Resolving Forward-Reverse Logistics Multi-Period Model Using Evolutionary Algorithms

Abstract

In the changing competitive landscape and with growing environmental awareness, reverse logistics issues have become prominent in manufacturing organizations. As a result there is an increasing focus on green aspects of the supply chain to reduce environmental impacts and ensure environmental efficiency. This is largely driven by changes made in government rules and regulations with which organizations must comply in order to successfully operate in different regions of the world. Therefore, manufacturing organizations are striving hard to implement environmentally efficient supply chains while simultaneously maximizing their profit to compete in the market. To address the issue, this research studies a forward-reverse logistics model. This paper puts forward a model of a multi-period, multi-echelon, vehicle routing, forward-reverse logistics system. The network considered in the model assumes a fixed number of suppliers, facilities, distributors, customer zones, disassembly locations, re-distributors and second customer zones. The demand levels at customer zones are assumed to be deterministic. The objective of the paper is to maximize the total expected profit and also to obtain an efficient route for the vehicle corresponding to an optimal/ near optimal solution. The proposed model is resolved using Artificial Immune System (AIS) and Particle Swarm Optimization (PSO) algorithms. The findings show that for the considered model, AIS works better than the PSO. This information is important for a manufacturing organization engaged in reverse logistics programs and in running units efficiently. This paper also contributes to the limited literature on reverse logistics that considers costs and profit as well as vehicle route management.

Keywords: Reverse Logistics; Supply Chain; AIS; PSO; Vehicle Routing; Profit; Cost

1. Introduction

Supply chain management (SCM) has nowadays become a crucial strategy for firms to increase their profitability and stay competitive (Li *et al.*, 2006; Tan *et al.*, 2002). Thus, over the last decade, researchers and practitioners have increased the degree of attention paid to SCM. This has resulted in a rich stream of research mainly focused on particular management aspects of supply chains that include, among many others: supplier alliances (Lee *et al.*, 2009; Kannan and Tan, 2004), supplier selection (Ageron *et al.*, 2013; Viswanadham and Samvedi, 2013), supplier management (Reuter *et al.*, 2010), involvement of suppliers (Johnsen, 2011), upstream supply chain (SC) related research (Finne and Holmström, 2013; Oosterhuis *et al.*, 2012), supply chain resilience (Carvalho *et al.*, 2014), manufacturer and retailers linkages (Li and Zhang, 2015; Zhao *et al.*, 2008) and SCM practices (Narasimhan and Schoenherr, 2012; Li *et al.*, 2006; Li *et al.*, 2005). Traditionally, SCM research has concentrated on improving profitability, efficiency, customer satisfaction, quality and responsiveness, which had been the dominant concern for organisations (Green *et al.*, 2012), However, in order to respond to governmental environmental regulations and the growth of customer demands for products and services that are environmentally sustainable, companies have now been forced to rethink how they manage their supply chains to also consider the environmental dimension.

Evidence suggests that in order to support organizations to align with governmental regulations and respond to the 'environmental push' of customers, academic research has also focused on the recently emerged green aspect of SCM, particularly in the areas of sustainable supply chains (Jabbour *et al.*, 2015; Dadhich *et al.*, 2015; Hassini *et al.*, 2012), green supply chains (Kumar *et al.*, 2015; Bhattacharya *et al.*, 2014; Green *et al.*, 2012), circular economy supply chains (Genovese *et al.*, 2015; Pan *et al.*, 2015; Ying and Li-jun, 2012) and reverse logistics (Abdulrahman *et al.*, 2014; García-Rodríguez *et al.* 2013; Mishra *et al.* 2012; Vishwa *et al.*, 2010). However, despite this relatively abundant research, many manufacturing organizations are still struggling to implement environmentally efficient supply chains while simultaneously maximizing profit while competing in the marketplace (Srivastava, 2007). There is limited research focused on the cost of the whole supply chain including reverse logistics activities (Srivastava, 2007; El-Sayed et al. 2010). To address this issue, this paper proposes a forward-reverse logistics model, in particular, a model for a multi-period, multi-echelon, vehicle routing, forward-reverse logistics system to maximize the total expected profit and also to obtain an

efficient route for the vehicle corresponding to an optimal/ near optimal solution. The proposed model is resolved using an evolutionary Artificial Immune System (AIS) algorithm.

