significance weight matrix of main criteria (reasons for Return).

Criteria	Alternatives	DM1	DM2	DM3	Aggregated significance ($\widetilde{w}_{hj}$)			Normalized significance ($\widetilde{w}^*{}_{hj}$)		
EOL(R2**)**	A1	VL	L	VL	(0.33	1.50	2.67)	(0.02	0.07	0.13)
	A2	VL	VL	VL	(0.00	1.00	2.00)	(0.00	0.05	0.10)
	A3	L	M	L	(1.67	3.33	5.00)	(0.08	0.16	0.24)
	A4	M	H	M	(4.00	5.83	7.67)	(0.19	0.28	0.37)
	A5	VH	H	VH	(7.33	9.17	9.67)	(0.35	0.44	0.46)

Finally, the following results are obtained as shown in table 11.4:

Table 11.4: Ranking results obtained for characteristic values of λ

		Liou & Wang					
Overall Performance Index Y_j^O		**λ=0** Ẍ	**Rank**	**λ=0.5** Ẍ	**Rank**	**λ=1** Ẍ	**Rank**
A1	(0.0030,0.0055,0.0167)	0.0042	**4**	0.0007	**4**	0.0056	**5**
A2	(0.0000,0.0040,0.0247)	0.0020	**5**	0.0082	**5**	0.0143	**3**
A3	(0.0187,0.0250,0.0113)	0.0218	**3**	0.0143	**3**	0.0068	**4**
A4	(0.0788,0.1020,0.0585)	0.0904	**2**	0.0853	**2**	0.0803	**2**
A5	(0.1701,0.1980,0.1107)	0.1840	**1**	0.1692	**1**	0.1543	**1**

According to the crisp overall performance indices of the Five alternatives, the ranking order of five alternatives is determined as A5>A4>A3>A1>A2. The disposal alternative is determined as the most appropriate reprocessing destination for that evaluated product from the End of life return products.

4.8 Comparison with Modified Fuzzy VIKOR method application

4.8.1 Introduction to Fuzzy Vikor method

In this section, we solve the same problem based on the concept of fuzzy set theory and VIKOR method. The proposed modified fuzzy VIKOR method has been applied to find the best compromise solution for the multi-person multi-criteria decision-making supplier selection problem. VIKOR is a Serbian name that stands for 'VlseKriterijumska Optimizacija I Kompromisno Resenje', which means multi-criteria optimization and compromise solution were developed by Opricovic (Opricovic and Tzeng, 2004). It is suitable for ranking and selecting the best of alternatives when conflicting multi-criteria are involved, i.e., some criteria are to be maximized (Higher is better criteria) and others are to be minimized (lower is better criteria).

The fundamental principle of VIKOR is determining the positive ideal solution as well as the negative ideal solution in the first place (Wu and Liu, 2011). The positive ideal solution is the best value of alternatives under the considered criteria, and the negative-ideal solution is the worst value of alternatives under the considered criteria. For a compromise ranking of multi-criteria measurement, VIKOR adopted a following form of LP-metric aggregate function (Yu, 1973):

$$L_{Pj} = \left\{\sum_{i=1}^{n}\left[w_i\left(f_i^* - f_{ij}\right)/(f_i^* - f_i^-)^P\right]\right\}^{1/P} \quad (41)$$

Here, $1 \leq P \leq \infty$; *i* = 1*, ..., n,* with respect to criteria and the variable *j* = 1*, ..., m,* represent the number of alternatives such as $A_1, A_2, \ldots, A_m$. For alternative,A_j the evaluated value of the *i*th criterion is denoted by *fij*, and *n* is the number of criteria. The measure L_{Pi}shows the distance between alternative A_J and the positive-ideal solution. Within the VIKOR methodL_{1j} (as S_j in Eq. (4)) and $L_{\infty i}$ (as $R_j$in Eq. 5) has been used to formulate the ranking measure. The value obtained by minimum S_j is with a maximum group utility ('majority' rule) and the solution obtained by minimum R_j is with a minimum individual regret of the 'opponent' (Sanayei et al., 2010).

In this study, the traditional VIKOR method (Chang, 2010) is modified to make it readily applicable in solving reverse logistics alternative selection problems. Ratings of the alternatives and the weights of each criterion are the two most significant data that can affect the results of decision-making problems. In our study, the reasons for return are treated as the main criteria for categorizing return products, and this is extended to second level sub-criteria that shall be used to calculate further the best alternatives to be selected.

The proposed modifications shall include:

1. The importance weight, $\widetilde{w}_{ij}$, is assigned to criteria, *i*, with respect to each alternative under consideration.

2. The returned product is accessed and performance rating, $\tilde{x}_{ghi}$ for each criterion is assigned.

3. The importance weight $\widetilde{w}_{hj}$ is assigned on first level main criteria under consideration, *h* (i.e. reason for return) with respect to each alternative, *j*, under consideration.

The proposed algorithm consists of the following steps:

Step 1: *Constitute a group of decision makers* (DM_k, *k*=1,2,…, K), who shall assess the *m* alternatives (A_j, *j=1,2,…, m*) using n criteria (C_i, *i=1,2,…,* n).

Step 2: *Identify appropriate linguistic variables and their positive triangular fuzzy numbers.* Linguistic variables are used to calculate the importance weights of each criterion with respect to each alternative and the performance ratings of the criteria with respect to the current assessed product, for example, linguistic variable “Very High (VH)” which can be defined by a triangular fuzzy number (0.8; 1; 1).

Step 3: *Construct a fuzzy decision matrix by pulling the decision makers' opinions to get the aggregated fuzzy weight of the criteria, and the aggregated fuzzy rating of alternatives.* Let *k* is the number of decision makers in a group and, the aggregated fuzzy weights ($\widetilde{w}_{ij}$) of each sub-criterion with respect to each alternative can be calculated as:

$$\widetilde{w}_{ij} = \frac{1}{k}\left[\widetilde{w}_{ij1} + \widetilde{w}_{ij2} + .. + \widetilde{w}_{ijk}\right] \quad (42)$$

And also the aggregated fuzzy performance rating ($\tilde{x}_{ghi}$) of alternatives with respect to each criterion can be calculated as:

$$\tilde{x}_{ghi} = \frac{1}{k}\left[\tilde{x}_{ghi1} + \tilde{x}_{ghi2} + .. + \tilde{x}_{ghik}\right] \quad (43)$$

Where: g=1,2,….P is the return product being accessed; h=1,2,…, R is the reason for return under consideration; i=1,2,…n is the sub-criteria.

In the alternative selection problem, the values of aggregated ratings and weight are expressed in matrix format as shown:

$$\widetilde{D} = \left[\tilde{x}_{11}, \tilde{x}_{12, \ldots\ldots\ldots\ldots} \tilde{x}_{1n}\right], \widetilde{w} = \begin{bmatrix} \widetilde{w}_{11} & \cdots & \widetilde{w}_{in} \\ \vdots & \ddots & \vdots \\ \widetilde{w}_{im} & \cdots & \widetilde{w}_{mn} \end{bmatrix}$$

i = 1*, ...,n* for criteria, and *j* = 1*, ….., m,* for Alternatives.

Step 4: *Defuzzify the fuzzy decision matrix and fuzzy weight:* The crisp value of a triangular fuzzy number set *A*1 can be determined by de-Fuzzification which locates the Best Non-fuzzy Performance (BNP) value. Thus, the BNP values of a fuzzy number are calculated by using the center of the area (COA) method as follows: (Moeinzadeh and Hajfathaliha, 2010):

$$BNP_{ij} = \frac{[(c-a)+(b-a)]}{3} + a \; \forall i, j \tag{44}$$

Step 5: Determine best crisp value (f_i^*) and the worst crisp values (f_i^-) for all the importance weightage criteria, (i=1,2,….n) using the relations:

$$f_i^* = \begin{cases} Max_{j=1,2..m}\widetilde{w}_{ij}, & i \in C1 \\ Min_{j=1,2..m}\widetilde{w}_{ij}, & i \in C2 \end{cases} \tag{45}$$

$$f_i^- = \begin{cases} Min_{j=1,2..m}\widetilde{w}_{ij}, & i \in C1 \\ Max_{j=1,2..m}\widetilde{w}_{ij}, & i \in C2 \end{cases} \tag{46}$$

Here, *i* = 1*, ..., n* and C1 is a benefit type criteria set, C2 is a cost type criteria set.

Step 6: Compute the values of S_j and R_j (j=1,2,…,m), by using the following modified relations from VIKOR:

$$S_j = \sum_{i=1}^{n}\left[\widetilde{w}_{ij}\left(f_i^* - f_{ij}\right)/(f_i^* - f_i^-)\right] \times \left(1 - \ddot{w}_j\right) \tag{47}$$

$$R_j = Max_{i=1,..n}\left[\widetilde{w}_{ij}\left(f_i^* - f_{ij}\right)/(f_i^* - f_i^-)\right] \times \left(1 - \ddot{w}_j\right) \tag{48}$$

Here, S_j is the aggregated value of *jth* alternatives with a maximum group utility and R_j is the aggregated value of *jth* alternatives with a minimum individual regret of 'opponent'; $\widetilde{w}_{ij}$ is the crisp weighted average of each sub-criterion with respect to each alternative; $\ddot{w}_j$ is the crisp weighted average of the considered main criteria (reason for return) for all alternatives (Given in Table 15.4).

Step 7: Compute the values of Q_j for j=1,2,…,m using the following modified relation:

$$Q_j = \left\{\left[\tau\left(S_j - S^-\right)/(S^* - S^-) + (1-\tau)\left(R_j - R^-\right)\right]/(R^* - R^-)\right]\right\} \times \left(1 - \ddot{w}_j\right) \tag{49}$$

Where: $S^- = Min_{j=1,..m}S_j$; $S^* = Max_{j=1,..m}S_j$; $R^- = Min_{j=1,..m}R_j$; $R^* = Max_{j=1,..m}R_j$; and τ is the weight for the strategy of maximum group utility; $(1-\tau)$ is the weight of individual regret. The compromise is selected by 'voting with majority' ($\tau > 0.5$), 'with consensus ($\tau = 0.5$)' or with 'veto' ($\tau < 0.5$)

Step 8: Rank the alternatives by sorting, S_j R_j and Q_j values in ascending order.

Step 9: Select the best alternative by choosing $Q_j(A_m)$ as a best compromise solution with the minimum value of Q_j and must have to satisfy with the below conditions (Chitrasen et al., 2012).

Step 9: If the following two conditions are satisfied simultaneously, then the scheme with a minimum value of Q_j in ranking is considered the optimal compromise solution. That is;

CONDITION 1: If, $Q_j(A_2) - Q_j(A_1) \geq 1/(m-1)$, then $Q_j(A_1)$ has an *acceptable advantage* from other alternatives; where, A_1 is the alternative with first position in the ranking; A_2 is the alternative with the second position in the ranking and *m* is the number of alternatives.

CONDITION 2: The alternative $Q_j(A_1)$ is stable within the decision making process, i.e. it is also ranked best in S_j andR_j.

If condition C1 is not satisfied, that means $Q_j(A_m) - Q_j(A_1) \leq 1/(m-1)$ Then alternatives $A_1, A_2, \dots \dots A_m$ Have same compromise solutions, i.e. there is no comparative advantage of A_1, over other alternatives.

4.8.2 Application in the case study

i. Case 1: Market/stock returns from Customers/supply chain partners

In this section, a modified Fuzzy VIKOR approach is performed on a first quality product returned due to marketing or stock out reasons in the same problem of the computer manufacturing company. The proposed reverse logistic alternative selection has been done in the following steps:

Step 1: A group decision based on fuzzy VIKOR is formed having three decision makers DM_1 , DM_2 & DM_3 to evaluate the best alternative for the returned computers by the customers and supply chain partners being returned for various reasons. There are six qualitative criteria used to evaluate these products and subsequently match them to the most appropriate alternatives as shown in Fig. 6.4.

Step 2: The decision makers assign the appropriate linguistic variables and their positive TFN using table 12.4.The corresponding fuzzy numbers for the importance weight of the criteria with respect to each alternative and the performance rating of the criteria with respect to the assessed product are shown in their respective decision matrices in Table 13.4 and Table 14.4 respectively.

Table 12.4: Linguistic scales for importance weights and responses of Criteria

Linguistic Variable	$\mu_{triang}(x)$	TFN support
Very Low (VL)	(0,0,0.2)	2
Low (L)	(0.1,0.2,0.3)	2
Medium Low (ML)	(0.2,0.35,5)	4
Medium (M)	(0.4,0.5,0.6)	2
Medium High (MH)	(0.5,0.65,0.8)	3
High (H)	(0.7,0.8,0.9)	2
Very High (VH)	(0.8,1.0,1.0)	2

Table 13.4: The aggregated importance weights of sub-criteria on alternatives

Criteria	Alternatives	DM1	DM2	DM3	Aggregated Importance ($\tilde{w}_{ij}$)		
C1	A1	M	H	M	(0.50	0.60	0.70)
	A2	VH	VH	VH	(0.80	1.00	1.00)
	A3	H	M	L	(0.40	0.58	0.77)
	A4	L	M	L	(0.17	0.33	0.50)
	A5	VL	L	VL	(0.03	0.15	0.27)
C2	A1	M	M	L	(0.23	0.42	0.60)
	A2	VH	H	VH	(0.73	0.92	0.97)
	A3	L	M	H	(0.33	0.50	0.67)
	A4	L	M	L	(0.17	0.33	0.50)
	A5	VL	L	VL	(0.03	0.15	0.27)
C3	A1	H	M	L	(0.33	0.50	0.67)
	A2	VH	VH	VH	(0.80	1.00	1.00)
	A3	M	H	L	(0.43	0.75	0.73)
	A4	L	L	VL	(0.07	0.20	0.33)
	A5	VL	VL	VL	(00.00	0.10	0.20)
C4	A1	H	M	VH	(0.40	0.58	0.77)
	A2	VH	H	VH	(0.73	0.92	0.97)
	A3	L	VL	M	(0.13	0.28	0.43)
	A4	VL	VL	L	(0.03	0.15	0.27)
	A5	VL	VL	VL	(0.00	0.10	0.20)
C5	A1	L	M	L	(0.17	0.32	0.47)
	A2	VL	VL	VL	(0.00	0.10	0.20)
	A3	M	L	M	(0.23	0.42	0.60)
	A4	H	H	VH	(0.67	0.83	0.93)
	A5	VH	VH	VH	(0.80	1.00	1.00)
C6	A1	L	M	L	(0.17	0.32	0.47)
	A2	VL	VL	VL	(0.00	0.10	0.20)
	A3	M	L	H	(0.33	0.50	0.67)
	A4	H	VH	VH	(0.67	0.83	0.93)
	A5	VH	VH	VH	(0.80	1.00	1.00)

Table 14.4: The aggregated performance response of Market/stock balance return product on each criteria/objective

Criteria/objectives	DM1	DM2	DM3	Aggregated values ($\tilde{x}_{ghi}$)
C1	VH	H	VH	(0.77,0.93,0.97)
C2	H	VH	VH	(0.77,0.93,0.97)
C3	VH	H	VH	(0.77,0.93,0.97)
C4	H	VH	VH	(0.77,0.93,0.97)
C5	VL	VL	L	(0.03,0.13,0.23)
C6	L	L	M	(0.20,0.30,0.40)

Step 3: The aggregated importance weights of reason for return (market/stock out returns) criteria and their crisp numbers obtained using Eq. 44 is obtained as shown in Table 15.4:

Table 15.4: Crisp values of aggregated importance weights for reason for return criteria on alternatives

Alternatives	DM1	DM2	DM3	Aggregated ($\tilde{x}_{ghi}$)	Crisp Value ($\ddot{w}_j$)
A1	M	L	M	(0.30,0.40,0.50)	0.40
A2	VH	VH	H	(0.77,0.93,0.97)	0.89
A3	H	H	VH	(0.73,0.87,0.93)	0.84
A4	H	M	M	(0.50,0.60,0.70)	0.60
A5	L	VL	L	(0.07,0.17,0.27)	0.17

Step 3: Compute the crisp values of the performance rating (Table 13.4) and importance weights matrix of each sub criterion (Table 14.4) using Eq. 44. The results are presented as shown in Table 4.16.

Table 16.4: Crisp values for importance weights matrix and performance rating of each criterion.

	Criteria					
	C1	C2	C3	C4	C5	C6
Performance rating	0.89	0.89	0.89	0.89	0.13	0.30
Opt.	Max	Max	Max	Max	Min	Min
A1	0.60	0.42	0.50	0.58	0.32	0.32
A2	0.93	0.87	0.93	0.87	0.10	0.10
A3	0.58	0.50	0.64	0.28	0.42	0.50
A4	0.33	0.33	0.20	0.15	0.81	0.81
A5	0.15	0.15	0.10	0.10	0.93	0.93

Step 4: Determine best crisp value (f_i^*), and the worst crisp values (f_i^-), for the importance weights of criteria using Eq. 45 and Eq. 46 as presented in table 17.4 below:

Table 17.4: The Best and Worst Crisp values for each criterion

	Criteria					
	C1	C2	C3	C4	C5	C6
f_i^*	0.93	0.87	0.93	0.87	0.10	0.10
f_i^-	0.15	0.15	0.10	0.10	0.93	0.93

Step 5: Compute the values of S_j and R_j (j=1,2,…,m), by using the modified relations in Eq. 47 and Eq. 48 to obtain results as shown in Table 4.18. The alternatives are then ranked in ascending order as shown.

Table 18.4: The values of S, R & Q and the ranking.

Alternative	Sj	Rj	Qj	Ranking		
				By S	By R	By Q
A1	1.23	0.34	0.24	4	4	4
A2	0.05	0.00	0.00	1	1	1
A3	0.32	0.11	0.02	2	2	2
A4	1.21	0.33	0.17	3	3	3
A5	2.96	0.74	0.83	5	5	5

Step 6: From Table 18, it has been shown that the Alternative A2 (repackaging & reselling) is best ranked by Q (lower value is better). However condition C1 is not satisfied i.e. $(A_2) - Q(A_1) \leq 1/(5-1)$, hence A2 has no comparative advantage over A3 (Cannibalizing and Remanufacturing) which indeed requires that the return product is of high quality. A1 is best ranked by R and S also. Therefore, A1 is the best selected alternative for the best compromise solution.

ii. Case 2: End of Life/Use returns from Customers/supply chain partners

The modified VIKOR method sensitivity was achieved by using products returned due to End of Life. The linguistic variables and the aggregated importance weights of sub-criteria as given in Tables12.4 and Table 13.4 were used.

Step1: The aggregated response of End of Life product on each criterion was determined by three decision makers as shown in Table 19.4:

Table 19.4: The aggregated performance response of End of Life return product on each criteria/objective

Criteria	DM1	DM2	DM3	Aggregated ($\tilde{x}_{ghi}$)
C1	VL	VL	VL	(0.00,0.10,0.20)
C2	VL	VL	VL	(0.00,0.10,0.20)
C3	VL	VL	VL	(0.00,0.10,0.20)
C4	VL	L	VL	(0.03,0.13,0.23)
C5	VH	VH	VH	(0.80,1.00,1.00)
C6	VH	H	H	(0.73,0.87,0.93)

Step 2: The aggregated importance weights of End of Life/use returns criteria and their crisp numbers obtained using Eq. 44 is obtained as shown in Table 20.4:

Table 20.4: Crisp values for aggregated importance weights EoL criteria on alternatives

Alternatives	DM1	DM2	DM3	Aggregated ($\tilde{x}_{ghi}$)	Crisp Value ($\ddot{w}_j$)
A1	VL	L	VL	(0.03,0.13,0.23)	0.13
A2	VL	VL	VL	(0.00,0.10,0.20)	0.10
A3	L	M	L	(0.20,0.30,0.40)	0.30
A4	M	H	M	(0.50,0.60,0.70)	0.60
A5	VH	H	VH	(0.77,0.93,0.97)	0.89

Step 3: The crisp values of the performance rating and importance weights matrix of each sub criterion were determined using Eq. 44 and presented in Table 21.4:

Table 21.4: Crisp values for importance weights matrix and performance rating of each criterion.