The remainder of the paper is organised as follows: Section 2 provides a review on reverse logistics to serve as a preamble for the development of the forward-reverse logistics model proposed; the model is then introduced in Section 3 and algorithm is described in Section 4; Section 5 discusses the findings of this study and Section 6 presents the conclusions.

2. Literature Review

2.1 Emergence of Reverse Logistics

Environmental issues were largely ignored by manufacturing firms until they were forced by government agencies and regulations to implement environmentally friendly methods to reduce the CO_2 emissions generated by their supply chains, production systems and practices. This led to the emergence of 'sub-areas' in the field of supply chain management that included green supply chains (Mohanty and Prakash, 2014; Zhu *et al.*, 2008), green logistics (Ubeda *et al.*, 2011) and reverse logistics (Mishra *et al.*, 2012; Sarkis, 2003; Huang *et al.*, 2012). These sub-areas have nowadays become of prime interest to researchers and practitioners around the world. Reverse logistics gained momentum since the mid-nineties especially with legal enforcement of product and material recovery or disposal both in Europe and in the US. Despite its emergence in early to mid-nineties Dowlatshahi (2000) reported that there was a lack of theory development in the area of reverse logistics. As a result over the past decade a number of papers have been published addressing various problems surrounding reverse logistics operations in different industrial settings (Choudhary et al. 2015; Abdulrahman *et al.*, 2014; García-Rodríguez et al. 2013; Huang et al., 2012; Mishra et al. 2012; Vishwa et al. 2010; Sarkis 2003). De Brito and Dekker (2002) presented a comprehensive review of reverse logistics literature and definitions. In addition, they presented a decision framework for reverse logistics based on a long, medium and short term perspective. Following de Brito and Dekker's (2002) work several other researchers discussed the evolution of reverse logistics and highlighted the significance of reverse logistics operations to manufacturing organisations (Ko and Evans, 2007; Mishra *et al.* 2012; Wang *et al.*, 2012). A review of recent research shows that reverse logistics is still attracting much interest, however the direction of research is now moving towards incorporating

sustainability (Sarkis *et al.*, 2010; Brix-Asala *et al.*, 2016) and circular economy concepts in conjunction with reverse logistics (Meng, 2013; Chen *et al.*, 2015). The next section provides a brief overview of reverse logistics definitions.

2.2 Definitions

With the increasing worldwide importance of green supply chains much research work has been carried out both in the forward logistics part of the supply chain as well as in reverse logistics (Ko and Evans, 2007; de la Fuente, 2008; El-Sayed *et al.*, 2010; Pishvaee, Farahani, & Dullaert, 2010). Several researchers have put forward definitions of reverse logistics: Kroon and Vrijens (1994) referred to reverse logistics as the logistic management skills and activities involved in reducing, managing and disposing of hazardous and non-hazardous waste from packaging and products. Dowlatshahi (2000) defined reverse logistics as the process by which the manufacturer systematically accepts previously shipped products or parts from the point of consumption for possible recycling, remanufacturing or disposal. Rogers and Tibben-Lembke (1999) similarly defined reverse logistics 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 value, or proper disposal. This definition was further modified by De Brito and Dekkar (2002) who emphasized the point of recovery rather than the point of origin. These definitions show a broad agreement on the main elements of reverse logistics.