	Criteria					
	C1	C2	C3	C4	C5	C6
Performance rating	0.10	0.10	0.10	0.13	0.93	0.84
Opt.	Max	Max	Max	Max	Min	Min
A1	0.60	0.42	0.50	0.58	0.32	0.32
A2	0.93	0.87	0.93	0.87	0.10	0.10
A3	0.58	0.50	0.64	0.28	0.42	0.50
A4	0.33	0.33	0.20	0.15	0.81	0.81
A5	0.15	0.15	0.10	0.10	0.93	0.93

Step 4: Determine best crisp value (f_i^*), and the worst crisp values (f_i^-), for the importance weights of criteria using Eq. 45 and Eq. 46 as presented in table 22.4 below:

Table 22.4: The Best and Worst Crisp values for each criterion.

	Criteria					
	C1	C2	C3	C4	C5	C6
f_i^*	0.93	0.87	0.93	0.87	0.10	0.10
f_i^-	0.15	0.15	0.10	0.10	0.93	0.93

Step 5: Compute the values of S_j and R_j (j=1,2,…,m), by using the modified relations in Eq. 47 and Eq. 48 to obtain results as shown in Table 23.4. The alternatives are then ranked in ascending order as shown:

Table 23.4: The values of S, R & Q and the ranking

Alternative	Sj	Rj	Qj	Ranking		
				By S	By R	By Q
A1	1.32	0.60	0.66	4	4	4
A2	1.60	0.84	0.90	5	5	5
A3	0.88	0.41	0.35	3	3	3
A4	0.25	0.05	0.04	2	2	2
A5	0.05	0.01	0.00	1	1	1

Step 6: From Table 23.4, it can be shown that the Alternative A5 (Disposal) is best ranked by Q (lower value is better). However condition C1 is not satisfied i.e., $Q(A_2) - Q(A_1) \leq 1/(5-1)$ hence, A5 has no comparative advantage over A4 (Recycling) which indicates that the company can as well opt for recycling this product. A5 is best ranked by R and S also. Therefore, A5 is the best selected alternative for the best compromise solution.

4.9 Conclusions

Decision-makers face up to the uncertainty and vagueness from subjective perceptions and experiences in the decision-making process. By using fuzzy MOORA and fuzzy VIKOR methods, uncertainty and ambiguity from subjective judgment and the experiences of decision-maker can be adequately represented to reach a more practical decision. In this study, reverse logistics alternative selection with modified fuzzy MOORA and fuzzy VIKOR methods has been proposed. The decision criteria were Performance/functional level, Physical condition, perceived market value, quality of product life, Environmental impact Reprocessing requirements (Chang et al., 2013). These criteria were evaluated to determine the order of alternatives for selecting the most appropriate one. Although two methods have the same objective of selecting the best reverse logistics options for the company, they have differences. In fuzzy MOORA, decision makers used the linguistic variables to assess the importance of the criteria to each alternative and to evaluate the responses of the product with respect to each criterion. These linguistic variables converted into triangular fuzzy numbers and fuzzy decision matrix was formed. Then the normalized fuzzy decision matrix and weighted, normalized fuzzy decision matrix were formed. After the performance rating for criteria to be maximized and those to be minimized were defined, the overall performance rating for each alternative was calculated. According to the overall performance index of five options, the ranking order of five alternatives has been determined as A2>A3>A1>A4>A5. In fuzzy VIKOR, decision-makers assigned the appropriate importance weight of each criterion to all the alternatives and the performance rating of the criteria with respect to the return product in the form of linguistic variables. Then these linguistic variables are transformed into positive triangular fuzzy numbers, and the fuzzy value aggregated. The crisp values of the importance weight and a performance rating of criteria is determined. According to the best crisp values and worst crisp values obtained, the maximum group utility (S), the minimum individual regret (R) and Q values are established. According to the modified fuzzy MOORA, the best alternative is A2 (Repackaging & Reselling), and the ranking order of the alternatives is A2>A3>A1>A4>A5. This is the same as the one obtained by using fuzzy VIKOR approach.

Companies should choose the appropriate method for their problem, according to the situation and the structure of the problem they have. In our proposed model, individual products from each category of reasons for return are assessed, and a decision for its best reprocessing alternative achieved. For this reason, the products may end up into different reprocessing alternatives even though they belong to the same category depending on their individual overall performance index based on the considered qualitative criteria.

In future studies, other multi-criteria methods like fuzzy PROMETHEE and ELECTRE can be used to handle Reverse logistics alternative selection problems. Likewise, the proposed methods can be applied to other multi-criteria decision problems such as supplier selection to the individual industries, personnel selection to departments, software selection for various applications, project selection for different regions and machine selection for different jobs of companies.

Chapter 5:
Reverse Logistics Network Structure and Analysis

5.1 Introduction

Product returns have become a significant management issue and an unavoidable cost for a business. This situation made firms consider the possibility of managing product returns in a more cost-efficient way, whereas increasing the revenue opportunities for these returned products. Many activities are included in Reverse Logistics (RL) concept such as the reuse of used products, disassembly, and processing of excess inventory of products, parts, and/or materials (Daugherty et al., 2005). Typically, a product return involves the collection of returned products at designated regional distribution centers or retail outlets, the transfer and consolidation of returned products at centralized return centers (CRCs), the asset recovery of returned products through repairs, refurbishing, and re-manufacturing, and the disposal of returned products with no commercial value (Min et al., 2006a). Logical planning should set collection options that provide consumers with the motivation to return products without any extra hassle such as finding a collection center. Implementation of reverse logistics, especially in product returns would allow not only for savings in inventory carrying cost, transportation cost, and waste disposal cost due to returned products, but also for the improvement of customer loyalty and future sales (Lee et al., 2009). The collection of used products is very complicated and needs a well-estimated structure in reverse logistics (Lee and Dong, 2009).

In this section, we provide an integrated holistic conceptual framework that combines the use of Multi-criteria decision making (MCDM) techniques i.e. Fuzzy MOORA and Fuzzy VIKOR used to categorize returns and make best alternative selection of recovery and disposal option after which, the mixed integer linear program model (MILP) is solved optimally using LINGO 15, in which the decoding procedures adapted to the characteristic of ss-TP are applied to minimize the transportation and fixed opening costs and maximize the profits by the revenues gained from reprocessed products in a multistage reverse logistics network as well as perform capacity allocation of opened centres at the methodological level. We also provide detailed solutions for network configuration and design at the topological level, by carrying out experimentation with our conceptual model.

5.2 Literature Review

The implementation of reverse logistics network optimization involves a broad range of design, planning, and control optimization problems. Various mathematical modelling approaches such as Mixed Integer Linear Programming (MILP), Mixed Integer

Non-Linear Programming (MINLP), Continuous Approximation (CA), System Dynamic Modelling (SDM) and Fuzzy Goal Programming (FGP) (Sadrnia et al., 2014) have been used by researchers to design mathematical modelling Green supply chain (GrSC) problems. For the last decade, increasing concerns over environmental degradation and increased opportunities for cost savings or revenues from returned products have prompted some researchers to formulate more effective reverse logistics strategies using mathematical models. These researchers include Caruso et al. (1993) proposed a multiple objective mixed-integer program and a heuristic solution procedure for solving the location-allocation of waste service users, processing plants, and sanitary landfills with capacity constraints. Considering multiple recovery options, Thierry et al., (1995) defined the five product recovery system; Remanufacturing, repairing, Refurbishment, cannibalization, and recycling. Their study included a comprehensive discussion of the product design approach for recovery, the preparation of customer for green products and environmental legislative issues for recovery systems. Kroon and Vrijens (1995) present a return logistics system for returnable containers that was developed in a case study for a logistics service organization in The Netherlands. The system is concerned with the transportation, maintenance, and storage of empty containers. A classical plant location model is formulated to analyze the number of containers, the number of depots and their locations.

Del Castillo and Cochran (1996) presented a pair of linear programs (one aggregated and another disaggregated) and a simulation model to optimize configure the reverse logistics network involving the return of reusable containers in such a way that the number of reusable containers was maximized. However, they did not take into account transportation issues related to reverse logistics. In an effort to recycle construction waste as sieved sand, Barros et al., (1998) proposed a mixed-integer program that determined the locations of regional depots for receiving the flow of sieved sand and treatment. Similarly, Krikke et al., (1999) developed a mixed-integer program to determine the locations of shredding and melting facilities for the recovery and disposal of used automobiles while determining the amount of product flows in the reverse logistics network. In the study, they proposed a quantitative model in which identified two critical areas with regards to reverse logistics.

First is the managerial area called product recovery management (PRM) which deals with the collection of returns and processing them by a recovery strategy based on quality dependent decision rules regarding their degree of disassembly and processing options (processing routes) and secondly is the physical network design of an RL system i.e. the locations and capabilities of processing facilities where optimization of good flow between facilities is determined. They introduced the concepts of entry routes, processing routes and delivery routes. A detailed and updated review of product recovery network models has been contributed by Fleischmann et al., (1997), and Fleischmann, (2003). Recently, evolution of reverse logistics concepts and strategies in the retail industry is dealt by Bernon and Cullen (2007). Mangesh and Anand, (2005) developed an inventory model for production systems which presented a model that will assist in decision making on the percentage of the total returns to remanufacture, to stock, to dispose-off and how much to manufacture a new, so that the total inventory cost is minimized. The model is based on an optimization problem formulation, and problem is solved using Sequential Quadratic Programming (SQP). More recently, Srivastava, (2007) presented a multi-product, multi-echelon, profit maximizing RL and value recovery network model covering activities from collection to First stage of remanufacturing to determine the optimal number and locations of remanufacturing facilities for electronic equipment. However, rigid constraints are imposed for the main model to determine the disposition decision of returns and the various factors such as the reasons for returns, sources of returns are not considered. Alumur et al., (2011) proposed a multi-period reverse logistics design in which profit maximization MILP was formulated. They claimed that the model developed was flexible to incorporate most of the reverse network structures plausible in practice, possibility of making future adjustments in the network configuration to allow gradual changes in the network structure and in the capacities of the facilities by considering a multi-period setting as well as a multi-commodity. Soleimani and Govindan, (2014) studied a reverse logistics network design and planning utilizing conditional value at risk (CVaR) as a risk evaluator. They first considered return amounts and prices of second products as two stochastic parameters. Then, the optimum point was achieved in a two-stage stochastic structure regarding a mean-risk (mean-CVaR) objective function. Ene and Öztürk, (2014) proposed a MILP model for multi stage and multi period reverse supply chain network, which maximizes total profit of the network for open loop reverse supply chain networks. The proposed model determines facility locations and material flows between stages in each period.

Recently, with regards to literatures, in most of cases considering environmental constraints, parameters and variables along with economic issues to RL leads to complex models. In this situation the coordination between all aspects across the RL is more difficult in comparison with the traditional supply chains. This is because most of such problems are nonlinear, non-convex or maybe has multiple local optima. In addition to wide range activity that should be considered in GrSC the consideration of supply chain design with multi-objective optimization (generally incompatible objectives) is a new trend worthy of study and it causes more complicity in the models to be solved. Since most of these models belong to the class of NP-hard problems (Amir, 2006) they cannot be successfully analysed by analytical models. More ever, exact and traditional techniques such as Branch-and-Bound (B&B) and ε-constrain either cannot solve the models or computational requirements increase tremendously as models become more realistic (Sadrnia et al., 2014). In the few decades, researchers have tried to develop various approximate algorithms and modern heuristic algorithm to escape the problem. Heuristics and meta-heuristics as approximate algorithms seek to obtain acceptable near-optimal solutions and require low computation requirements and time. They work based on stochastic search methods, are inspired from nature processes or animal swarm behaviour. These techniques can help researchers to overcome the complexity issues in RL (Sadrnia et al., 2014) and have gained popularity in the optimization of grass problems because usually they use a collection of agents (like ants or honey bees) and perform a parallel search with multiple starting points in solution space. It is noticeable that meta-heuristic algorithm may solve some problems better and some problems worse than other methods so that researchers should select proper algorithms regarding to the problem characteristics, available time to implementation of the model, computational requirement, and required solution quality (Sadrnia et al., 2014).

Naturally inspired meta-heuristic optimization techniques are divided into two main categories (although there are minor other sub-branches) (Sadrnia et al., 2014): (i) evolutionary algorithms such as Genetic algorithm GA (Holland,1975), Evolutionary programming EP (Fogel et al., 1966) and Differential evolutionary algorithm, DEA (Storn, 1996) and (ii) algorithms based on swarm intelligence, such as Particle swarm optimization, PSO (Kennedy and Eberhart, 1995), Artificial bee colony (ABC) (Karaboga, 2005), Gravitational search algorithm, GSA (Rashedi et al., 2005), Ant colony Optimization, ACO (Dorigo et al., 2006) etc. . Besides EAs and SIs algorithms, there are some other meta-heuristics algorithms that are inspired natural processes and events such as simulated annealing (SA) algorithm and Tabu search (TS). Recently, the application of evolutionary and swarm intelligence algorithms, particularly in the field of GrSC, reverse logistics, closed-loop supply chain, green logistics and logistics network design has been studied by many researchers. Yanchao *et al*., (2008) established a reverse logistics network multi-objective optimization model that considered environment effect and the waste recycling factors, such as locations of facilities and frequency transportations. Then they improved PSO by adopting the grouping and the cataclysm theory and solved the complex model. Zhen-Hua et al., (2012) proposed an improved particle swarm optimization called PSOsm for solving multi-echelon reverse supply chain with specified returns. PSOsm Introduces the saltation mechanism into the procedure of the original PSO to increase the search area, which prevents the solution being laid on the local solution. Xiang-Cheng et al., (2012) studied a genetic particle optimization algorithm for computation of minimum remanufacturing closed loop supply chain network costs. Their simulated results showed that the proposed algorithm can gain global optimal solution with good convergent performance and rapidity. McGovern and Gupta, (2006) studied and implemented ACO to minimize the number of remanufacturing work stations, minimize idle time, and balances product disassembly line in recycling and remanufacturing systems. They emphasized ACO can be used to provide a feasible solution very fast, near-optimal solution to the multiple objective for that particular problem. Bautista *et al.,* (2008) developed a wastes collection facility location model to minimize waste collection cost using ACO as solution method. The basic nature of the considered problem is that of a capacitated arc routing problem, although it has several specific characteristics, mainly derived from traffic regulations. Ding et al., (2010) used ACO to solve multi objective optimization for minimizing the use of precious resources and maximizing the level of process capability in the disassembly line balancing problems for automated disassembly of disposal products. Vinay and Sridharan, (2012) presented a solution methodology using ant colony optimization (ACO) for a distribution–allocation problem in a two-stage supply chain with fixed cost for a transportation route. Taguchi method for robust design was adopted for finding the optimum combination of parameters of the ACO algorithm. A comparative analysis between the predicted signal-to-noise (S/N) ratio and the actual S/N ratio revealed that the error deviation in the experiment was minimal.

GA is a one the most popular EA that is implemented by scholars to optimize hard combinatorial problems and GrSC problems. Several authors have shown the effectiveness of using GA for reverse and closed-loop logistics network Optimization and facility location optimization. Min et al., (2004) first developed nonlinear mixed integer programming model to determine the number and location of centralized return centres for products returns from online sales. The multi-echelon RL network was optimized using a genetic algorithm approach. Gen et al., (2006) developed a priority based genetic algorithm(Pb-GA) to solve an extended version of two-stage transportation problem (tsTP) in order to minimize the total logistic cost including the opening costs of distribution centres (DCs) and shipping cost from plants to DCs and from DCs to customers. A new crossover operator called as Weight Mapping Crossover (WMX) was used.

Lee et al., (2008) formulated a mathematical model of a remanufacturing system as three-stage logistics network model for minimizing the total of costs to reverse logistics shipping cost and fixed opening cost of the disassembly centres and processing centres using hybrid genetic algorithm with priority-based encoding method consisting of 1^{st} and 2nd stages combined with a new crossover operator called as weight mapping crossover (WMX). Lee and Lee, (2012) developed a MINLP for the integrated closed loop supply chain network while considering order or next arrival of return goods. Their study proposes a reverse logistics optimization method to minimize the order volume or the next arrival of goods using Just-in-Time delivery. The priority based algorithm proposed by Gen et al., (2006) and the modified hybrid GA is used to design the chromosomes and improve the search ability of GA respectively. Ghezavati and Nia, (2014) develop a mixed integer non-linear programming model of a three-stage logistics network to optimize the number and location of collection/inspection centers and recovery centers as well as the collection frequency with the objective of minimizing the total costs which include the reverse logistics, shipping costs and fixed costs of opening facilities The MINLP was solved using genetic algorithm and results compared with simulated annealing (SA). Pishvaee et al., (2010) proposed a mixed integer linear programming model to minimize the transportation and fixed opening costs in a multistage reverse logistics network and applied a simulated annealing (SA) algorithm with special neighbourhood search mechanisms to find the near optimal solution. In other research, Lee et al., (2009) used SA to solve two-stage stochastic programming of multi-period reverse logistics network model.

5.3 RL Network Optimization modelling

A reverse supply chain refers to the flow of material through different facilities, starting with products from end user or supply chain partner and ending with the products delivered to final reprocessing facilities such as repair & servicing, cannibalizing & re-manufacturing, repackaging and reselling, recycling centers and disposal centers

(Rodgers and Tibben-Lembke, 1998). A multi-stage distribution problem is a typical problem for firms with supply chain networks. In this research, two scenarios have been studied for comparison. The first scenario is a single-stage transportation problem (ss-TP) involving the freight transportation network of retailers/distributors to reprocessing centers i.e. no collection centers are opened. These retailers/DCs are generally assumed to have capacitated or un-capacitated storage facilities. The ss-TP considered in the study aims to determine the distribution network to satisfy the customer returns quantities at minimum cost subject to the retailers and reprocessing canters'(RCs) capacity and also the minimum number of RCs to be opened. We assumed that the customer and retailer locations and their demand were known in advance. The numbers of potential RCs locations as well as their maximum capacities were also known. The second scenario is a two- stage transportation problem (ts-TP) in which the freight transportation network from customers/retailers to reprocessing centers through Centralized Return Centers (CRCs) or warehouses shall be studied. The second scenario reckons with the opening cost of a CRC and also per unit transportation cost from a retailer to a CRC. The ss-TP considered in the study aims to identify the potential location in the region where the company has decided to locate the CRC to satisfy the customer returns quantities at minimum cost subject to the retailers and reprocessing centers (RCs) capacity and also the minimum number of RCs to be opened. The proposed model is solved optimally using LINGO 15, in which the decoding procedures are used to adapt to the characteristic of ss-TP. The model, determined the optimum number of reprocessing centers to open and optimum material flow between retailers, reprocessing, recycling and disposal centers.

5.4 Problem definition:

This research proposes a two stage optimization problem presentation namely (1) First stage/ Pre-reprocessing optimization stage which is a single-stage transportation problem (ss-TP) involving the freight transportation network of retailers/distributors to reprocessing centers i.e. a cost minimization MILP model that minimizes investment (fixed and running costs of the facilities as well as transportation costs)from all retailers to the respective reprocessing centers (ii) Second stage/ post-reprocessing optimization stage that seek to optimize the profits/ minimize the cost of transportation from the reprocessing facilities when repaired materials are either transported back to the retailers for customer collection or resold to secondary markets, re-manufactured products will be transported to second-hand market for selling, recycled products will be transported to the manufacturing facility as raw material etc. However, post-reprocessing stage is usually considered to be in the *forward supply chain*. An original equipment manufacturer (OEM) is considered to open and operate multiple reprocessing centers for each alternative i.e. multiple repair centers, repackaging centers, re-manufacturing centers, recycling centers as well as disposal centers which are the destinations for the returned products. In this study, two optimization models shall be considered. In the first case, direct transportation from the major retailers to the respective reprocessing centres (scenario 1) and secondly, when return product are from the retailers are collected at the collection center for sorting and inspection before being transported to respective reprocessing centres.

5.5 Scenario-I: Direct shipment network to reprocessing centres.

The distributors comprises of the retailers which sell and receive returned products directly from the end users/customers which are returned for various reasons; end-of-use returns, commercial return, warranty returns, production scrap, by-products and packaging return (Rogers and Tibben-Limbke, 2001). In the first scenario, the decision support system studied in chapter 4 is used to categorize and select the best reprocessing alternative for the return products and after elapsing of the expected collection time, the return products are transported directly to their respective reprocessing centers as shown in Fig. 1.5.

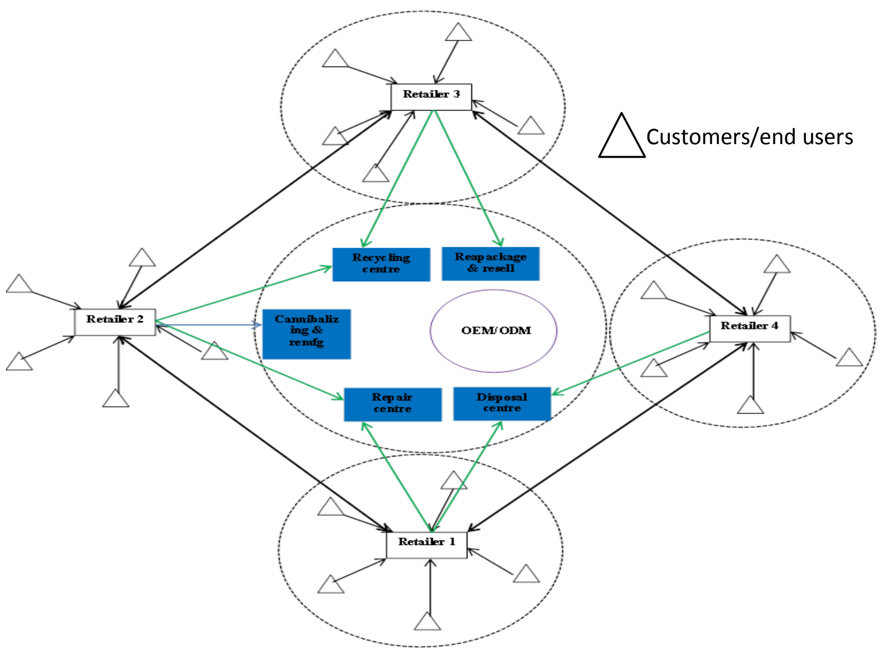


Fig.1.5: Single stage Reverse logistics network concept

Returned products, collected from customers, will be inspected and categorized at retailers/Point of return (POR) and classified into reprocessing groups according to their quality levels: repair/servicing reusable, recoverable and disposal. Repairable products will be transported to repair centers, reusable products will be transported to the re-manufacturing center, recoverable products will be transported to recycling center and unrecoverable products will be transported to disposal center. Reprocessed/ re-manufactured products will be transported to second-hand market for selling. Recycled products will be transported to the manufacturing facility as raw material (see Fig. 2.5).

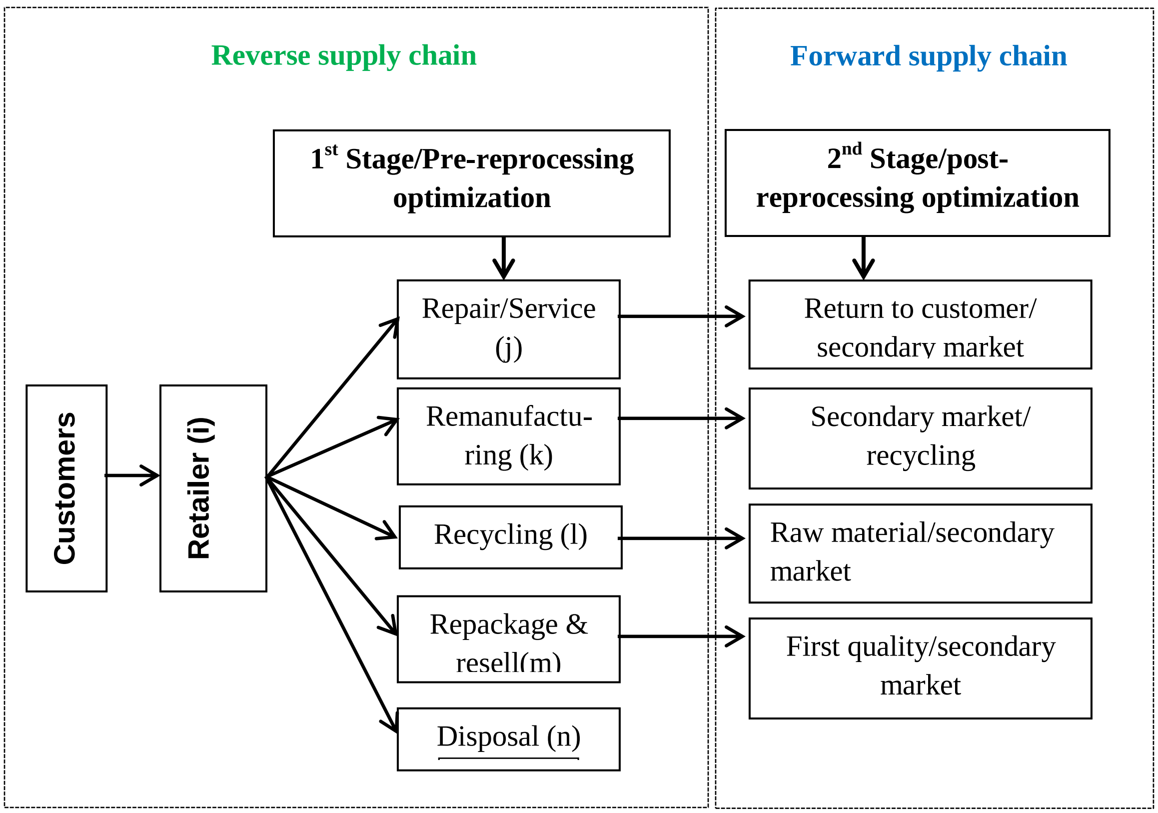


Figure 2.5: Structure of the proposed open loop reverse supply chain network.

5.5.1 Mathematical model formulation

The mixed integer programming model, proposed for network design, determines the optimum number of reprocessing centers to open, the retailers to supply which reprocessing center and optimum material flow between retailers, reprocessing, recycling and disposal centers. The objective in the single-stage FCTP is to minimize total transportation cost between a set of retailers and a set of corresponding reprocessing center for the returned products/materials as shown in the integrated open loop reverse supply chain in Fig. 3.5.

The sets, decision variables, parameters and constraints used in the model are defined as follows:

Indices

$i = 1, 2, 3, \dots\dots, I$ Set of retailers

$j = 1, 2, 3, \dots\dots, J$ Set of repair centers

$k = 1, 2, 3, \dots\dots, K$ Set of repackaging and reselling centers

$l = 1, 2, 3, \dots\dots, L$ Set of cannibalizing and re-manufacturing centers.

$m = 1, 2, 3, \dots\dots, M$ Set of recycling centers

$n = 1, 2, 3, \dots\dots, N$ Set of disposal centers

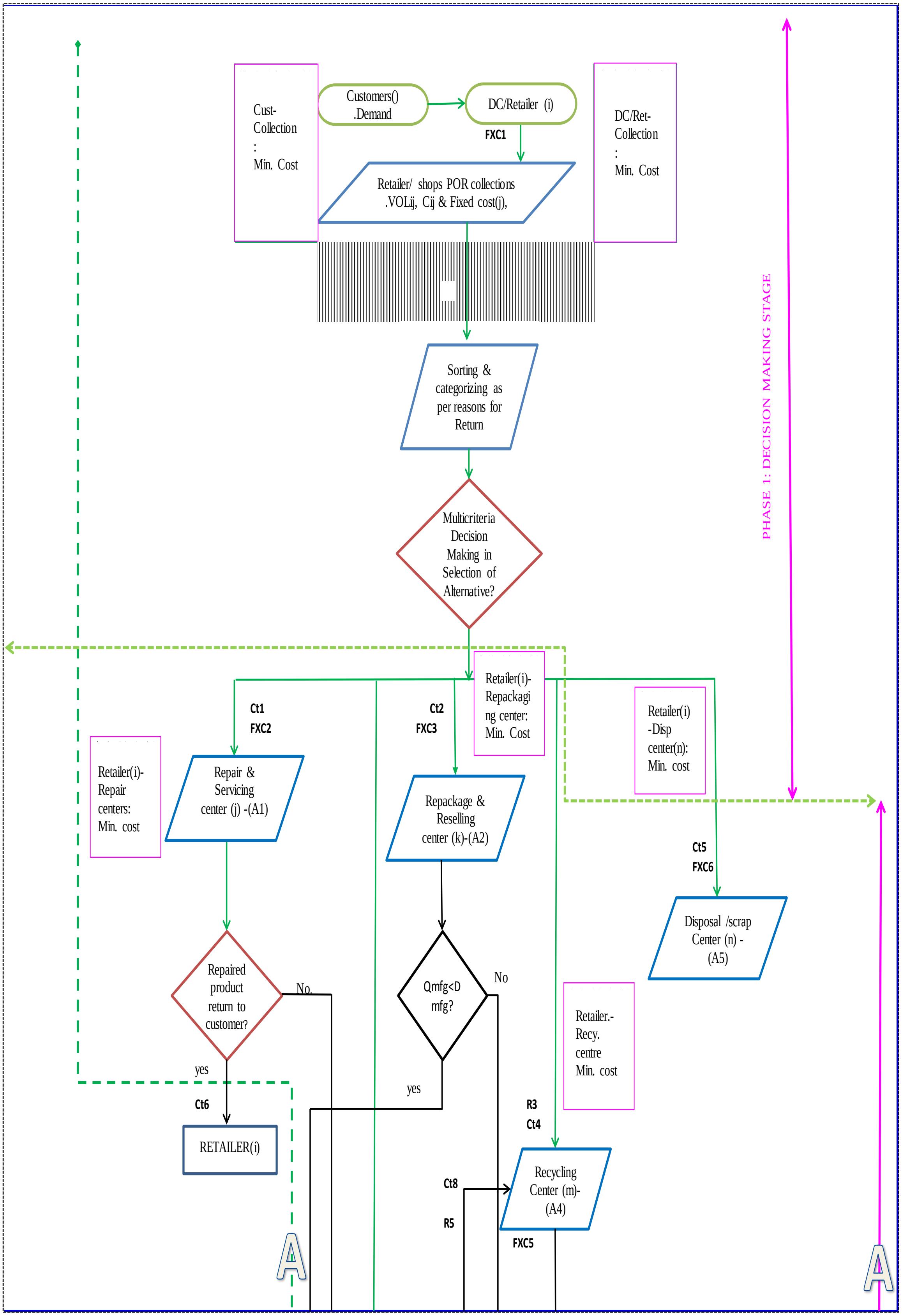
$t = 1, 2, 3, \dots\dots, T$ Set of periods

Decision variables

$$a_j = \begin{cases} 1, & \text{If a repair center is open at location } j \\ 0, & \text{Otherwise} \end{cases}$$

$$b_k = \begin{cases} 1, & \text{If a repackaging and reselling center is open at location } k \\ 0, & \text{Otherwise} \end{cases}$$

$$c_l = \begin{cases} 1, & \text{If a re} - \text{manufacturing center is open at location } l \\ 0, & \text{Otherwise} \end{cases}$$



Cust-Collection : Min. Cost
Customers() .Demand
DC/Retailer (i)
FXC1
DC/Ret-Collection : Min. Cost
Retailer/ shops POR collections .VOLij, Cij & Fixed cost(j),
Sorting & categorizing as per reasons for Return
Multicriteria Decision Making in Selection of Alternative?
PHASE 1: DECISION MAKING STAGE
Retailer(i)-Repackaging center: Min. Cost
Ct1
FXC2
Ct2
FXC3
Retailer(i) -Disp center(n): Min. cost
Retailer(i)-Repair centers: Min. cost
Repair & Servicing center (j) -(A1)
Repackage & Reselling center (k)-(A2)
Ct5
FXC6
Disposal /scrap Center (n) - (A5)
Repaired product return to customer?
No.
Qmfg<D mfg?
No
Retailer.-Recy. centre Min. cost
yes
yes
Ct6
RETAILER(i)
R3
Ct4
Ct8
Recycling Center (m)- (A4)
R5
FXC5
A
A

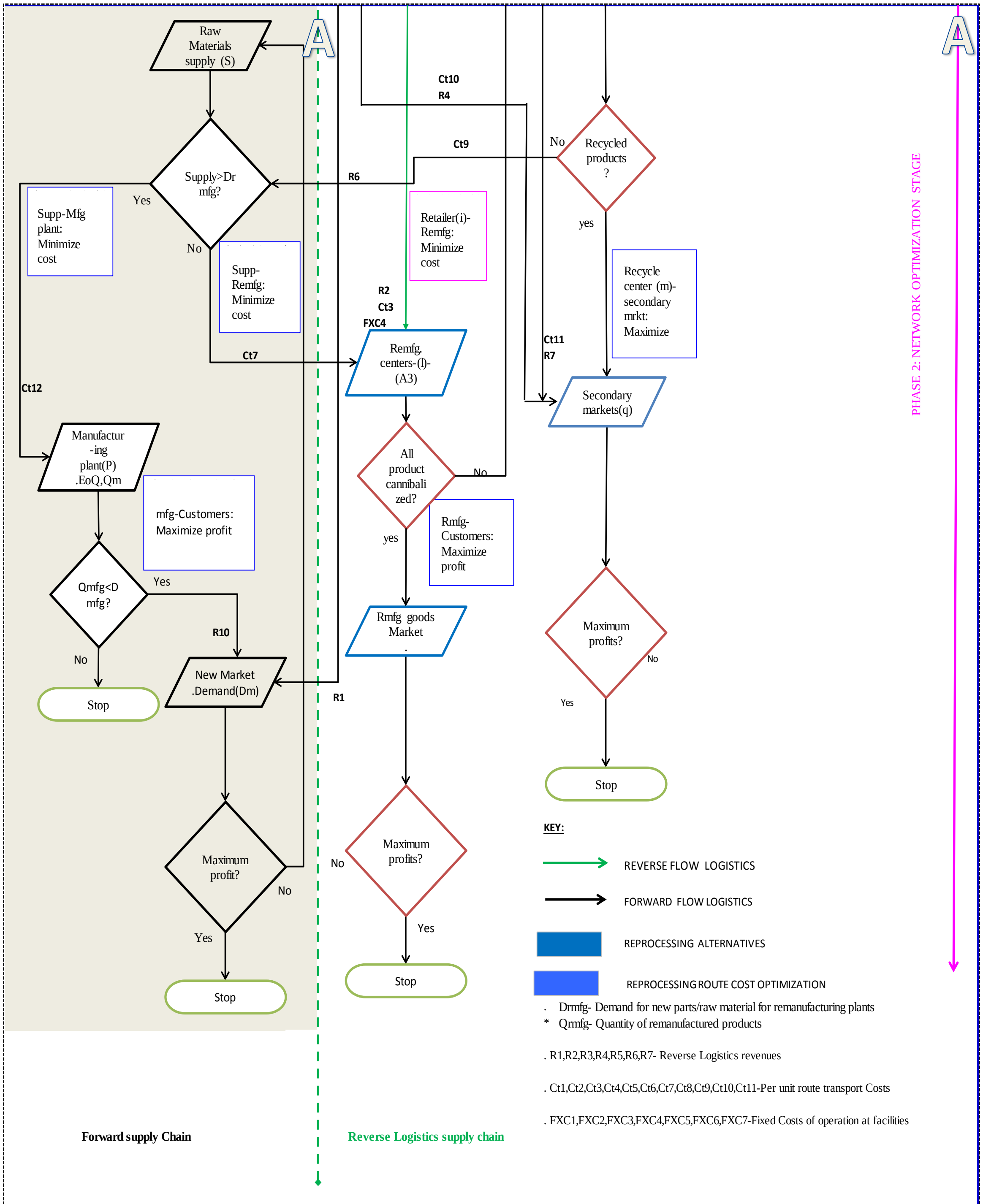


Fig 3.5: Integrated reverse-forward open loop supply chain

$$d_m = \begin{cases} 1, & \text{If a recycling center is open at location } m \\ 0, & \text{Otherwise} \end{cases}$$

$$e_n = \begin{cases} 1, & \text{If a disposal center is open at location } n \\ 0, & \text{Otherwise} \end{cases}$$

$f_o = \begin{cases} 1, & \text{If a retail/POR center is open at location } i \\ 0, & \text{Otherwise} \end{cases}$

v_{ijt} = Volume of materials/products shipped from customers/retailers *i,* to repair center *j* in time period *t.*

w_{ikt} = Volume of materials/products shipped from customers/retailers *i,* to repackage & reselling center *k* in time period *t.*

x_{ilt} = Volume of materials/products shipped from customers/retailers *i,* to cannibalize and re-manufacturing center *l* in time period *t.*

y_{imt} = Volume of materials/products shipped from customers/retailers, *i* to recycling center *m* in time period *t.*

z_{int} = Volume of materials/products shipped from customers/retailers *i* to disposal center *n* in time period *t.*

Parameters

FXC_i^1 = Fixed cost of opening and operating RL at retailer/POR at location, *i.*

FXC_j^2 = Fixed cost of opening and operating a repair center at location, *j.*

FXC_k^3 = Fixed cost of opening and operating a repackaging and reselling center at location, *k.*

FXC_l^4 = Fixed cost of opening and operating a re-manufacturing center at location, *l.*

FXC_m^5 = Fixed cost of opening and operating a recycling center at location, *m.*

FXC_n^6 = Fixed cost of opening and operating a disposal center at location, *n.*

Cap_j^1 = Capacity of the repair/service center, *j.*

Cap_k^2 = Capacity of the repackaging and reselling center, *k.*

Cap_l^3 = Capacity of the cannibalizing and re-manufacturing center, *l.*

Cap_m^4 = Capacity of the recycling center, *m.*

Cap_n^5 = Capacity of the disposal center, *k.*

Ct_{ij}^1 = Unit transport cost from retailer, *i* to repair center *j.*

Ct_{ik}^2 = Unit transport cost from retailer, *i* to repackaging and reselling center *k.*

Ct_{il}^3 = Unit transport cost from retailer, *i* to re-manufacturing center *l.*

Ct_{im}^4 = Unit transport cost from retailer, *i* to recycling center *m.*

Ct_{in}^5 = Unit transport cost from retailer, *i* to disposal center *n.*

q_{jt} = Quantity of materials/products received by customers/retailers *i,* going to repair center *j* in time period *t.*

r_{kt} = Quantity of materials/products received by customers/retailers *i,* going to re-selling center *k* in time period *t.*

s_{lt} = Quantity of materials/products received by customers/retailers *i,* going to re-manufacturing center *l* in time period *t.*

t_{mt} = Quantity of materials/products received by customers/retailers *i,* going to recycling center *m* in time period *t.*

u_{nt} = Quantity of materials/products received by customers/retailers *i,* going to disposal center *n* in time period *t.*

Assumptions

The above optimization model for ss-TP minimizes investment (fixed and running costs of the facilities as well as transportation costs) subject to following assumptions:

1) The returned materials/products are categorized into respective reprocessing alternative at the retailers/POR using a decision support tool/system.
2) The categorized products are shipped directly from the retailers to the respective reprocessing centers/facility.
3) The retailers/ POR have got unlimited capacity.
4) No transportation cost considered from customers to the retailers/PoR.
5) The locations of the retailers and reprocessing facilities are known and pre-determined.
6) The capacity of each reprocessing facility is limited and is known for each time period.
7) Customer zones known and fixed with deterministic demands.
8) The per unit transportation costs and fixed cost for opening and operating reprocessing facilities are pre-determined and static.
9) All products returned for repair/servicing are repaired and returned to the retailer for customer collection.
10) All products reprocessed/re-manufactured products are sold through re-manufactured goods market.