2.3 Previous Research

Research in the field of reverse logistics has been primarily centered on studying its benefits, determining the barriers that organizations face when implementing a reverse approach to their logistics operations, and essential elements (e.g. vehicle routing and cost) that comprise these operations. For example, recent research by Abdulrahman *et al.* (2014) focused on identifying the barriers of reverse logistics operations in the Chinese manufacturing sector. Their study identified as barriers: a lack of reverse logistics experts and low commitment, a lack of initial capital and funds for return monitoring systems, a lack of enforceable laws and lack of supportive government economic policies and, finally, a lack of systems for return monitoring. García-Rodríguez et al. (2013) showed that application of reverse logistics can be beneficial in

acquiring raw materials in developing countries as it can reduce the problem of acquisition of production inputs and mitigate environmental damage caused by the production of raw materials. A number of researchers have also investigated vehicle routing problem in reverse logistics operations (Dethloff, 2001; El-Sayed *et al.*, 2010; Shukla *et al.*, 2013; Tiwari and Chang, 2015; Soysal *et al.*, 2015; Kim and Lee, 2015). Since vehicle routing is an essential element of reverse logistics operations, it is important that manufacturing organizations manage this efficiently. As indicated earlier, several researchers have attempted to optimize vehicle routing operations but studies simultaneously focused combining this with maximizing profit still remain scant (Srivastava, 2007; El-Sayed et la. 2010; Soysal et al. 2015). Thus, this paper aims to address this research gap and add to the existing knowledge and understanding in this area.

Green distribution and marketing involves efficient route planning and fuel reduction as well as the promotion of eco-friendly products. Reverse logistics aims at the strict supervision and efficient management of waste materials. Fleischmann *et al.* (1997) presented quantitative models for reverse logistics and suggested key areas of research in distribution planning, inventory control, and production planning. Ravi et al. (2008), in their study of key issues involved in the environmentally friendly disposal of end-of-life (EOL) computers, proposed a hybrid approach comprising analytical network process (ANP) and zero one goal programming (ZOGP) to select the reverse logistics projects. Teunter (2001) proposed a reverse logistics valuation model for inventory control and argued that the proposed method is 'correct' from a discounted cash flow (DCF) point of view. The role of JIT in a reverse logistics model was studied by Chan *et al.* (2010) who found that a process model with JIT improves cost control, efficiency of reverse logistics activities as well as the product life cycle management. More recently Tiwari and Chang (2015) proposed a block recombination approach to solve the green vehicle routing problem. Their study primarily aimed at minimizing carbon dioxide emissions by vehicle during the transportation of goods from depot to customer while minimizing total distance travelled by the vehicle. These studies show that routing planning has been high on the agenda of researchers focusing on improving reverse logistics operations.

2.3.1 Reverse Logistics Costs

There are many costs involved in reverse logistics operations similar to those of forward logistics operations. Dowlatshahi (2000) emphasizes that firms should establish a cost and benefits structure for its reverse logistics system and should consider the operational costs, land fill and contingent liability costs. Dowlatshahi (2010) later explored the role of inbound and outbound transportation within the context of a reverse logistics (RL) system and puts forward eight propositions marking the importance of the transport system in reverse logistic operations. One of these propositions is related to transportation cost which proposes that the effectiveness of a transportation system in RL is positively related to the use of cost-efficient transportation rates. Bachlaus *et al.* (2008) designed a multi-echelon agile supply chain network with the aim of minimizing cost and maximizing plant flexibility and volume flexibility to increase the profitability of a manufacturing firm. Tsai and Hung (2009) studied the reverse logistics problem of waste electrical and electronic equipment (WEEE) focusing on treatment and recycling system optimization. They considered activity-based costing as a tool in WEEE reverse logistics management and proposed a concise supply-chain decision framework with producer responsibility. Weeks *et al.* (2010) carried out an empirical investigation to understand the impact of the product mix and product route efficiencies on operations performance and profitability. Their findings showed that operations management alone does not have a positive impact on profitability; rather it is the production mix efficiency and product route efficiency together that have a positive effect on profitability. More recently, Soysal *et al.* (2015) presented a multi-period inventory routing model that included load dependent distribution costs for a comprehensive evaluation of CO_2 emission and fuel consumption, perishability, and a service level constraint for meeting uncertain demand. Their proposed integrated model showed significant savings in total cost while satisfying the service level requirements and thus offering better support to decision makers. These studies highlight the significance of cost related issues in the overall success of a reverse logistics model.

2.3.2 Cost Optimization

Many researchers have presented algorithms to find a path by which costs associated with the supply chain can be minimized. As simultaneous delivery and pickup activities are preferred by customers, this aspect is considered by Dethloff (2001) as a vehicle routing problem with

simultaneous delivery and pick-up (VRPSDP). Choudhary *et al.* (2015) proposed a quantitative optimization model for integrated forward–reverse logistics with carbon-footprint considerations. They implemented a modified and efficient forest data structure to derive the optimal network configuration, minimizing both the cost and the total carbon footprint of the network. Their proposed method outperformed the conventional genetic algorithm (GA) for large problem sizes. Zheng and Zhang (2008) proposed a genetic algorithm to solve a vehicle routing problem with simultaneous pickup and delivery. Ko and Evans (2007) also applied a genetic algorithm-based heuristic for the dynamic integrated forward/reverse logistics network for third party logistics providers. They compared their solutions to optimal solutions using different test problems to show the efficacy of the evolutionary algorithm in resolving reverse logistics problems. Pishvaee, Farahani, & Dullaert (2010) proposed a memetic algorithm for bi-objective integrated forward/reverse logistics network design model. Their proposed algorithm outperformed the existing multi-objective genetic algorithm. A stochastic mixed integer linear programming model was put forward by El-Sayed *et al.* (2010) to solve forward-reverse logistics problems with the objective of maximizing total expected profit. These studies show that a variety of algorithms have been applied by researchers to resolve reverse logistics issues. In this paper El-Sayed *et al.'s* (2010) model is modified to include the importance of vehicle routing in a reverse logistics scenario and is solved using Artificial Immune System (AIS) and Particle Swarm Optimization (PSO) evolutionary algorithms.

Srivastava (2007) reviewed the literature on green supply chain management and observed that much research has been focused on delivering product to end customers at lower supply chain cost but limited research has been carried out on the cost of the whole supply chain including reverse logistics activities. For example, Kheljani *et al.*, (2009) attempted to optimize the total cost of the supply chain rather than only the buyer's cost. However, the total cost of their supply chain includes only buyer's cost and suppliers' costs. Pettersson and Segerstedt (2013) following the same line focused on measuring the Supply Chain Cost (SCC), and this study too did not take in to account the reverse logistics costs which show the gap that exists in the literature. We therefore aim to fill this research gap and contribute in this domain.

Given that customers generally do not prefer delivery and pickup activities separately but prefer them to be carried out simultaneously, we suggest that there should be some fixed route for a

vehicle, given a fixed number of agents in the supply chain, by which costs for the entire chain can be optimized. In the remainder of the paper we put forward a model whereby total expected profit of a forward-reverse logistic situation is maximized and where the route that a vehicle should follow is determined using an AIS clonal-selection algorithm. The upcoming sections discuss the AIS algorithm more in detail.

3. Model Description

The model proposed in this study is a modification of and extension to the forward-reverse logistics network design problem proposed by El-Sayed *et al.* (2010). However, our proposed model is different from El-Sayed *et al.'s* (2010) work in a number of ways. As compared to El-Sayed *et al.'s* (2010) work, the major contribution of our paper is the integration of vehicle routing into modified (as compared to earlier model) network structure of forward-reverse logistics network. The flow in our model has also been modified by including recycling and repair center to handle repair parts. In addition, our study considers vehicle routing (path) integer variable as a constraint to get transportation path for the model.

The network is multi-period and multi-echelon, and consists of suppliers, facilities, distributors and first customers and in the forward direction and in the reverse direction it consists of disassembly, disposal, recycling locations, redistribution locations and second customers. The objective of the paper is to maximize profit in a reverse logistics environment while considering vehicle constraints and minimizing the cost of transportation.