Considering the notation described above, open loop reverse supply chain network design problem can be formulated as follows:

Objective function:

Min Total cost [TC]

$$= \sum_{i=1}^{I} f_o.FXC_i^1 + \sum_{j=1}^{J} a_j.FXC_j^2 + \sum_{k=1}^{K} b_k.FXC_k^3 + \sum_{l=1}^{L} c_l.FXC_l^4 + \sum_{m=1}^{M} d_m.FXC_m^5 + \sum_{n=1}^{N} e_n.FXC_n^6 + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} v_{ijt}Ct_{ij}^1 + \sum_{i=1}^{I}\sum_{k=1}^{K}\sum_{t=1}^{T} w_{ikt}Ct_{ik}^2 + \sum_{i=1}^{I}\sum_{l=1}^{L}\sum_{t=1}^{T} x_{ilt}Ct_{il}^3 + \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{t=1}^{T} y_{imt}Ct_{im}^4 + \sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{t=1}^{T} z_{int}Ct_{in}^5 \quad (1)$$

Subject to:

$\sum_{j=1}^{J} v_{ijt} \leq q_{jt} \qquad \forall i,t$ (2)

$\sum_{i=1}^{I} v_{ijt} \leq Cap_j^1 a_j \qquad \forall j,t$ (3)

$\sum_{k=1}^{K} w_{ikt} \leq r_{kt} \qquad \forall i,t$ (4)

$\sum_{i=1}^{I} w_{ikt} \leq Cap_k^2 b_k \qquad \forall k,t$ (5)

$\sum_{l=1}^{L} x_{ilt} \leq s_{lt} \qquad \forall i,t$ (6)

$\sum_{i=1}^{I} x_{ilt} \leq Cap_l^3 c_l \qquad \forall l,t$ (7)

$\sum_{m=1}^{M} y_{imt} \leq t_{mt} \qquad \forall i,t$ (8)

$\sum_{i=1}^{I} y_{imt} \leq Cap_m^4 d_m \qquad \forall m,t$ (9)

$\sum_{n=1}^{N} z_{int} \leq u_{nt} \qquad \forall i,t$ (10)

$\sum_{i=1}^{I} z_{int} \leq Cap_n^5 e_n \qquad \forall n,t$ (11)

$\sum_{j=1}^{J} v_{ijt} + \sum_{i=1}^{K} w_{ikt} + \sum_{l=1}^{L} x_{ilt} + \sum_{m=1}^{M} y_{imt} + \sum_{n=1}^{N} z_{int} = \sum_{j=1}^{J} q_{jt} + \sum_{i=1}^{K} r_{kt} + \sum_{l=1}^{L} s_{lt} + \sum_{m=1}^{M} t_{mt} + \sum_{n=1}^{N} u_{nt}$ (12)

$v_{ijt}, w_{ikt}, x_{ilt}, y_{imt}, z_{int}, q_{ijt}, r_{kt}, s_{lt}, t_{mt}, u_{nt} \geq 0$ (13)

$a_j, b_k, c_l, d_m, e_n, f_o \in \{0,1\}$ (14)

Objective function (1) minimizes total of the network. Constraint 2 specifies that inbound and outbound flow of material from between retailers/ PoR and repair centers must be satisfied in each period. Constraint 3 ensures that in each period, total product shipped to opened repair centers cannot exceed the capacity of the centers. Constraint 4 specifies that inbound and outbound flow of material from between retailers/PoR and repackaging & reselling centers must be satisfied in each period. Constraint 5 states that total product shipped to open repackaging and reselling centers in each period cannot exceed the capacity of the centers. Constraint 6 satisfies flow balance between retailers/ PoR and re-manufacturing centers in each period. Constraints 7 ensure that total product shipped to cannibalizing and re-manufacturing centers cannot exceed their capacities in each period. Constraint 8 satisfies flow balance between retailers/PoR and recycling centers in each period. Constraints 9 ensure that total product shipped to recycling centers cannot exceed their capacities in each period. Constraint 10 satisfies flow balance between retailers/ PoR and disposal centers in each period. Constraints 11 ensure that total product shipped to recycling centers cannot exceed their capacities in each period. Constraint 12 satisfies flow balance between retailers/ PoR and reprocessing centers in each period. Constraint 13 specifies that decision variables *q, r, s, t, u, v, w, x, y, z,* must be greater than 0. Constraint 14 states that decision variables *a, b, c, d, e, and f* must be 1 or 0.

5.5.2 Case study and application

Our application is related to the cost minimization problem for return products of a ABZ Computer Manufacturing Company operating in Orissa state of India. This company has experienced a growth in the returns for its products due to various reasons both marketing and reprocessing legislative requirements from its retailer shops throughout the country. In order to ensure a responsive and efficient reverse logistics network, they propose that after the decision in the selection of the best reprocessing alternative is made at the points of return (Customer end) using the decision support system (DSS), the products can be are shipped directly to the respective reprocessing centres. The Company operates four major retailer shops, three repair/service centres, three repackaging and redistribution centres, three remanufacturing plants, three recycling centres and three disposal centres that are distributed throughout the state. Table 1.5 shows the unit transportation cost between major retailer shops and repair centres, Ct_{ij}^{1} , the capacity of repair/service centres (Cap_j^1) and supply quantity of retailers, q_i. Table 2.5 depicts the unit transportation cost between major retailer shops and repackaging/reselling centres, Ct_{ik}^{2} , the capacity of plants (Cap_k^2) and supply quantity of retailers, q_i. Table 3.5 shows the unit transportation cost between major retailer shops and re-manufacturing centres, Ct_{il}^{3} the capacity of re-manufacturing centres (Cap_l^3) and supply quantity of retailers, q_i. Table 4.5 shows the unit transportation cost between major retailer shops and recycling centres, Ct_{im}^4 , the capacity of recycling centres (Cap_m^4) and supply quantity of retailers, q_i. Table 5.5 shows the unit transportation cost between major retailer shops and disposal centres,Ct_{in}^5 the capacity of disposal centres (Cap_n^5) and supply quantity of retailers, q_i. Table 6.5 provides the fixed costs of opening and operating per unit at the repair/ service centres, repackaging and reselling centres, cannibalizing and re-manufacturing plants, recycling centres and disposal centres respectfully.

Table 1.5: Transportation cost matrix between retailers and repair centres.

	DC/Retailers				
	BBSR	SND	BRP	BHA	Cap.
Repair					
SNPR	42.54	55.17	163.86	25.95	5000
JJPR	9.43	131.02	35.01	184.06	1000
PLKMD	66.10	74.00	244.92	43.16	2500
SUPPLY	1700	1800	2000	1000	

Table 2.5: Transportation cost matrix between retailers and repackaging & reselling centres

	DC/Retailers				
	BBSR	SND.	BRP.	BHA.	Cap
Resell					
SMPR	74.71	27.62	120.30	52.92	5000
BHSWR	33.10	166.89	7.96	280.75	1000
JGSPR	11.69	151.16	74.00	207.11	2500
SUPPLY	1700	1800	2000	1000	

Table 3.5: Transportation cost matrix between retailers and re-manufacturing centres.

	DC/Retailers				
	BBSR	SND	BRP	BHA	Cap
Remfg					
PUR	7.48	163.10	87.61	181.27	2500
NPDA	187.06	134.42	326.78	14.09	4000
MKNGR	345.72	384.78	629.55	67.32	1500
SUPPLY	1500	1800	1500	800	

Table 4.5: Transportation cost matrix between retailers and recycling centres

	DC/Retailers				
	BBSR	SND	BRP	BHA	Cap
Recy.					
BHGR	102.68	43.16	152.96	34.63	5000
KRPT	203.22	322.78	450.70	42.13	1000
CHTPR	25.95	240.35	145.76	102.58	2500
SUPPLY	1500	1800	1500	800	

Table 5.5: Transportation cost matrix between retailers and re-manufacturing centres

	DC/Retailers				
	BBSR	SND	BRP	BHA	Cap
Disposal					
JSGPR	102.58	13.48	129.31	75.33	2500
RYGD	120.30	233.48	337.49	20.16	4000
BHDK	19.41	134.76	19.41	205.85	1500
SUPPLY	1500	1800	1500	800	

Table 6.5: Fixed costs facility centres

	Retail	Repair	Resell	Rem.	Recy.	Disp.
FxC						
1	0.5	1	1	5.6	9	3
2	1	0.5	0.5	3.5	7.8	2.7
3	0.4	0.62	0.62	6.8	6.9	4.3
4	1.5					

5.5.3 Results and discussion

The proposed model is solved optimally with LINGO 15. The model, determines optimum costs, number of reprocessing centers to open and optimum material flow between major retailer centres, repair/ servicing centers, repackaging and reselling centres, re-manufacturing centres, recycling and disposal centers. All experiments are performed on a Intel Core i7 -4770 3.40 GHz computer with 2 GB RAM. Optimum results of the test problems are presented in Figure 4.5.

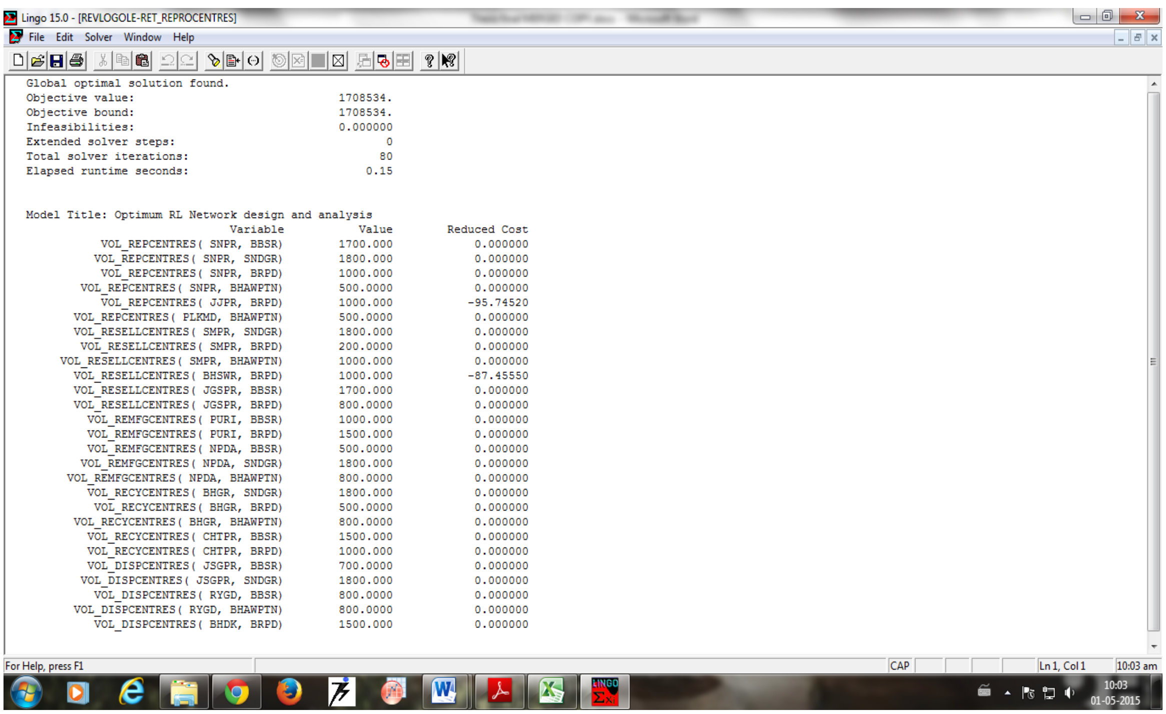


Fig. 4.5: LINGO 15 optimization results output.

Also, the optimum material flow between major retailer centres, repair/ servicing centers, repackaging and reselling centres, re-manufacturing centres, recycling and disposal centers Table 7.5-11.5:

Table 7.5: Optimum quantities transported between retailers and repair centres.

Table 8.5: Optimum quantities transported between retailers and repackaging & reselling centres

	DC/Retailers				
	BBSR	SNDGR	BRPD	BHAWP TN	CAPACIT Y
Repair					
SNPR	1700	1800	1000	500	5000
JJPR	0	0	1000	0	1000
PLKMD	0	0	0	500	500
SUPPLY	1700	1800	2000	1000	

	DC/Retailers				
	BBSR	SNDG R	BRPD	BHAWP TN	CAP
Resell					
SMPR	0	1800	200	1000	3000
BHSWR	0	0	1000	0	1000
JGSPR	1700	0	800	0	2500
SUPPLY	1700	1800	2000	1000	

Table 9.5: Optimum quantities transported between retailers and re-manufacturing centres.

Table 10.5: Optimum quantities transported between retailers and recycling centres

	DC/Retailers				
	BBSR	SNDGR	BRPD	BHAWP TN	CAPACIT Y
Remfg.					
PUR	1000	0	1500	0	2500
NPDA	500	1800	0	800	3100
MKNGR	0	0	0	0	0
SUPPLY	1500	1800	1500	800	

	DC/Retailers				
	BBSR	SNDG R	BRPD	BHAWP TN	CAP
Recy.					
BHGR	0	1800	500	800	3100
KRPT	0	0	0	0	0
CHTPR	1500	0	1000	0	1500
SUPPLY	1500	1800	1500	800	

Table 11.5: Optimum quantities transported between retailers and Disposal centres

	DC/Retailers				
	BBSR	SNDGR	BRPD	BHAW	Capacity
Disposal					
JSGPR	700	1800	0	0	2500
RYGD	800	0	0	800	1600
BHDK	0	0	1500	0	1500
SUPPLY	1500	1800	1500	800	

It can be concluded from the results that the number of returned products, the location of the facilities, and capacities affects the total cost of network over the considered time periods. In that case it is clearly understood from the obtained results that companies can use this model to decide on the locations where the facilities will be established and the capacity to be assigned to each facility. Similarly, the model can be used to identify lanes along which products will be transported. In order to maximize profit gained from the returned product while satisfying the customer needs, the company should provide suitable incentives in a planning period to customers or retailers for increasing number of returned used products.

5.6 Scenario-II: Shipment networks using centralized return centre (CRC)

5.6.1 Problem definition:

The ABZ company management felt that building a major centralized return centre (CRC) to serve the local market shall reduce the cost by centralizing the return management activities as opposed to decentralizing them to the retailer outlets where the returned products are sorted and categorized before being transported directly to the respective reprocessing centres. They suggested that a central potential location be identified where they can locate the collection centre. The model aims to identify the suitable location and the optimal costs and compare with the first scenario in order to enable the management make a decision on the suitable approach to use in their reverse logistics system.

5.6.2 Centroid method

The centroid method is a technique for locating single facilities that considers existing facilities, the distances between them and the volume of goods to be moved/ shipped. The method can be used to find a location that minimizes the cost of transporting return products from the major retailer outlets and the reprocessing centres to be served. The centroid method assumes that the retail (sources) and the reprocessing centres (depots) can be located as grid points on the plane. All distances are calculated as the geometric distances between two points on the plane. This model also assumes that the transportation cost grows linearly with the quantity shipped.

5.6.3 Mathematical model formulation

The optimal location is that minimizes the total transportation cost between a set of retailers and a set of corresponding reprocessing center for the returned products/materials.

The sets, decision variables, parameters and constraints used in the model are defined as follows:

Indices

x_n, y_n : coordinate location of either a source or depot *n.*

F_n : cost of shipping one unit for one kilometre between the facility and either the depot or the source

D_n : Quantity to be shipped between facility and depot or source *n*

(x, y) : Location of facility (collection centre).

d_n : Distance between the facility at location (x, y) and the source or depot *n.*given by:

$$d_n = \sqrt{(x - x_n)^2 + (y - y_n)^2} \quad (15)$$

The Objective function:

$$Min\ TC = \sum_{n=1}^{k} d_n\, D_n F_n \quad (16)$$

5.6.4 Methodology

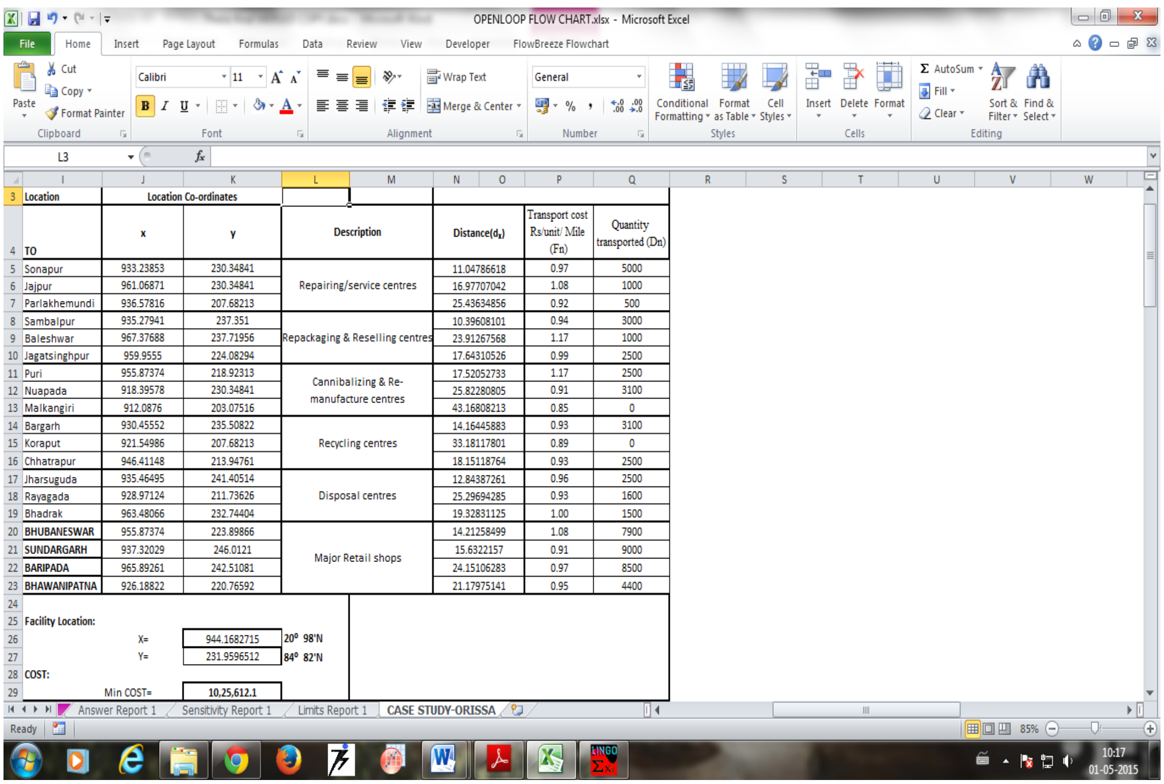
The optimal solution of ABZ was obtained using solver tool in Excel as shown in Fig. 5.5.

Step 1: Enter the problem data as shown in the cells I5:Q23.

Step 2: Set the decision variables (x, y) corresponding to the location of the collection centre in cells K26 and K27, respectively.

Step 3: In cells N5:N23, calculate the distances d_n from the facility location (x, y) to each source or depot using Eq. 15.

Step 4: Calculate the Total cost (TC) in cell K29 using Eq. 16.



OPENLOOP FLOW CHART.xlsx - Microsoft Excel

Location / TO	Location Co-ordinates x	y	Description	Distance(d_x)	Transport cost Rs/unit/ Mile (Fn)	Quantity transported (Dn)
Sonapur	933.23853	230.34841	Repairing/service centres	11.04786618	0.97	5000
Jajpur	961.06871	230.34841		16.97707042	1.08	1000
Parlakhemundi	936.57816	207.68213		25.43634856	0.92	500
Sambalpur	935.27941	237.351	Repackaging & Reselling centres	10.39608101	0.94	3000
Baleshwar	967.37688	237.71956		23.91267568	1.17	1000
Jagatsinghpur	959.9555	224.08294		17.64310526	0.99	2500
Puri	955.87374	218.92313	Cannibalizing & Re-manufacture centres	17.52052733	1.17	2500
Nuapada	918.39578	230.34841		25.82280805	0.91	3100
Malkangiri	912.0876	203.07516		43.16808213	0.85	0
Bargarh	930.45552	235.50822	Recycling centres	14.16445883	0.93	3100
Koraput	921.54986	207.68213		33.18117801	0.89	0
Chhatrapur	946.41148	213.94761		18.15118764	0.93	2500
Jharsuguda	935.46495	241.40514	Disposal centres	12.84387261	0.96	2500
Rayagada	928.97124	211.73626		25.29694285	0.93	1600
Bhadrak	963.48066	232.74404		19.32831125	1.00	1500
BHUBANESWAR	955.87374	223.89866	Major Retail shops	14.21258499	1.08	7900
SUNDARGARH	937.32029	246.0121		15.6322157	0.91	9000
BARIPADA	965.89261	242.51081		24.15106283	0.97	8500
BHAWANIPATNA	926.18822	220.76592		21.17975141	0.95	4400

Facility Location:

X= 944.1682715 20⁰ 98'N

Y= 231.9596512 84⁰ 82'N

COST:

Min COST= **10,25,612.1**

Answer Report 1 | Sensitivity Report 1 | Limits Report 1 | CASE STUDY-ORISSA

Fig. 5.5: Optimized centralized return centre location using solver for ABZ Company.