The model considers a company which has a fixed number of locations for each type of agent in the supply chain. We consider two suppliers, two distributors and three customer zones, and one each of the remaining agents: facility, facility store, disassembly location, disposal center, recycling center, redistribution location and second customer zone. The company has one vehicle which every period goes from the transport depot to collect and deliver goods from one location to the other.

3.1 Network Flows

The facility receives raw materials from the suppliers and goods manufactured at the facility will be stored in the facility store after every period. Distributors receive goods either directly from

the facility or from the facility store. The distributors service the customers according to the demand. Used goods are collected from customers and shipped to the disassembly location. Here, goods are sorted and sent to the recycling and repair center. Goods for disposal are sent to the disposal location and repaired and recycled goods are sent to respective locations: goods to be remanufactured are sent to the facility; repaired goods to the redistribution centre and recycled goods to the facility from which they enter the supply chain again as raw materials. The redistribution center in turn receives remanufactured goods from the facility and repaired goods from the recycling and repair center. These used products after repairing and remanufacturing are sold to secondary customers according to demand. These are usually sold at low prices compared to fresh goods. An example for such a model is given in Figure 1.

[Insert Figure 1 here]

Costs considered at different nodes of the model are as follows:

1) Suppliers: These include material costs and transportation costs.

2) Facilities: These include manufacturing costs, remanufacturing costs, storage costs and transportation costs.

3) Facility store: These include holding costs and transportation costs.

4) Distributors: These include shortage costs, storage costs and transportation costs.

5) Disassembly locations: These include costs for disassembly operations, inspection and sorting costs, repairing costs and transportation costs.

6) Recycling Center: These include costs for recycling of materials.

7) Redistribution Centers: These include costs for transportation.

8) Disposal Locations: These include disposal costs and transportation costs.

3.2   Model Assumptions

The following are the major assumptions made with respect to the model:

1) The model is multi-period and multi-echelon.

2) The locations of the chain are fixed and the number of each location is given.

3) Cost parameters are known for each location and time period.

4) The demand quantities at first customer zone are known.

5) Capacity of each location is not limited.

6) The holding cost depends on the residual inventory at the end of period.

7) The path considered for the model is in the order: depot, supplier, facility, facility store, distributor, first customer zone, disassembly location, recycling center, facility, redistributors, and second customer.

8) The disposal center is assumed to be near to the disassembly location.

3.3 Model Formulation

3.3.1 Decision Variables

$Q_{(d)(c)(t)}$ – flow of goods from distributor(d) to first customer(c) in period 't'

$Q_{(d1)(c2)(t)}$ –.flow of goods from re-distributor(d1) to second customer(c2) in period 't'

$Q_{(s)(f)(t)}$ – flow of goods from supplier(s) to facility(f) in period 't'

$Q_{(f)(d)(t)}$ – flow of goods from facility(f) to distributor(d) in period 't'

$Q_{(f1)(d)(t)}$ – flow of goods from facility store (f1) to distributor(d) in period 't'

$Q_{(l)(r1)(t)}$ – flow of goods from disassembly location(l) to recycling center(r1) in period 't'

$Q_{(f)(r1)(t)}$ – flow of goods from facility(f) to recycling center(r1) in period 't'

$Q_{(r1)(d1)(t)}$ – flow of goods from recycling center(r1) to re-distributor center(d1)   in period 't'

$Q_{(c)(l)(t)}$ – flow of goods from first customer(c) to disassembly location(l) in period 't'

$Q_{(c)(r1)(t)}$ – flow of goods first customer(c) to recycling center(r1) in period 't'

$Q_{(l)(g)(t)}$ – flow of goods from disassembly location(l) to disposal location(g) in period 't'

$Qrm_{(l)(f)(t)}$ – flow of goods from disassembly location(l) to facility(f) in period 't'

$Qrd_{(l)(r1)(t)}$ – flow of goods from disassembly location(l) to recycling center(r1) in period 't'

$Qrd_{(l)(d1)(t)}$ – flow of goods from disassembly location(l) to re-distributor center(d1) in period 't'