Step 5: The next step is to invoke solver Tool. Within the solver parameter dialog box (Fig. 6.5), the following information is entered to represent the problem:

Set Target Cell: K29

Equal to: Select *Min.*

By changing Cells: K26:K27

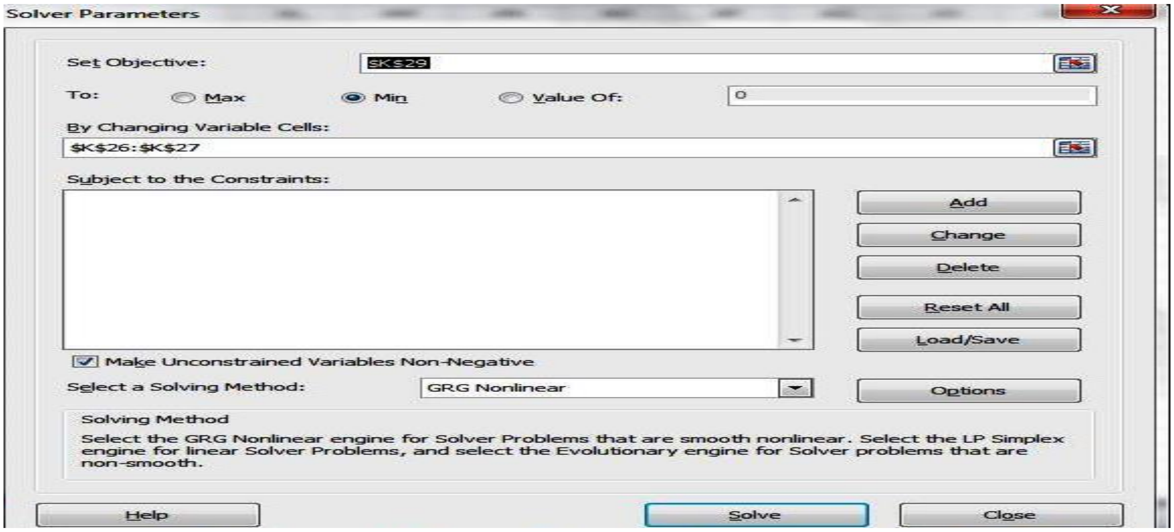


Fig. 6.5: Solver parameter box to optimize location for ABZ Company.

Step 6: Click on the solve button. The optimal solution is returned in cells K26 and K27.

5.6.5 Results and discussion

The proposed model is solved optimally with Solver Tool in excel. The model, determined optimum location that minimizes the total transportation costs between major retailer centres and repair/ servicing centers, repackaging and reselling centres, re-manufacturing centres, recycling and disposal centers. All experiments are performed on a Intel Core i7 -4770 3.40 GHz computer with 2 GB RAM. Optimum results of the test problems are presented in Fig. 7.5.

The model, thus identifies the coordinates (x, y)= $(9441682.715, 23195966.512)$ taken from (0^0N,0^0E) reference point, as the location of the collection centre that will minimize the total transportation cost as shown in Fig. 7.5. From a map in Appendix 5.2, these coordinates represent a location on 20^0 98’N & 84^0 82'N, when converted from X&Y coordinate to Latitude and longitudes, which is close to Baudh area. The precise coordinate provided by the centroid method may not correspond to a feasible location; hence the management should look for a desirable site close to the optimal coordinates that have the required infrastructure.

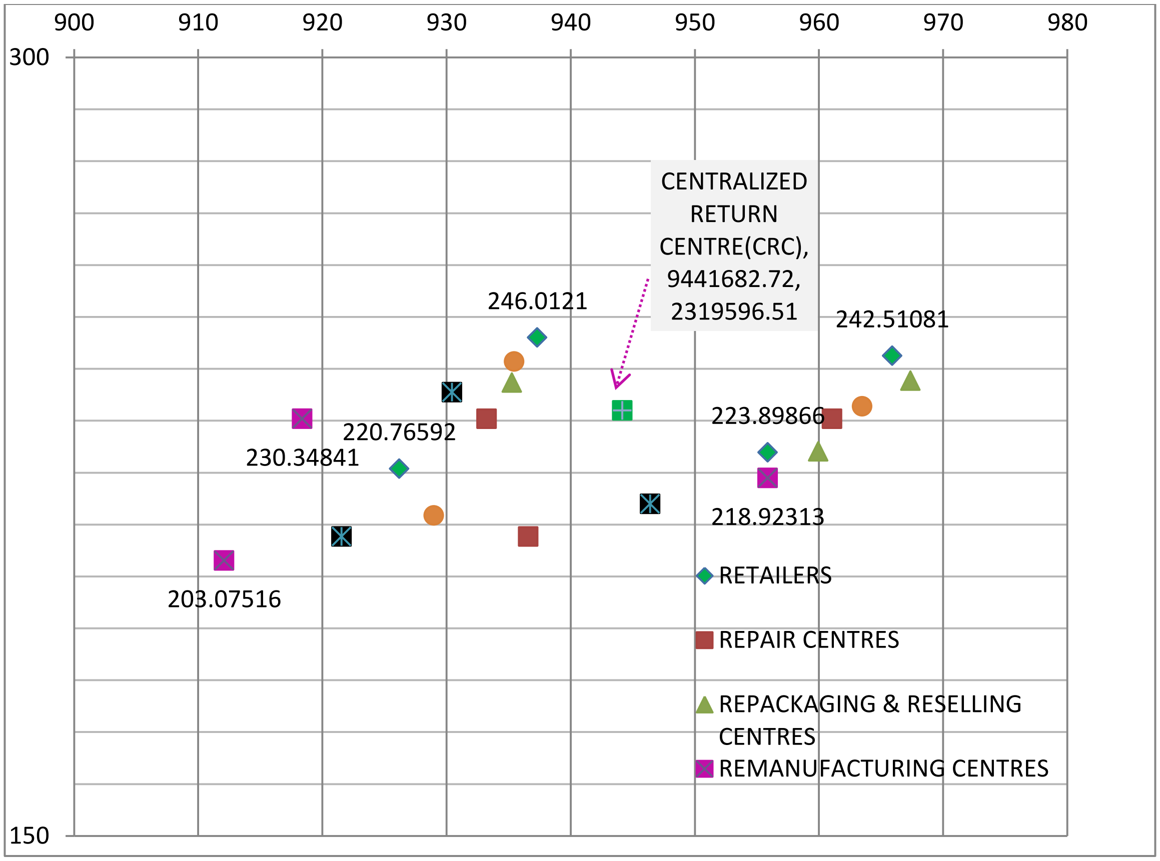


Fig. 7.5: Geographical mapping of the facility location using the centroid method.

5.7 Conclusions

Network design is one of the most important planning activities in supply chain management. Furthermore, in recent years, reverse supply chain operations has a gaining and critical value for researchers and companies with extending environmental regulations of product recovery. This research presents a mixed integer linear programming model for an open loop multi stage multi period reverse supply chain network design. The model is validated with different problem sets from a case study. Obtained results showed the applicability and efficiency of the model. The model proposed in this study is a strategic decision making tool for reverse supply chain network design problem of any product type.

From the results obtained, it can be observed that the cost of network is minimum when the centralized return centres are used (scenario I) compared to direct shipping from points of return/ retailers to the reprocessing centres. This system has the benefit of creating the largest possible volumes for each of the reverse logistics flow customers, which often leads to higher revenues for the returned items. With direct shipping model, a retailer or manufacturer can utilize “milk runs” to pick up returned goods. This way, a company can move more goods, increasing consolidation and thereby reducing freight costs. The downside to a completely centralized system is that handling and transportation costs can increase because all products must be transported from the retail locations to the centralized facility. If a product is going to be disposed, transporting it to a centralized facility just to throw it away increases costs, but does not increase revenues, because the product is still thrown away. Table 12.5 shows the comparison between the various transportation network options in RL.

Table 12.5: Comparisons between various transportation network models

Transportation mode	Descriptions
Direct Shipment Network	Pros: -Goods are shipped directly to reprocessing centres hence reduce time. -Routing of each shipment is known -Operation and coordination is simple -Eliminates need for intermediate handling -Transportation decisions are completely localized Cons: -High inventories , high transportation costs incase of LTL returns, high receiving costs,
Direct shipping with milk runs	-Delivery from multi-retailers/PoR to multi-reprocessing centres. -Eliminates the need for intermediate CRCs. -In cases where returns are less than Tonne loads (LTL),Transportation can be consolidated thus lowering transportation costs. -Increased coordination complexity
Through Centralized return centres (CRCs)	-Goods routed through CRCs. Retailers/ PoR are divided into geographical regions served by CRC -Serves two functions:- Store inventory and act as transfer location -Useful if return quantities are large and reprocessing centres are far from PoR/retailers -Increased coordination complexity
Cross docking	-Take return goods from retailers and deliver them directly to the reprocessing centres with little handling. -Reduces handling charges, operation costs, increases throughput, reduces inventory levels

All transportation decisions in reverse supply chains network must take into account their impact on inventory costs, facility and processing costs, the costs of coordinating operations as well as the level of responsiveness provided to customers. Therefore, the trade-offs to be considered will include: (1)Transportation cost and inventory cost trade-off (2) Transportation cost and customer responsiveness trade-off.

Chapter 6:
Reverse Logistics management system: Implementation

6.1 Case study

Currently the Reverse Logistics team of ABZ computer Distributors Company on behalf of an OEM does not acquire any sort of tool to help evaluate, assess, or manage risks as well as to sort, categorize and select the best reprocessing alternative and to further optimize the reverse supply networks in the process of returned products/material. ABZ Management has asked that a model or tool be developed in order to assist them in solving the above problems in the return stream of products. In order to do so, both the sales and return programs needed to be analysed to understand the processes involved in reverse logistics involved. After carefully analysing the customers' returns, supply chain partners' returns, reprocessing alternatives, locations, and processes affecting the returns stream, the implementation of the reverse logistics management tool seemed necessary for ABC Computer distributors Company .

The reverse supply chain of ABZ computer Distributors Company was used to demonstrate how the proposed reverse logistics management tool can be effective in the process of returned products. The identity of ABZ Company has been concealed in order to protect intellectual property agreements. The reverse logistics management tool developed is to be used by the OEM management and other supply chain partners, i.e. retailers/ PoR in the Reverse Logistics team. Management for this system and all of the receiving facilities involved in the reverse supply chain is located mainly at the OEM's head office in Bhubaneswar. The Reverse Logistics team at ABC Company is responsible for all products being returned to the company within Orissa state of India. Various information and communications are held daily to keep the team up to date with the latest information regarding returned materials.

The management tool developed for the Reverse Logistics group is intended to be reviewed periodically basis to check the changes that may have occurred. The tool will assist in identifying the status of each risk factor, make decisions based on actions requirement plans to be implemented, make decisions on the quality and usability of the return products, execute network optimization and perform material flow routing. The reverse supply chain of ABC Company was used in the demonstration of this RL management tool.

6.2 The system layout and architecture

The management of product returns is complex, dynamic and costly, and increasingly so as devices become more intelligent and feature rich. The proposed reverse logistics management system (Revlogix) streamlines and expedites reverse processing by systematically dealing with the condition, compliance and return scenarios that impact how a product gets handled. The end result is a system that enables companies to process units with great speed and accuracy in order to maximize asset recovery for the OEM. Fig. 1.6 is a block diagram showing a typical high level architecture for the computer system.

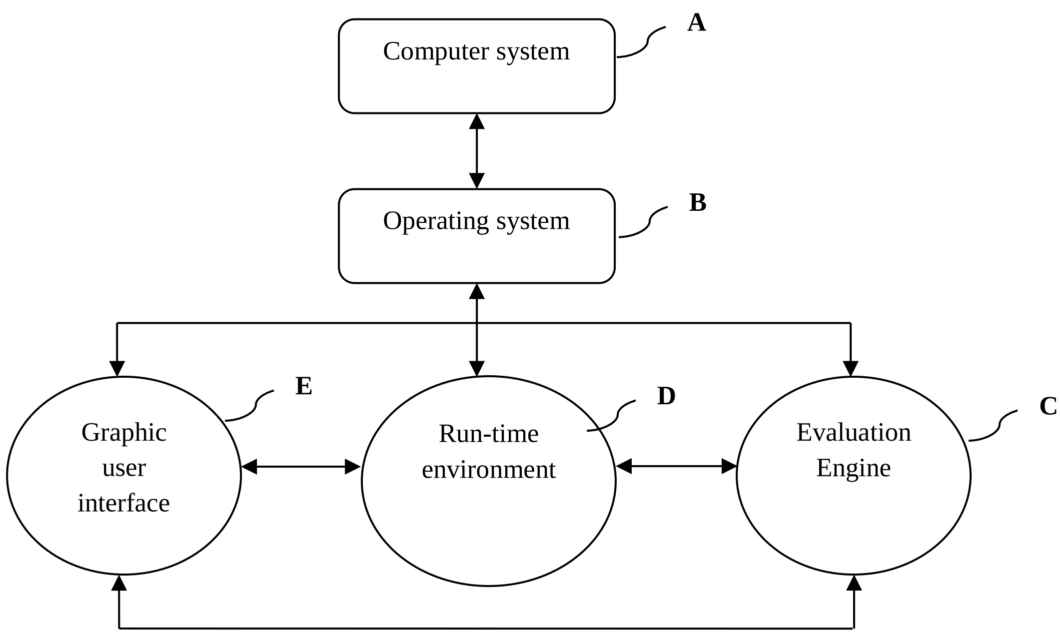


Fig: 1.6: Block diagram of a typical high level architecture for the computer system.

Fig. 2.6 is a flow chart illustrating a process for automatically evaluating a status of each risk factors, make decisions on the quality and usability of the return products, selection of best reprocessing alternative for the evaluated product, execute network optimization and display material flow routing.

6.3 Detailed description of the system

The proposed reverse logistics management tool can help to automatically evaluate the status of each RL risk factors, make decisions on the quality and usability of the return products, selection of best reprocessing alternative for the evaluated product, execute network optimization and display material flow routing. Fig. 1.6 illustrates a preferred architecture for an automatic transition evaluation apparatus of local computer system A at the points of return (PoR) or retailers. In addition, the apparatus can include an operating system B, a run-time environment D, an evaluation engine C in accordance with the inventive arrangements, and a graphical user interface E for displaying output generated and transferred by the OEM's evaluation engine 13. Fig. 2.6 is a flow chart illustrating a process for automatically evaluating a decision on the quality and usability of the return products, selection of suitable reprocessing alternative, execute network optimization and material flow routing. In a typical product return process, material can are returned and accumulated at the retailers or Points of returns (PoR) waiting processing.

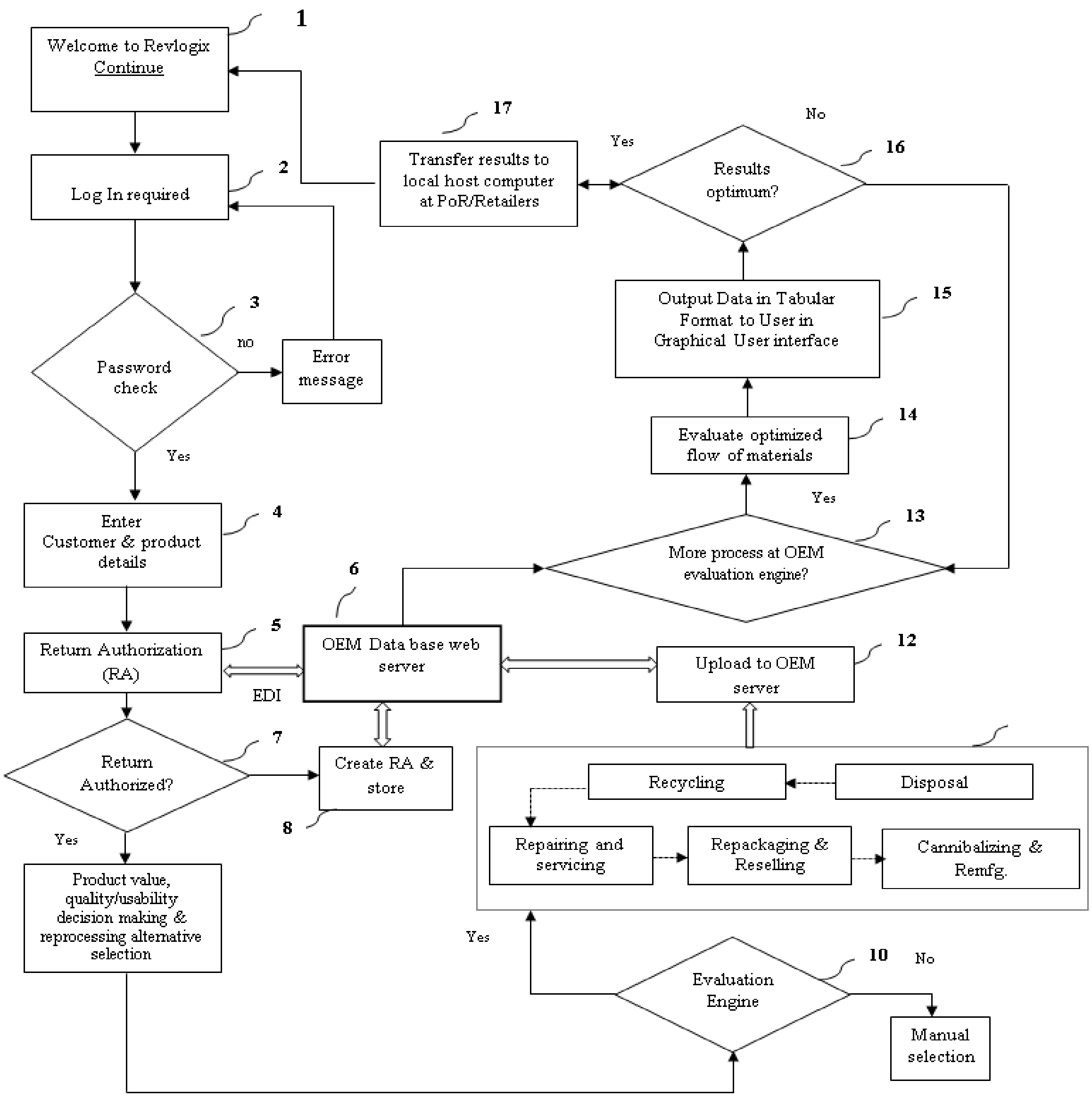


Fig: 2.6: Flow chart illustrating automatic decision process evaluation

They are usually returned due to various reasons such as repair/servicing, warranties, stock outs, defectives, order processing errors, disposal, etc. The products possesses different value, qualities and usability hence need for decision making with great speed and accuracy in order to maximize asset recovery for the OEM and credit refunds for the customers. This products subsequently can be transported to a suitable reprocessing alternative selected depending on the a set of criteria for evaluating their value, quality and usability using optimized routing that reduces the costs as determined by the centralized command at the operating company (OEM) and connected to all regional retailers/PoR thus completing the processing of materials form the retailers to the reprocessing centers. The overall re-processing of a return product may require many process steps. The evaluation of a suitable reprocessing alternative requires that information be analysed both at the process step level, and over the entire process. Minimally, the RL management tool requires the following information about a process step: the product identification, the fuzzy performance based on a set of criteria, the quantity/ volume of materials to be shipped at each process step, the fixed cost of opening and operating reprocessing centres, the utilization threshold, and the transport cost per unit product transported at each process step. Based on this information, a mathematical model and algorithm are used to generate evaluation information about the suitable reprocessing alternative and the network optimization and material flow routing that shall minimize the overall operating costs at the retailers/PoR and OEM respectively. The step by step evaluation process is as follows:

- In steps 1,2 and 3, the computer system A is logged in by the user with the correct user name and password stored in the data base for verification.
- In step 4, computer system A receives the data about a product/material returned at the retailer/PoR by the end user or supply chain partner.
- Having received the data, in step 5, the computer system, A, checks with product information stored at the OEM data base through electronic data interchange (EDI) for return authorization. Moreover, the OEM system 6 stores all the products manufactured and sold a list of data structures, the aggregation representing the entire supply chain process. If the product information is not available, the retailer creates a return authorization which is stored it in the OEM data base as per process step 8.
- In decision step 9, the computer system A can gather the product's value, quality and usability data pertinent to additional process steps in the reprocessing process using a set of evaluation criteria provided by the OEM and stored in the evaluation engine 10 .

- Subsequently, in step 11, the computer system A can evaluate the selection for a suitable reprocessing alternative for the return product. The computer system A can further submit or upload the decision selected to the OEM data base for all retailers.
- Using the evolutionary optimization algorithms, in step 13, an optimal volume/ quantity of materials and products to be transported in order to operate each reprocessing centers and retailers within the utilization threshold can be calculated.
- Finally, the evaluation engine C at the OEM's team outputs the data in tabular format to the users in the graphic user interface (GUI) and if the results are optimal they are transferred to the individual local host computers of the retailer/ PoR for action. The action will include the amount of quantities to be transported from their warehouses to the respective reprocessing centres, the routing and optimal costs involved.