$Qrd_{(r1)(d1)(t)}$ – flow of goods to recycling center(r1) to re-distributor center(d1) in period 't'

$Qrc_{(r1)(f)(t)}$ – flow of goods from recycling center(r1) to facility(f) in period 't'

$Qrc_{(r1)(d1)(t)}$ – flow of goods from recycling center(r1) to re-distributor center(d1) in period 't'

$I_{(f)(f1)(t)}$ – flow of goods from facility(f) to store(f1) in period 't'

$I_{(f1)(d)(t)}$ – flow of goods from facility store(f1) to distributor location(d) in period 't'

$R_{(f1)(t)}$ – residual inventory at facility store(f1) in period 't'

$R_{(d)(t)}$ – residual inventory at distributor location(d) in period 't'

$x_{(i)(j)}$ – binary variable = 1 if vehicle take goes from location 'i' to location 'j'

$$= 0 \text{ if vehicle doesn't take that path.}$$

3.3.2 Symbols

T1 – Number of Transport Depots

S – Number of Suppliers

F – Number of Facilities

F1 – Number of Facility Stores

D – Number of Distributors

C1 – Number of Primary Customers

L – Number of Disassembly Locations

R1–Number of Recycling and Repair Centers

G – Number of Disposal Locations

D1 – Number of Redistributing Locations

C2 – Number of Secondary Customers

T – Total number of time periods

N– Total number of Locations

MC – Material cost per unit supplied by supplier

RC – Recycling cost per unit recycled

FC – Manufacturing cost per unit manufactured

FH –Inventory holding cost per unit at facility store

PC – Purchasing cost (for recycling) per unit

SC – Shortage cost per unit per period

DAC – Disassembly cost per unit disassembled

RMC – Remanufacturing cost per unit remanufactured

RDC – Repairing cost per unit repaired

DC – Disposal cost per unit disposed

DH – Holding cost per unit per period at distribution location

$\mathbf{P_{(c)t}}$ – Unit price at first customer c in period t

$\mathbf{P_{(c2)t}}$ – Unit price at second customer c2 in period t

$\mathbf{D_{(c\}(t)}}$– Demand of first customer c in period t

$\mathbf{D_{(c2\}(t)}}$– Demand of second customer c2 in period t

$\mathbf{C_{(i)(j)}}$ – Transportation cost from moving from location 'i' to location 'j'

RR – Returning ratio at first customer

RM – Remanufacturing ratio

Rd – Redistribution ratio

RD – Disposal ratio

Rc – Recycling ratio

3.3.3   Objective Function

The objective is to maximize the total expected profit and to determine the path of the vehicle corresponding to that level of profit.

Total Expected Profit = Total expected income – Total expected cost

a. Total Expected Income

Total expected income = first sales + second sales

$$First\ sales = \sum_{d=1}^{D} \sum_{c=1}^{C1} \sum_{t=1}^{T} Q_{(d)(c)t}\, P_{(c)t} \qquad \ldots(1)$$

$$Second\ sales = \sum_{d1=1}^{D1} \sum_{c2=1}^{C2} \sum_{t=1}^{T} Q_{(d1)(c2)t}\, P_{(c2)t} \qquad \ldots(2)$$

Where P_{ct} is unit price paid by customer 'c' at time 't'

b. Total Expected Cost

The total expected cost is the sum of the costs associated with the whole chain considering both forward and reverse logistics activities. They include costs associated with material purchase, manufacturing excluding its profits from reverse logistic activities, shortage, purchasing costs from customers for reverse chain, disassembly of materials, disposal, recycling, redistribution and remanufacturing, inventory holding and transportation.