By presenting the analysis results in a table, the Reverse logistics team at the OEM can investigate the cost of handling and operating the reverse supply chain, the volumes and quantities returned to the system at each retailers/PoR, the selected reprocessing alternatives for each return product and so on. Subsequently, prior to exiting in step 17, in step 14, the OEM RL team can modify the RL costs data provided in step 1 to further evaluate the effect of changes to a reverse logistics System. Thus, the reverse logistics management tool and corresponding apparatus provide a method of evaluating the current state, projecting a future advanced RL state, and predicting the performance of that RL system setup without the necessity of specialists having expertise in supply chain management systems and computer simulation.

6.4 The system functionalities and features

The proposed reverse logistics management system (Revlogix) shall streamline and expedites reverse logistics processing by systematically dealing with the condition, compliance and return scenarios that impact how a product gets handled. The end result is a system that enables companies to process units with great speed and accuracy in order to maximize asset recovery for the OEM.

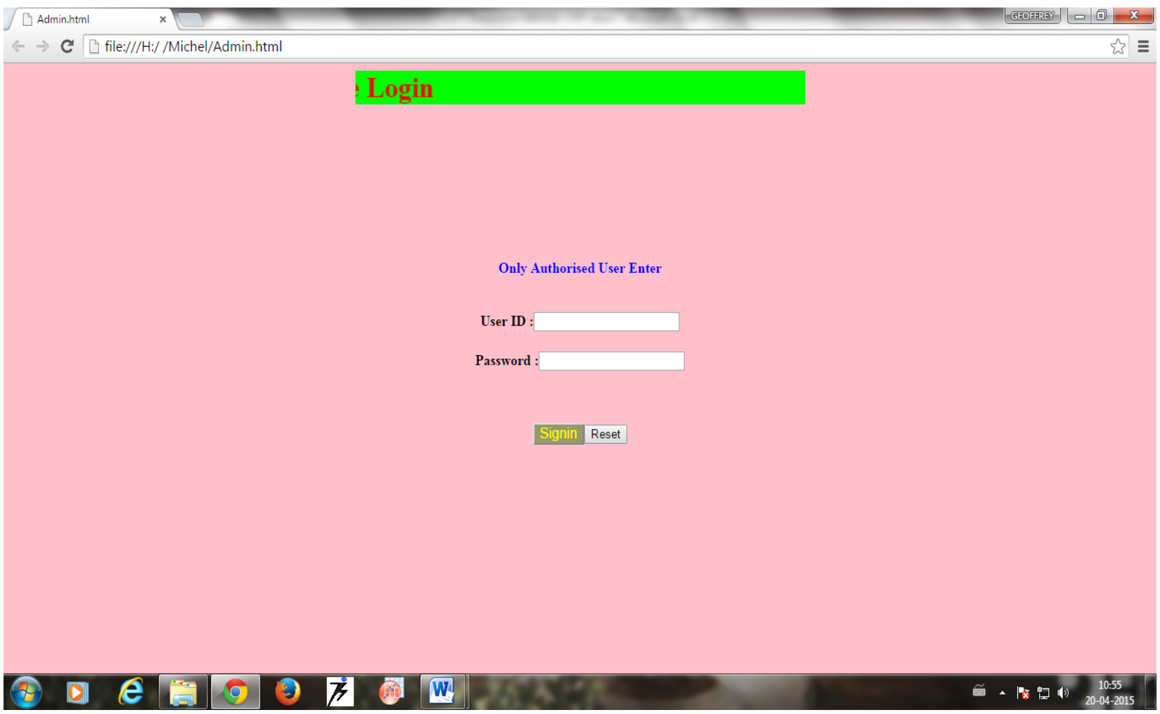
The following features and functionalities shall be embedded in the proposed RL management system:

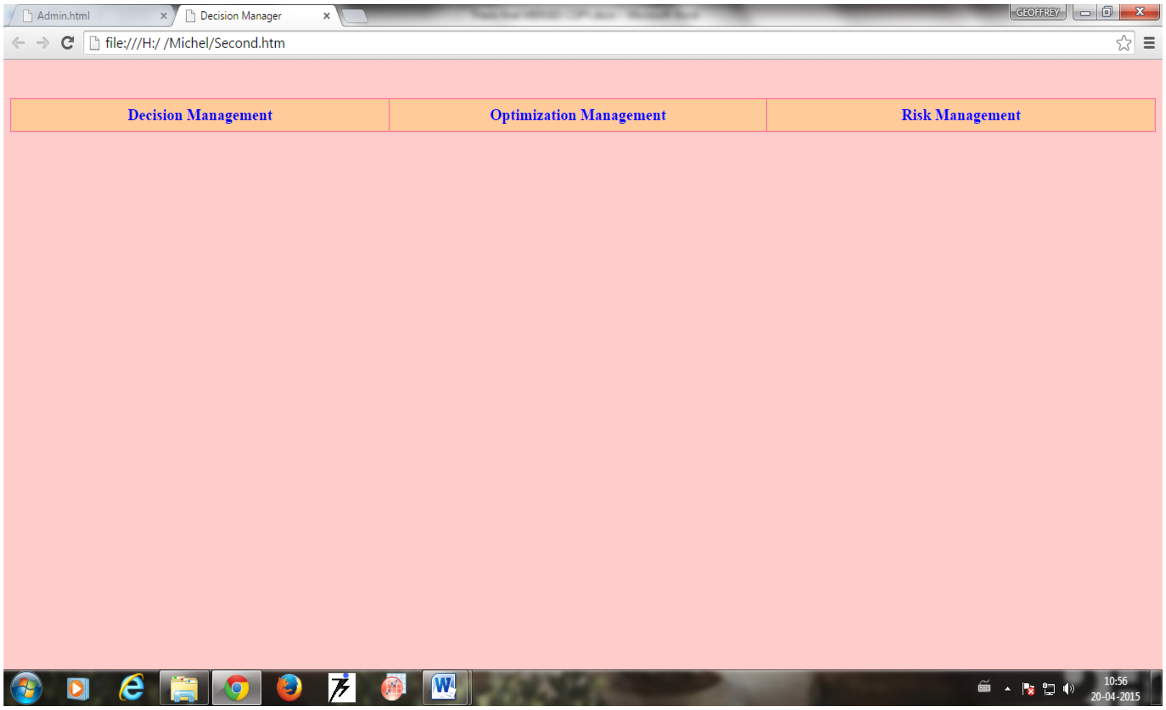
a. Risk manager: A developed automated system for identification of RL impacting factors as risk drivers that affect the various key players/ departments of a reverse logistics system (RLS) and the actions requirement plans to be implemented to optimize and effect the sustainability of an effective RL system thus providing a decision tool that would help the users choose the alternative needed to be taken when a certain risk occurs.

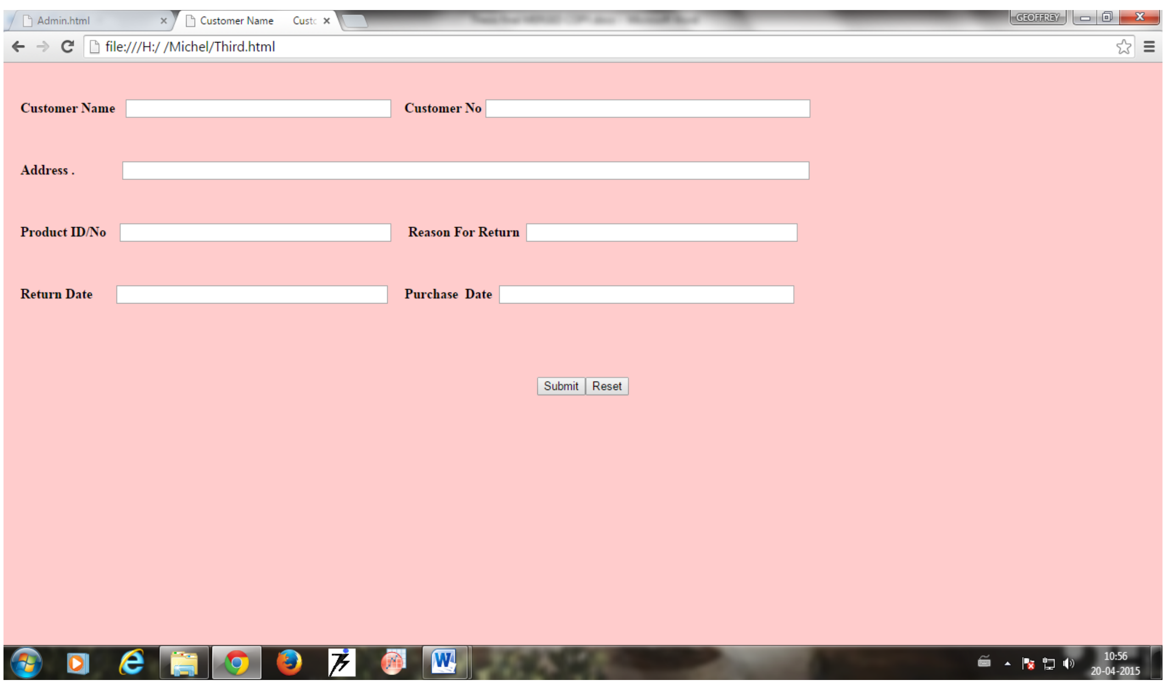
b. Decision manager: A developed decision support system for categorization of returned materials and selection of reprocessing alternatives to gain value based on their quality and usability.

c. Optimization manager: A network optimization tool for the system which can be used for network optimization to ensure controlled flow of returned goods and minimize the costs involved.

d. Graphic user Interface (GUI) for implementing the reverse logistics management system. Fig. 3.6 is a GUI showing the various graphic window functionalities of the system.




Admin.html
Decision Manager
file:///H:/ /Michel/Second.htm
Decision Management
Optimization Management
Risk Management
10:56
20-04-2015


Admin.html
Customer Name
file:///H:/ /Michel/Third.html
Customer Name
Customer No
Address .
Product ID/No
Reason For Return
Return Date
Purchase Date
Submit
Reset
10:56
20-04-2015

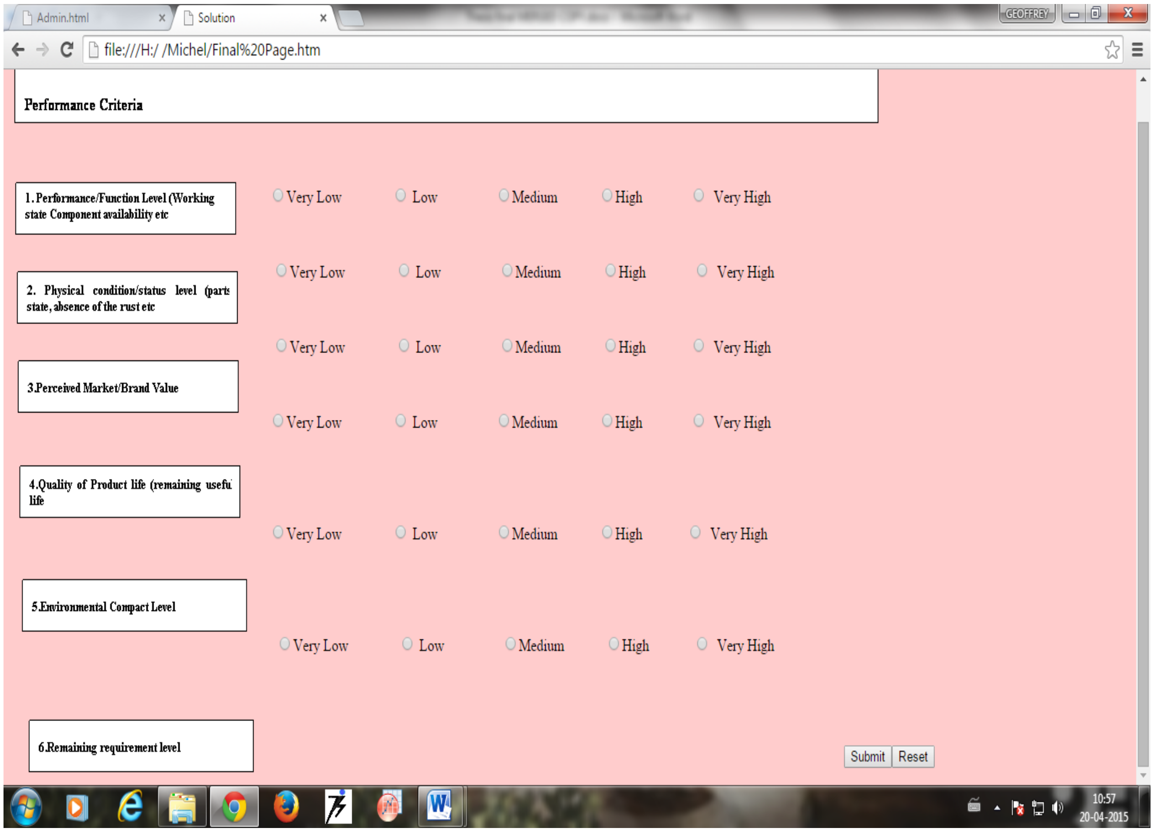


Fig. 3.6: Graphical user interfaces for various graphic window functionalities of the RL management system.

Chapter 7:
Conclusions and Recommendations

This chapter summarizes the research effort. It will review the achievements of research objective questions and present the research contribution. Additionally, it will discuss the factors that limited the research and propose topics for future research.

7.1 Achievements of research objectives

The focus of this research was to study the modelling of decision support tools for managing reverse supply chains. The following objective questions were to be achieved: How does the various supply chain risks affect the sustainability and optimum implementation of the RL program? To answer the question, this research explored the topic of reverse logistics and identified factors that tend to impact RL program performance. These factors were then used to formulate interview questions that established a basis for risk rating and ranking to establish the extent of impact of each risk. The use of information technology (IT) systems was identified as the highest ranking risk factor. Next, we examined how can the returned products can be sorted, categorized and selection for the best reprocessing alternative be achieved at the points of return (PoR)/ retailers? To answer this question, a decision support system (DSS) was developed based on Multi-attribute decision making (MADM) fuzzy approach for categorization of returned materials and selection of reprocessing alternatives to gain value. Further, the response of the DSS to various return scenarios was achieved by conducting a sensitivity and parametric analysis on the proposed MADM to unveil the output response of the developed methodologies. This research also introduced the subject of RL networks optimization to further explore the controlled flow of returned goods and minimize the costs involved as well as resource commitment using evolutionary optimization techniques and resource-based theory. Finally, a RL management systems can be developed that can be used to achieve implementation of the robust methodologies for RL risk ranking, decision making and optimization. This research proposes and develops a simple to implement web-based reverse logistics management system that can interlink all PoR/retailers and OEM through which information on RL risks assessment, decisions on the quality and usability of the return products, network optimization and material flow routing can processed and shared by all supply chain partners.

7.2 Research contributions

The proposed research methodologies uses existing principles of risk management, multi-criterial decision making (MADM), fuzzy sets and operations research optimization techniques in supply chain; however, it is unique because the characteristics of the new decision tools are solely developed for the reverse supply chain. Supply chain management methods in the past have been designed for familiar forward supply networks where materials are sent from the manufacturer to the customer. In the flow of returned products, several customers return new or used products to the manufacturer, which then are sent to specific locations based on the quality and usability of the product.

In this research, the variety of different factors that influence on the performance and efficiency of reverse logistics system risks in the reverse supply chain were analysed, quantified, and a framework for categorizing different risk factors proposed on the basis of a distinguished range of risk ratings (crisp). Consequently, an action requirement plan has been suggested for providing guidelines for the managers to successfully manage the risk in the context of reverse logistics. The research further aimed at developing a faster, 'localized' and easy-to-use decision-making framework that can be used to hasten categorization and grading of returns at the point of return (POR)/ retailers based on the quality and usability of the product. The model proposed the use of fuzzy linguistic process to pass a judgment on the perceived depreciation, quality and suitability of the return product based on the source, reasons for return and perceived depreciation, i.e. physical depreciation level, Time depreciation, Performance depreciation and Market depreciation, environmental impact and legislation requirements to remotely decide the suitable recovery and disposal alternative. Further, the research focuses on RL networks optimization to further offer the controlled flow of returned goods and minimize the costs involved as well as resource commitment using evolutionary optimization techniques and resource-based theory. Finally, it proposes and develops a simple to implement web-based reverse logistics management framework that can interlink all PoR/retailers and OEM through which information on RL risks assessment, decisions on the quality and usability of the return products, network optimization and material flow routing can processed and shared by all supply chain partners.

The proposed RL management tools allows the users to quantify and locate all risks, make decisions on the alternative needed to be taken when a certain risk occurs based on the action plans, make decisions on the best reprocessing alternative and optimize the supply chain networks .These features allow the user to achieve the overlying goal of managing the reverse logistics and developing alternatives quickly and efficiently in the least amount of time. Since the tools may be used for different organizations, many different factors affect the parameters that lie in the reverse network of the organization. Therefore, the effectiveness of these tools will vary among different companies.

7.3 Future research

In this research, the variety of different factors that influence on the performance and efficiency of reverse logistics system risks in the reverse supply chain were analysed, quantified, and a framework for categorizing different risk factors proposed on the basis of a distinguished range of risk ratings (crisp). Consequently, an action requirement plan has been suggested for providing guidelines for the managers to successfully manage the risk in the context of reverse logistics. The research further aimed at developing a faster, ‘localized’ and easy-to-use decision-making framework that can be used to hasten categorization and grading of returns at the point of return (POR)/ retailers based on the quality and usability of the product. The model proposed the use of fuzzy linguistic process to pass a judgment on the perceived depreciation, quality and suitability of the return product based on the source, reasons for return and perceived depreciation, i.e. physical depreciation level, Time depreciation, Performance depreciation and Market depreciation, environmental impact and legislation requirements to remotely decide the suitable recovery and disposal alternative. Further, the research focuses on RL networks optimization to further offer the controlled flow of returned goods and minimize the costs involved as well as resource commitment using evolutionary optimization techniques and resource-based theory. Finally, it proposes and develops a simple to implement web-based reverse logistics management framework that can interlink all PoR/retailers and OEM through which information on RL risks assessment, decisions on the quality and usability of the return products, network optimization and material flow routing can processed and shared by all supply chain partners.

The framework may be further developed and tested among many organizations in the fast moving commodity goods (FMCG) industry and high-tech industry sector, in order to validate the effectiveness. In addition, the reverse logistics management tool may be generalized and expanded for the utilization of different industries to include other aspects of RL such as recovery and disposal strategies to deal with returned goods/ products, RL relationships through marketing, Inventory management, RL planning and control and Information technology (DeBrito et al., 2002). Overtime, the framework may be continuously improved by the progression of future developments such as advanced formulations, computer-aided models, or user-based software.

Once the reverse logistics management system has been implemented, the next step that should be taken is developing alternatives for the product life cycle tracking/ tracing, secondary markets demand forecasting, new parts requirements for remanufacturing inventories and so on. Further, there will be need to develop the system as a E-manufacturing system linking the customer (through the marketing persons) to the factory (several plants) through reverse logistics on to process planning, material flow, inventory control and cost estimates by internet technology. Online technology provides a low-cost, extremely efficient way to display merchandise, attract customers and handle purchase orders and customer complaints and returns. This would be a very high level analytical process that may be time consuming, costly, and company specific. It may be beneficial in situations to have a model that more accurately reflects the decisions needed to be made in time of product returns.

7.4 Summary

In this era of global business competition, companies must adopt reverse logistics strategies that shall give them strategic advantage as well as a competitive edge. Businesses are now geared towards increased revenue, reduced costs and improved collaboration through elimination of waste, improvement of quality, continuous improvement and green manufacturing. Customer satisfaction and sustainability hold a high priority in the eyes of organizations today. For most companies, as product sales increase, so do product returns, which in tum has companies' eager to maintain their customer satisfaction ratings. The forward and reverse supply chains have unique characteristics that vary among different organizations. Most organizations manage and quantify various parameters in the forward supply chain by utilizing various available supply chain management systems. These supply chain management system have been developed solely for the forward supply chain. Currently, a framework does not exist to implement management in the reverse supply chain. This research presented the development and implementation of various methodologies to be used in various reverse logistics management aspects such as risks, decision making and optimization.

Implementation of these system at ABZ computer retailing Company demonstrates how the reverse logistics management tool is used in order to be beneficial to the organization. The system is developed to be easily implemented at minimal cost and serves as a valuable tool for personnel faced with important and costly decisions regarding risk occurrence, reprocessing alternative selection and network optimization in the reverse supply chain network.