The costs and profits are as follows:

1) Material cost

$$\sum_{s=1}^{S} \sum_{f=1}^{F} \sum_{t=1}^{T} Q_{(s)(f)(t)}MC \qquad \ldots(3)$$

2) Manufacturing costs

$$\sum_{f=1}^{F} \sum_{d=1}^{D} \sum_{t=1}^{T} Q_{(f)(d)(t)}FC + \sum_{f1=1}^{F1} \sum_{d=1}^{D} \sum_{t=1}^{T} I_{(f1)(d)(t)}FC \qquad \ldots(4)$$

3) Material cost(for returned units)

$$\sum_{l=1}^{L} \sum_{f=1}^{F} \sum_{t=1}^{T} Qrm_{(l)(f)(t)}(-MC+RC) \qquad \dots (5)$$

4) Shortage Cost

$$(\sum_{c=1}^{C1} (\sum_{t=1}^{T} (D_{(c)(t)} - \sum_{d=1}^{D} Q_{(d)(c)(t)})))SC \qquad \dots (6)$$

5) Purchasing costs

$$\sum_{c=1}^{C1} \sum_{l=1}^{L} \sum_{t=1}^{T} Q_{(c)(l)(t)}(PC) \qquad \dots (7)$$

6) Recycling costs

$$\sum_{r1=1}^{R1} \sum_{f=1}^{F} \sum_{t=1}^{T} Qrc_{(r1)(f)(t)}(RC) \qquad \dots (8)$$

7) Disassembly costs

$$\sum_{c=1}^{C1} \sum_{l=1}^{L} \sum_{t=1}^{T} Q_{(c)(l)(t)}(DAC) \qquad \dots (9)$$

8) Remanufacturing costs

$$\sum_{l=1}^{L} \sum_{f=1}^{F} \sum_{t=1}^{T} Qrm_{(l)(f)(t)}(RMC) \qquad \dots (10)$$

9) Repairing costs

$$\sum_{l=1}^{L} \sum_{r1=1}^{R1} \sum_{t=1}^{T} Qrd_{(l)(r1)(t)}(RDC) \qquad \dots (11)$$

10) Disposal costs

$$\sum_{l=1}^{L} \sum_{g=1}^{G} \sum_{t=1}^{T} Q_{(l)(g)(t)}^{(DC)} \qquad \qquad \dots (12)$$

11) Inventory Holding costs

$$\sum_{f1=1}^{F1} \sum_{t=1}^{T} R_{(f1)(t)}^{(FH)} + \sum_{d=1}^{D} \sum_{t=1}^{T} R_{(d)(t)}^{(DH)} \qquad \qquad \dots (13)$$

12) Transportation costs

$$\sum_{i=1}^{N} \sum_{j=1}^{N} C_{(i)(j)} x_{(i)(j)} \qquad \qquad \dots (14)$$

3.3.4   Constraints

a. Balance Constraints

1) The flow of goods entering the facility from all suppliers and after recycling is equal to the sum of goods exiting from this facility to facility store and distributor:

$$\sum_{s=1}^{S} \sum_{f=1}^{F} Q_{(s)(f)(t)} = \sum_{f=1}^{F} \sum_{d=1}^{D} Q_{(f)(d)(t)} + \sum_{f=1}^{F} \sum_{f1=1}^{F1} I_{(f)(f1)(t)}, \quad \forall t \in \{1,2,\dots,T\} \qquad \dots(15)$$

2) The sum of flow of goods entering the facility store and the residual from the previous period is equal to the sum of the existing flow of goods to each distributor and the residual inventory of the current period:

$$\sum_{f=1}^{F}\sum_{f1=1}^{F1} I_{(f)(f\,1)(t)} + \sum_{f1=1}^{F1} R_{(f1)(t\,-1)} = \sum_{f1=1}^{F1} R_{(f1)(t)} + \sum_{f1=1}^{F1}\sum_{d=1}^{D} Q_{(f1)(d)(t)}, \forall t \in \{1,2,..., T\}$$

...