The framework proposed will assist the user such that they have the ability to identify, quantify, and manage risks, make decisions on the best reprocessing alternative and optimize the networks in the reverse supply chain, without previous reverse logistics management experience. By analysing several formulation methods, the proposed methodologies of analysing the reverse logistics provide a vital tool that will help the users effectively manage their reverse logistics.

In order to validate the effectiveness of the formulated framework, measures need to be made to check the benefits they have on the organizations. The most significant measure to be made is time. By using the methodologies developed, and referencing the reverse logistics management visual model developed, the user should save a lot of time finding the impact of the various risk factors within the organization, categorizing and selecting the appropriate reprocessing alternatives as well as finding the optimum network routing that shall minimize the costs of the reverse supply chain. By saving time, the organization is avoiding costs, which is the main purpose of the developed methodologies. Cost avoidance is important in any organization, and by implementing the framework, the value of processing time for return products correlates with cost savings as well as maximizing the product recovery value.

8. References

1. Abdullah, L. M., and Verner, J. M. (2012). Analysis and application of an outsourcing risk framework. *The Journal of Systems and Software*, 85, 1930–1952.
2. Ahluwalia, Poonam K., Arvind K. Nema, 2006, "Multi-objective Reverse Logistics Model for Integrated Computer Waste Management." *Waste Management & Research*. 24: 514-525.
3. Alumur, S. A., Nickel, S., Saldanha-da-Gama F. & Verter, V., 2012, 'Multi-period reverse logistics network design', *European Journal of Operational Research,* 220, 67-78.
4. Amiri, A., 2006, "Designing a distribution network in a supply chain system: Formulation and efficient solution procedure," *European journal of operational research,* vol. 171, pp. 567-576.
5. Bakker, F. de and A. Nijhof. "Responsible chain management: a capability assessment framework," *Business Strategy and the Environment*, (11), 2002, pp. 63–75.
6. Banisalam, S., 2008, 'A Risk Management Tool for reverse Supply Chain network', *California Polytechnic State University*, pp.2-36.
7. Barros, A. I.; Dekker, R.; Scholten V., 1996, 'A two–level network for recycling sand: A case study', *Econometric Institute Report Series 9673/A*, Erasmus University Rotterdam, The Netherlands.
8. Bastiaan, J.; Peter Schuur; Marisa P. DeBrito, 2010, 'A reverse logistics diagnostic tool: the case of the consumer electronics industry', *The International Journal for advanced manufacturing technology*, 47, pp.495–513.
9. Bautista, J.; Fernández, E. and Pereira, J., 2008, 'Solving an urban waste collection problem using ants heuristics', *Journal for Computers & Operations Research* 35:pp. 3020 – 3033.
10. Beamon, Benita M., 1999, 'Designing the Green Supply Chain', *Logistics Information Management*, 12: pp.332-342.
11. Berkeley, D.; Humphreys, P.C. and Thomas, R.D., 1991, 'Project risk action management', *Construction management and economics*, Vol. 9, pp 3-17.
12. Bernon M.; Cullen J., 2007, 'An integrated approach to managing reverse logistics', International *Journal of Logistics: Research and Applications*, Vol. 10, pp. 41-56.
13. Brauers, W. K., 2004a, 'Multi-objective optimization for facilities management', *Journal of Business Economics and Management,* 5 (4): 173–182.
14. Brauers, W. K. M.; Zavadskas, E. K. 2006, 'The MOORA method and its application to privatization in Transition economy', *Control and Cybernetics*, 35 (2): 443–468.

15. Brauers, W. K. M., 2004b, ‘Optimization methods for a stakeholder society, a revolution in economic thinking by multi-objective optimization. Boston: *Kluwer Academic Publishers*. p.342. http://dx.doi.org/10.1007/978-1-4419-9178-2.

16. Carter, C.R. and Rogers, D.S., “A framework of sustainable supply chain management: moving towards new theory,” *International Journal of Physical Distribution & Logistics Management,* (38:5), 2008, pp. 360–387.

17. Caruso, C.; Colorni, A.; Paruccini, M., 1993,’The regional urban solid waste management system: A modelling approach’, *European Journal of Operational Research*, 70:16-30.

18. Castro, E. D. and Cochran, J. K., 1996, ‘Optimal short horizon distribution operations in reusable container systems’, *The journal for OR society* 47(1); pp. 48-60.

19. Chang, C. L., 2010, ‘A modified vikor method for multiple criteria analysis’, *Environmental Monitoring and Assessment*, 168, 339–344.

20 Chang, Kuei-Feng and Lin, I-Chieh, 2013, ‘A Study to Explore How Disposing Old-Goods Factors Influence Consumer’s Behavior’, *Journal of Advanced Management Science Vol. 1, No. 4, December 2013.*

20. Chen, C. T. 2000. Extensions of the TOPSIS for group decision-making under fuzzy environment, *Fuzzy Sets and Systems* 114(1): 1–9.

21. Chen, C.-B. and Klein, C.M., “A simple approach to ranking a group of aggregated fuzzy utilities, *IEEE Trans. Syst. Man Cybern.--Part B: Cybernetics* 27, 26-35, (1997).

22. Chen, L. and Lu, H., 2001, ‘An Approximate Approach for Ranking Fuzzy Numbers Based on Left and Right Dominance’, *Int. Journal for computers and mathematics with applications,* 41 (2001) 1589-1602.

23. Chen, S. H., 1985, “Ranking fuzzy numbers with maximizing set and minimizing set”, *Fuzzy Sets and Systems*, 17, pp. 113–129.

24. Chen, Shi-jay and Chen Shyi-Ming, 2007, “Fuzzy risk analysis based on the ranking of generalized trapezoidal fuzzy numbers”, *Appl. Intell*. (2007) 26:1–11.

25. Chitrasen, S. ; Datta, S.; Mahapatra, S., 2012, ‘Application of Fuzzy Based VIKOR Approach for Multi Attribute Group Decision Making (MAGDM): A Case Study in Supplier Selection’, *Decision making in manufacturing and services*, Vol. 6, No. 1 pp. 25-39.

26. Chitrasen, S.; Datta, S.; and Mahapatra, S., 2014, “Risk assessment in IT outsourcing using fuzzy decision-making approach: An Indian perspective”, *Expert Systems with Applications* 41 (2014) 4010–4022.

27. Choi, Tsan-Ming; Duan Li; Houmin Van and Chun-Hung Chiu, 2008, "Channel

Coordination in Supply Chains with Agents Having Mean-Variance Objectives", *Omega*, 36: 565-576.

28. Chopra, Sunil, Peter Meindl, 2002, “Supply Chain Management: Strategy, Planning, and Operation." *IIE Transactions*, 34: 221-222.
29. Chouinard, M.,2008, ‘A stochastic programming approach for designing supply loops’, The *International Journal of production economics* v. 113 pp. 557-577.
30. DeBrito, M. P.; Simme, D. P. Flapper; Rommert Dekker, 2002, ‘Reverse Logistics: a review of case studies’, *Econometric Institute Report* EI 2002-21Version.
31. Diaz, A.; Claes, B.; Solís, L. and Lorenzo, O., 2011, ‘Benchmarking Logistics and Supply Chain Practices in Spain’, *International Journal for Supply Chain Forum*, Vol. 12 -N°2 pp. 82-90.
32. Daugherty, P.J., Richey, R.G., Genchev, S.E. and Chen, H. 2005, "Reverse logistics: superior performance through focused resource commitments to information technology", *Transportation Research: Part E,* Vol. 41 No. 2, pp. 77-92.
33. Ding, Li-Ping; Feng, Yi-Xiong; Jian-Rong Tan and Yi-Cong Gao, 2010, ‘A new multi-objective ant colony algorithm for solving the disassembly line balancing problem’ *Int. J. Adv. Manuf. Technol*. 48:pp. 761–771.
34. Dragisa, Stanujkic, 2013, ‘An extension of the MOORA method for solving fuzzy decision making problems’, *Technological and Economic Development of Economy*, 19:sup1, S228-S255.
35. Elkington, J., 1997, ‘Cannibals with Forks: The Triple Bottom Line of 21st Century Business, Capstone, *Oxford*.
36. Ene, S. and Öztürk, N., 2014, ‘Open loop reverse supply chain network design’, *Social and Behavioural Sciences*, 109, pp. 1110 – 1115.
37. Ertuğrul, I.; Karakaşoğlu, N., 2007, ‘Comparison of fuzzy AHP and fuzzy TOPSIS methods for facility location selection’, *Int J Adv Manuf Technol* (2008) 39:783–795.
38. Fleischmann, M.; Bloemhof-Ruwaard, J.M.; Dekker, R.; VAN DER Laan, J.A.E.E.; VAN Nunen and L.M. VAN Wassenhov, 1997, "Quantitative models for reverse logistics: an overview", *European Journal of Operational Research*, 103(1), pp. 1-17.
39. Fleischmann M., H.R. Krikke, R. Dekker and S. D. P. Flapper (1999), ‘A characterisation of logistics networks for product recovery’, *Omega* 28(6):653-666.
40. Fleischmann, M.; J.A.E.E. VAN Nunen and Grave, B., 2003, "Integrating closed-loop supply chains and spare-parts management at IBM", *Interfaces* 33(6); pp. 44-56.
41. Ghezavati, V. and Nia, N. S., 2014, ‘Development of an optimization model for product returns

using genetic algorithms and simulated annealing', *Int. J. of soft computing*,

42. Gunasekaran, A., Patel, C. and E. Tirtiroglu, 2001, "Performance measures and metrics in a supply chain environment," *International Journal of Operations Production Management*, (21:1/2): pp. 71–87.

43. Grewal, S. S.; Shah, M. and Salunke, S., 2009, 'Risk Management reverse supply chain*', San Jose State University*. 60-73.

44. Gooley, Toby B., 1998, "Reverse Logistics: Five Steps to Success." *Logistics Management and Distribution Report*, 37:pp. 45-50.

45. Guide, Jr., V.D.R., (2000), 'Production planning and control for remanufacturing: industry practice and research needs', *Journal of Operations Management*, vol. 18, pp. 467-483.

46. Horvath, Philip A., Chad W. Autry, and William E. Wilcox. "Liquidity of Implication of Reverse Logistics for Retailers: A Markov Chain Approach." *Journal of Retailing*. 81 (2007): 191-203.

47. Hwang, C. L.; Yoon K., 1981, 'Multiple attributes decision making methods and applications', *Springer*, Berlin.

48. Jain, R., 1976, ' Decision making in the presence of fuzzy variables', *IEEE Transactions on Systems Man and Cybernetics*, 6, 698–703.

49. Kahramana, C.; Ufuk Cebecia; Ruan, D., 2002, 'Multi-attribute comparison of catering service companies using fuzzy AHP: The case of Turkey', *Int. J. Production Economics* 87 p. 171–184.

50. Kaufmann, A., & Gupta, M. M. (1991), 'Introduction to fuzzy arithmetic: Theory and applications', *New York: Van Nostand Reinhold*.

51. Kärnä, A. and E. Heiskanen, 1998, "The challenge of 'product chain' thinking for products development and design – the example for electrical and electronic products", The *Journal for Sustainable Product Design*, (4): pp. 26–36.

52. Kim, K. and Park, K., 1990, "Ranking fuzzy numbers with index of optimism", *Fuzzy Sets and Systems* 35, 143-150.

53. Kopicky, R.J., Berg, M.J., Legg, L., Dasappa, V. and Maggioni, C.,(1993), 'Reuse and Recycling: Reverse Logistics Opportunities', *Council of Logistics Management*, Oak Brook,IL.

54. Kostecki, M., (1998), 'The durable use of consumer products: new options for business and consumption', *Kluwer Academic Publishers*, Dordrecht, The Netherlands

55. Kou, Y.-C., & Lu, S.-T., 2013, 'Using fuzzy multiple criteria decision making approach to enhance risk assessment for metropolitan construction projects', *International*

Journal of Project Management, 31, 602–614.

56. Krikke, H.R.; Kooi, E.J. and Schuur, P.c., 1999, 'Network design in reverse logistics: a quantitative model', *Erasmus University Rotterdam management report* No. 06.

57. Krikke, H. R., 1998, 'Recovery strategies and reverse logistics network design', [S.l.]: [s.n.].

58. Kroon, Leo; Gaby Vrijens, 1995, 'Returnable containers: an example of reverse logistics', *International Journal of Physical Distribution & Logistics Management, Vol. 25, Iss. 2*: pp. 56 – 68.

59. Kuei-Feng Chang; I-Chieh Lin, 2013, 'A Study to Explore How Disposing Old-Goods Factors Influence Consumer's Behaviour', *Journal of Advanced Management Science Vol. 1, No. 4*.

60. Lee, D. and Dong, M., 2009, 'Dynamic network design for reverse logistics operations under uncertainty', *Transportation Research*: Part E 45(1):61–71.

61. Lee, Jeong-Eun and Lee, Kang-Dae, 2012, 'Modelling and optimization of closed-loop supply chain considering order or next arrival of goods', *Int. J. of innovative computing, information and control*, Vol. 9: pp. 3639-3654.

62. Lee, JE; Gen, M.; Rhee, KG, 2009, 'Network model and optimization of reverse logistics by hybrid genetic algorithm', *Comput. Ind. Eng.* 56(3):951–964.

63. Mangesh, S. G. and Anand, M. D., 2005, 'Optimal Remanufacturing Strategies in Reverse Logistics', *TACTiCS – TCS Technical Architects*' Conference'05.

64. McGovern, S. M. and Gupta, S. M., 2006, 'Ant colony optimization for disassembly sequencing
with multiple objectives', *Int. J. Adv. Manuf. Technol*., 30: pp. 481–496.

65. Min, H.; Ko, H. J. ; Ko, C. S., 2006a, 'A genetic algorithm approach to developing the multi-echelon reverse logistics network for product returns', *Omega* 34(1):56–69.

66. Modarres, M., & Nezhad, S. S., 2001, "Ranking fuzzy numbers by preference ratio", *Fuzzy Sets and Systems*, 118(3), 429–436.

67. Moeinzadeh, P.; Hajfathaliha, A., 2010, 'A combined fuzzy decision making approach to supply chain risk assessment', *International Journal of Human and Social Sciences,* 5 (13), 859–875.

68. Mitchell, V.W., 1995, "Organizational Risk Perception and Reduction", *British Journal of Management*, 6: pp.115-133.

69. New, S. J., 1997, "The scope of supply chain management research," *Supply Chain Management: An International Review*, (2:1): pp. 15–22.

70. Opricovic, S.; Tzeng, G. H., 2004, 'Compromise solution by MCDM methods: A

comparative analysis of VIKOR and TOPSIS', *European Journal of Operational Research 156(2)*, 445–455.

71. Pishvaee, M. S.; Kianfar, K. and Karimi, B., 2010, 'Reverse logistics network design using simulated annealing', Int J. Adv. Manuf. Technol.,v. 47:pp. 269–281.

72. Ravi, V.; Shankar, R.; Tiwari, M., 2005, 'Analysing alternatives in reverse logistics for end-of-life computers: ANP and balanced scorecard approach', *Computers & Industrial Engineering 48,*327–356.

73. Rogers, D. S.; Tibben-Lembke, S. Ronald, 1999, 'Going backwards: Reverse logistics trends and practices'. *Pittsburgh: RLEC Press*.

74. Rogers, D. S.; Tibben-Lembke, S. Ronald, 2001, 'An examination of Reverse logistics practices', *Journal for Business logistics, vol. 22, No. 2*.

75. Rogers, D. S.; Douglas, M. Lambert; Keely, L. Croxton; Sebastián, J. García-Dastugue, 2002, 'The Returns Management Process', *The International Journal of Logistics Management, Vol. 13, Iss* 2 pp. 1 – 18.

76. Saaty, T. L., 1980, 'The analytic hierarchy process'. *McGraw-Hill, New York*.

77. Sadrnia, A., Soltani, H. R., Zulkifli, N., Ismail, N. and M. K. A. Ariffin, 2014, 'A Review of Nature-Based algorithms applications in Green Supply Chain Problems', *IACSIT International Journal of Engineering and Technolog*y, Vol. 6, No. 3.pp. 204-211.

78. Sanayei, A.; Farid Mousavi, S.; Yazdankhah, A., 2010, 'Group decision making process for supplier selection with vikor under fuzzy environment', *Expert Systems with Applications,* 37(1), 24–30.

79. Sarkis, J. "Benchmarking for agility," *Benchmarking: An International Journal*, (8:2), 2001a, pp. 88–107.

80. Saskumar, P.; Noorul, A., 2010, 'Integration of closed loop distribution supply chain network and 3PRLP selection for the case of battery recycling', *International Journal of Production Research*, 49:11, 3363-3385.

81. Seuring, S. and Müller, M., 2008, 'From a literature review to a conceptual framework for sustainable supply chain management', Journal *of Cleaner Production*, (16) : pp. 1699–1710.

82. Shyur, Hyan-Jyh, 2008, "A Quantitative Model for Aviation Safety Risk Assessment." *Computers & Industrial Engineerin*g, 54: 34-44.

83. Soleiman, H. and Govindan, K., 2014, 'Reverse logistics network design and planning utilizing conditional value at risk', *European Journal of Operational Research,* 237, pp. 487–497.

84. Srivastava, S. K., 2007, 'Network design for reverse logistics', *International Journal of Logistics Management*, Vol. 36:pp. 535 – 548.

85. Stock, J.R., 1992, ‘Reverse Logistics, Council of Logistics Management’, *Oak Brook, IL*.

86. Stock, J. R., 1998, ‘Development and implemmentation of Reverse Logistics programs’, *Council of Logistics Management*, Oak Brook, IL.

87. Teuscher, P., Grüninger, B. and N. Ferdinand, 2006, “Risk management in sustainable supply chain management (SSCM): lessons learnt from the case of GMO-free soybeans,” *Corporate Social Responsibility and Environmental Management*, (13:1), pp. 1–10.

88. Tohamy, N., 2008, "Predictive Markets: Harvesting the Wisdom of Crowds to Manage Supply Chain Risk", *available from www.amrresearch.com*.

89. Thierry, M.; Solomon, M.; Nunen, J. V.; Wassenhov, L. N., 1995, ‘Strategic Issues in Product Recovery Management’, *California Management Review,* Vol. 37, No. 2 winter 1995.

90. Thorani, Y. L. P., Rao, P. P. B., & Shankar, N. R., 2012a, ‘Ordering generalized trapezoidal fuzzy numbers using orthocenter of centroids’, *International Journal of Algebra*, 6, 1069–1085.

91. Thorani, Y. L. P., Rao, P. P. B., & Shankar, N. R., 2012b, ‘Ordering generalized trapezoidal fuzzy numbers’, *International Journal of Contemporary Mathematical Sciences*, 7, 555–573.

92. Vachon, S. and Klassen, R.D., 2006, “Extending green practices across the supply chain: the impact of upstream and downstream integration,” *International Journal of Operations & Production Management*, (26:7), pp. 795–821.

93. Vinay, V. P. and Sridharan, R., 2013, ‘Taguchi method for parameter design in ACO algorithm
for distribution–allocation in a two-stage supply chain’, *Int. J. Adv. Manuf. Technol*. 64:pp. 1333–1343.

94. Waddock, S. and Bodwell, C., 2004, “Managing responsibility: what can be learned from the quality movement?” *California Management Review*, (47:1), pp. 25–37.

95. Wadhwa, S.; Madaan, J.; Chan, F., 2007, ‘Flexible decision modelling of reverse logistics system: A value adding MCDM approach for alternative selection’, *Robotics and Computer-Integrated Manufacturing* 25 (2009) 460–469.

96. Wang, X., & Kerre, E. E. (2001a). Reasonable properties for the ordering of fuzzy quantities (I). Fuzzy Sets and Systems, 118, 375–385.

97. Wang, X., & Kerre, E. E. (2001b). Reasonable properties for the ordering of fuzzy quantities (II). *Fuzzy Sets and Systems*, 118, 387–405.

98. Wang, D.; Zhuang, H.; Bai, Y., 2006, ‘Fundamentals of Fuzzy Logic Control – Fuzzy Sets, Fuzzy Rules and Defuzzification’, *Advanced fuzzy Logic technologies for industrial application*, Vol.25, p.334.

99. Wang, Ying-Ming, Jun Liu, and Taha M.S. Elhag. "An Integrated AHP-DEA Methodology for Bridge Risk Assessment." *Computers & Industrial Engineering*. 54 (2008): 513-525.

100. Welford, R. and S. Frost. “Corporate social responsibility in Asian supply chains,” *Corporate Social Responsibility and Environmental Management*, (13:3), 2006, pp. 166–176.

101. Williams, T. M., “Risk-management infrastructures”, *Int’ Project Management,* 1993, 11 (1) pp 5-10.

102. Wu, M.; Liu, Z. J., 2011, ‘The supplier selection application based on two methods: VIKOR algorithm with entropy method and Fuzzy TOPSIS with vague sets method’, *International Journal of Management Science and Engineering Management* 6 (2), p. 936–946.

103. Xian-cheng, Z.; Zhi-xue, Z.; Kai-jun, Z. and Cai-hong, H., 2012, ‘Remanufacturing closed-loop supply chain network design based on genetic particle swarm optimization algorithm’, *J. Cent. South Univ*. Vol. 19: pp. 482−487.

104. Yanchao, L.; Xiaoyan, L. and Litao, L., 2008, "Multi-objective optimization of reverse logistics network based on improved particle swarm optimization," in *Proc. 7th World Congress on Intelligent Control and Automation, WCICA 2008.* pp. 7476-7480.

105. Yu, P., 1973, ‘A class of solutions for group decision problems’, *Management Science* 19 (8), 936–946.

106. Zadeh, L. A., 1965, ‘Fuzzy sets’, *Information and Control* 8(3): pp. 338–353.

107. Zadeh, L. A., 1975a, ‘The concept of linguistic variable and its application to approximate reasoning – I’, *Information Sciences* 8 (3): 199–249.

108. Zhen-Hua, Che ; Chiang, Tzu-And Yu-Chun Kuo, 2012, ‘Multi-echelon reverse supply chain network design with specified returns using PSO’, *International Journal of Innovative Computing, Information and Control,* Vol. 8, Number 10 (A).pp. 6719-6733.

Appendices

Appendix 1.3: General survey invitation letter

…………………………………………………………………………………………………..

General survey Letter

Microsoft Word 2010 Doc

…………………………………………………………………………………………………

TO: 28th February, 2015

Dear Sir/Madam,

REVERSE LOGISTICS RISK ASSESSMENT SURVEY

I am a graduate student at the National Institute of Technology (NIT) -Rourkela, India, working on a research project on 'Design and analysis of reverse logistics in supply chain systems' under the supervision of Prof. Siba Sankar Mahapatra from the department of Mechanical Engineering.

Your assistance is critical to understanding the extents of the Risks involved in the reverse supply chain network and the measures carried out to mitigate those risks by the companies you represent or by various companies that undertake reverse logistics activities. Please assist me to have the attached questionnaire on http://goo.gl/forms/pKbtqEFfpt filled and returned online at your earliest convenience. If you are unable to complete the questionnaire, please forward it to the appropriate person in your organization.

All responses shall be kept strictly confidential. Only I and my supervisor shall view any of the raw data and no company data will be identified in our final thesis report. Should you have any questions, please call us at (+91)7750853518. If you wish to receive a copy of the survey results, please indicate 'Yes' in the questionnaire.

I sincerely appreciate your help in filling this questionnaire. Your prompt response is critical to completing this research work.

Thank you again for your kind assistance.

Omosa B Michael Geoffrey

M. Tech. Student

Mechanical Engineering Department-NIT-Rourkela

Appendix 1.5: LINGO 15 RL network Optimization algorithm

```
MODEL:
TITLE Optimum RL Network design and analysis;
 ! Reverse Logistics Problem;
 SETS:
    RETAILERS1 / BBSR, SNDGR, BRPD, BHAWPTN/ :
SUPPLY_REPCENTRES;!,OPENRET,RETFXD_CST;

    REP_CENTRES / SNPR, JJPR, PLKMD/: REPFXD_CST, CAP_REPCENTRES,OPEN1;

    ARCS1(REP_CENTRES,RETAILERS1): COST_REPCENTRES, VOL_REPCENTRES;

    RETAILERS2 / BBSR, SNDGR, BRPD, BHAWPTN/ :
SUPPLY_RESELLCENTRES;!,OPENRET,RETFXD_CST;

    RESELLCENTRES / SMPR, BHSWR, JGSPR/: RESFXD_CST,
CAP_RESELLCENTRES,OPEN2;

    ARCS2( RESELLCENTRES,RETAILERS2)  :
COST_RESELLCENTRES,VOL_RESELLCENTRES;

    RETAILERS3 / BBSR, SNDGR, BRPD, BHAWPTN/ :
SUPPLY_REMFGCENTRES;!,OPENRET,RETFXD_CST;

    REMFGCENTRES / PURI, NPDA, MKNGR/: REMFGFXD_CST,
CAP_REMFGCENTRES,OPEN3;

    ARCS3( REMFGCENTRES,RETAILERS3)  :
COST_REMFGCENTRES,VOL_REMFGCENTRES;

    RETAILERS4 / BBSR, SNDGR, BRPD, BHAWPTN/ :
SUP_RECYCENTRES;!,OPENRET,RETFXD_CST;

    RECYCENTRES / BHGR, KRPT, CHTPR/: RECYFXD_CST,
CAP_RECYCENTRES,OPEN4;

    ARCS4( RECYCENTRES,RETAILERS4)  : COST_RECYCENTRES,VOL_RECYCENTRES;

    RETAILERS5 / BBSR, SNDGR, BRPD, BHAWPTN/ :
SUP_DISPCENTRES;!,OPENRET,RETFXD_CST;

    DISPCENTRES / JSGPR, RYGD, BHDK/: DISPFXD_CST,
CAP_DISPCENTRES,OPEN5;

    ARCS5( DISPCENTRES,RETAILERS5)  : COST_DISPCENTRES,VOL_DISPCENTRES;

 ENDSETS

!SUBMODEL minimize total cost:

 ! The objective;
    [TTL_COST] MIN = @SUM( ARCS1: COST_REPCENTRES * VOL_REPCENTRES) +
     @SUM( REP_CENTRES: REPFXD_CST * OPEN1)+@SUM( ARCS2:
COST_RESELLCENTRES * VOL_RESELLCENTRES) +
     @SUM( RESELLCENTRES: RESFXD_CST * OPEN2)+@SUM( ARCS3:
COST_REMFGCENTRES * VOL_REMFGCENTRES) +
```

```
     @SUM( REMFGCENTRES: REMFGFXD_CST * OPEN3)+@SUM( ARCS4:
COST_RECYCENTRES * VOL_RECYCENTRES) +
     @SUM( RECYCENTRES: RECYFXD_CST * OPEN4)+ @SUM( ARCS5:
COST_DISPCENTRES * VOL_DISPCENTRES) +
     @SUM( DISPCENTRES: DISPFXD_CST * OPEN5);


!Constraints:

 ! The supply constraints;
      @FOR( RETAILERS1(J): [SUPPLY1]!1;
            @SUM( REP_CENTRES(I): VOL_REPCENTRES( I, J))=
SUPPLY_REPCENTRES(J)

);
                  @FOR( REP_CENTRES( I): [CAPACITY]
                        @SUM( RETAILERS1( J): VOL_REPCENTRES( I, J))<=
CAP_REPCENTRES( I) * OPEN1( I)

);

      @FOR( RETAILERS2(J): [SUPPLY2]!2;
            @SUM( RESELLCENTRES(I): VOL_RESELLCENTRES( I, J)) =
SUPPLY_RESELLCENTRES(J)

);
                  @FOR( RESELLCENTRES( I): [CAPACITY2]
                        @SUM( RETAILERS2( J): VOL_RESELLCENTRES( I, J))
<= CAP_RESELLCENTRES( I) * OPEN2( I)

);

      @FOR( RETAILERS3(J): [SUPPLY3]!3;
            @SUM( REMFGCENTRES(I): VOL_REMFGCENTRES( I, J)) =
SUPPLY_REMFGCENTRES(J)

);
                  @FOR( REMFGCENTRES( I): [CAPACITY3]
                        @SUM( RETAILERS3( J): VOL_REMFGCENTRES( I, J))
<= CAP_REMFGCENTRES( I) * OPEN3( I)

);

      @FOR( RETAILERS4(J): [SUPPLY4]!4;
            @SUM( RECYCENTRES(I): VOL_RECYCENTRES( I, J)) =
SUP_RECYCENTRES(J)

);
                  @FOR( RECYCENTRES( I): [CAPACITY4]
                        @SUM( RETAILERS4( J): VOL_RECYCENTRES( I, J)) <=
CAP_RECYCENTRES( I) * OPEN4( I)

);
      @FOR( RETAILERS5(J): [SUPPLY5]
            @SUM( DISPCENTRES(I): VOL_DISPCENTRES( I, J)) =
SUP_DISPCENTRES(J)
```

```
);
                  @FOR( DISPCENTRES( I): [CAPACITY5]
                        @SUM( RETAILERS5( J): VOL_DISPCENTRES( I, J)) <=
CAP_DISPCENTRES( I) * OPEN5( I)

      );


 ! Make OPEN binary(0/1);
      @FOR( REP_CENTRES: @BIN(OPEN1)

      );
      @FOR( RESELLCENTRES: @BIN(OPEN2)

      );
      @FOR( REMFGCENTRES: @BIN(OPEN3)

      );
      @FOR( RECYCENTRES: @BIN(OPEN4)

      );
      @FOR( DISPCENTRES: @BIN(OPEN5)

      );


DATA:

! The Retailers & their supply quantities;

SUPPLY_REPCENTRES=@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres, their fixed costs;

REPFXD_CST = @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres and their Capacities;

CAP_REPCENTRES= @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The retailers to repair center cost/unit
shipment matrix;

COST_REPCENTRES =@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Retailers & their supply quantities;

SUPPLY_RESELLCENTRES=@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres, their fixed costs;

RESFXD_CST = @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres and their Capacities;

CAP_RESELLCENTRES= @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');
```

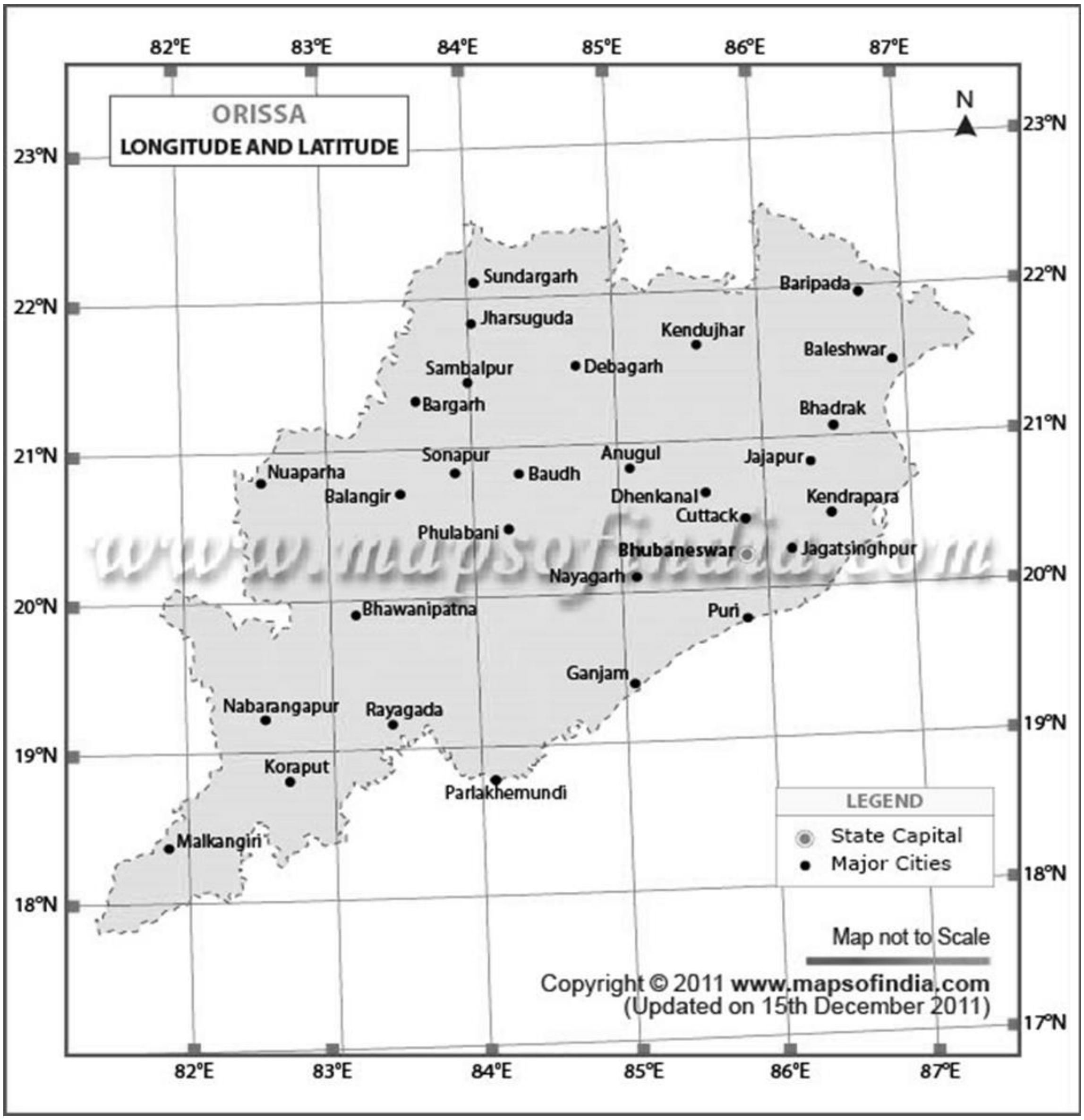
```
! The retailers to repair center cost/unit
shipment matrix;

COST_RESELLCENTRES =@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');


! The Retailers & their supply quantities;

SUPPLY_REMFGCENTRES=@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres, their fixed costs;

REMFGFXD_CST = @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres and their Capacities;

CAP_REMFGCENTRES= @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The retailers to repair center cost/unit
shipment matrix;

COST_REMFGCENTRES =@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Retailers & their supply quantities;

SUP_RECYCENTRES=@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres, their fixed costs;

RECYFXD_CST = @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres and their Capacities;

CAP_RECYCENTRES= @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The retailers to repair center cost/unit
shipment matrix;

COST_RECYCENTRES =@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Retailers & their supply quantities;

SUP_DISPCENTRES=@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres, their fixed costs;

DISPFXD_CST = @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The Repair centres and their Capacities;

CAP_DISPCENTRES= @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');

! The retailers to repair center cost/unit
shipment matrix;

COST_DISPCENTRES =@OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx');
```

```
!Export results to excel;

 @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx',
    'VOL_REPCENTRES') = VOL_REPCENTRES;
!Export results to excel;

 @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx',
    'VOL_RESELLCENTRES') = VOL_RESELLCENTRES;
!Export results to excel;

 @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx',
    'VOL_REMFGCENTRES') = VOL_REMFGCENTRES;
 !Export results to excel;

 @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx',
    'VOL_RECYCENTRES') = VOL_RECYCENTRES;
 !Export results to excel;

 @OLE('\LINGO14\Samples\OPENLOOP FLOW CHART.xlsx',
    'VOL_DISPCENTRES') = VOL_DISPCENTRES;



ENDDATA


END
```

Appendix 2.5: Latitudes and Longitudes of major towns in Orissa state

location	Latitude	Longitude	Location	Latitude	Longitude
Athgarh	20° 32' N	85° 41' E	Kalahandi Karond	19° 40' N	83° 00' E
Athmallik	20° 55' N	84° 30' E	Karanjia	21° 43' N	87° 07' E
Baleshwar	21° 30' N	86° 54' E	Karond Kalahandi	19° 40' N	83° 00' E
Banki	20° 21' N	85° 33' E	Kendrapara	20° 30' N	86° 28' E
Baramba	20° 25' N	85° 23' E	Keonjhar (Nijgarh)	21° 30' N	85° 30' E
Baripada	21° 56' N	86° 46' E	Khandpara	20° 16' N	85° 13' E
Baudh	20° 50' N	84° 52' E	Khondmals	20° 42' N	84° 20' E
Berhampur	19° 18' N	84° 51' E	Khurda	20° 11' N	85° 40' E
Bhadrakh	21° 03' N	86° 33' E	Kolabira	21° 49' N	84° 15' E
Bhawani Patna	19° 58' N	83° 12' E	Konarak Black Pagoda	19° 53' N	86° 08' E
Bhuban	21° 05' N	85° 52' E	Kotapad	19° 04' N	82° 24' E
Bhubaneshwar	20° 15' N	85° 52' E	Lahara	21° 26' N	85° 14' E
Black Pagoda (Konarak)	19° 53' N	86° 08' E	Mahanadi R.	20° 19' N	86° 45' E
Bolangir	20° 40' N	83° 30' E	Malkangiri	18° 22' N	81° 56' E
Bonaigarh	21° 49' N	85° 00' E	Narsinghpur	20° 28' N	85° 07' E
Borasambar	20° 58' N	83° 00' E	Nayagarh	20° 08' N	85° 08' E
Chatrapur	19° 21' N	85° 03' E	Nilgarh (Keonjhar)	21° 30' N	85° 30' E
Chilka Lake	19° 50' N	85° 30' E	Nilgiri	21° 27' N	86° 49 ' E
Cuttack	20° 28' N	85° 54' E	Palmyras Point	20° 45' N	87° 02 ' E
Daspalla	20° 19' N	84° 56' E	Paradip	20° 3' N	86° 55 ' E
Daspur	21° 58' N	86° 07' E	Parlakimidi	18° 47' N	84° 08 ' E
Deograh	21° 32' N	84° 46' E	Patna	20° 00' N	83° 12' E
Dhamra	20° 48' N	86° 56' E	Puri	19° 48' N	85° 52 ' E
Dhenkanal	20° 40' N	85° 38' E	Ramagiri-Udayagiri	19° 04' N	83° 55 ' E
False Point	20° 20' N	86° 46' E	Rampur	21° 05' N	84° 22 ' E
Ganjam	19° 22' N	85° 06' E	Ranpur	20° 04' N	85° 23 ' E
Gopalpur	19° 16' N	84° 57' E	Rayagada	19° 09' N	83° 27 ' E
Hindol	20° 36' N	85° 14' E	Rourkela	22° 25' N	85° 00' E
Hirakund Dam and Res.	21° 30' N	84° 00' E	Sambalpur	21° 28' N	84° 01 ' E
Jaypore	18° 52' N	82° 38' E	Talcher	20° 57' N	85° 16' E
Junagarh	19° 52' N	82° 59' E	Tigiria	20° 28' N	84° 34' E
Kainitira	20° 45' N	84° 37' E	Source: http://www.mapsofindia.com/lat_long/orissa/#		

Appendix 3.5: Map of Orissa



Reference:

1. <u>Convertion to X and Y co-ordinates</u>
   http://www.whoi.edu/marine/ndsf/utility/NDSFutility.html

Appendix 4.5: Transportation cost per tonne for electric appliance products in India

Class Rates	ELECTRIC APPLIANCES NOC		
Rate Class	Distance		Rate Per Ton
	From	To	
LR1	1	125	122.5
LR1	126	150	149.3
LR1	151	175	167.4
LR1	176	200	187.2
LR1	201	225	205.5
LR1	226	250	225.2
LR1	251	275	244.8
LR1	276	300	264.3
LR1	301	325	282.6
LR1	326	350	301.7
LR1	351	375	320.8
LR1	376	400	340.3
LR1	401	425	359.9
LR1	426	450	379.3
LR1	451	475	398.4
LR1	476	500	418.4
LR1	501	550	457.8
LR1	551	600	496.9
LR1	601	650	535.7
LR1	651	700	574.3
LR1	701	750	613.2
LR1	751	800	651.4
LR1	801	850	689.7
LR1	851	900	727.8
LR1	901	950	765.8
LR1	951	1000	803.8
LR1	1001	1100	880.6
LR1	1101	1200	957.5
LR1	1201	1300	1034.1
LR1	1301	1400	1110.3
LR1	1401	1500	1186.5
LR1	1501	1750	1357.4
LR1	1751	2000	1488.8
LR1	2001	2250	1592.3

LR1	2251	2500	1691.3
LR1	2501	2750	1799.7
LR1	2751	3000	1904.5
LR1	3001	3250	2006.2
LR1	3251	3500	

Reference:

1. Cost of transportation

   https://www.fois.indianrail.gov.in/FoisWebsite/html/Freight_Rates.htm