(16)

3) The sum of flows entering each distributor store from the facility and facility store is equal to sum of the flow exiting to all customers:

$$\sum_{f1=1}^{F1} Q_{(f\,1)(d)(t)} + \sum_{f1=1}^{F1} I_{(f\,1)(d)(t)} + R_{(d)(t\,-1)} = R_{(d)(t)} + \sum_{c=1}^{C1} Q_{(d)(c)(t)}, \forall t \in \{1,2,...T\}, \forall d \in \{1,2,...,D\}$$

... (17)

4) The sum of the flows entering each customer does not exceed the sum of the current period demand and the previous period's accumulated backorders:

$$\sum_{d=1}^{D} Q_{(d)(c)(t)} \le D_{(c)(t)} + \sum_{t=1}^{t} D_{(c)(t-1)} - \sum_{d=1}^{D} Q_{(d)(c)(t-1)}, \forall t \in \{1,2,..T\}, \forall c \in \{1,2,...,C1\}$$ ... (18)

5) The sum of the flows exiting from each customer zone to disassembly locations does not exceed the sum of those entering each customer:

$$\sum_{l=1}^{L} Q_{(c)(l)(t)} \le (\sum_{d=1}^{D} Q_{(d)(c)(t)})(RR), \forall t \in \{1,2,...12\}, \forall c \in \{1,2,...,C1\}$$ ... (19)

6) The sum of the flows entering the recycling and repair center is equal to the flows exiting as recycled for remanufacturing and redistribution:

$$\sum_{l=1}^{L}\sum_{r1=1}^{R1} Q_{(l)(r1)(t)} = \sum_{r1=1}^{R1}\sum_{f=1}^{F} Qrc_{(r1)(f)(t)} + \sum_{r1=1}^{R1}\sum_{d1=1}^{D1} Qrd_{(r1)(d1)(t)}, \forall t \in \{1,2,...,T\}$$ ... (20)

7) The flow exiting from disassembly location to recycling and repair center for recycling is equal to the flow entering to each disassembly location from all customers multiplied by recycling ratio:

$$\sum_{c=1}^{C1}\sum_{r1=1}^{R1} (Q_{(c)(r1)(t)})(Rc) = \sum_{r1=1}^{R1}\sum_{f=1}^{F} Qrc_{(r1)(f)(t)}, \forall t \in \{1,2,...,T\}$$ ... (21)

8) The flow exiting from disassembly location for remanufacturing is equal to the flow entering each disassembly location from all customers multiplied by the remanufacturing ratio:

$$\sum_{c=1}^{C1} \sum_{l=1}^{L} (Q_{(c)(l)(t)})(RM) = \sum_{l=1}^{L} \sum_{f=1}^{F} Qrm_{(l)(f)(t)} \ , \ \forall\, t \in \{1,2,...,T\} \qquad \dots (22)$$

9) The flow exiting from disassembly location for redistribution is equal to the flow entering each disassembly location from all customers multiplied by the redistribution ratio:

$$\sum_{c=1}^{C1} \sum_{l=1}^{L} (Q_{(c)(l)(t)})(Rd) = \sum_{l=1}^{L} \sum_{d1=1}^{D1} Qrd_{(l)(d1)(t)} \ , \ \forall\, t \in \{1,2,...,T\} \qquad \dots (23)$$

10) The flow exiting from disassembly location for disposal is equal to the flow entering each disassembly location from all customers multiplied by the disposal ratio:

$$\sum_{c=1}^{C1} \sum_{l=1}^{L} (Q_{(c)(l)(t)})(RD) = \sum_{l=1}^{L} \sum_{g=1}^{G} Q_{(l)(g)(t)} \ , \ \forall\, t \in \{1,2,...,T\} \qquad \dots (24)$$

11) The flow entering facility for remanufacturing is equal to the flow from the facility to the redistribution center:

$$\sum_{l=1}^{L} \sum_{f=1}^{F} Qrm_{(l)(f)(t)} = \sum_{f=1}^{F} \sum_{r1=1}^{R1} Q_{(f)(r1)(t)} \ , \ \forall\, t \in \{1,2,...,T\} \qquad \dots (25)$$

12) The flow entering redistribution center from the facility, recycling and the repair center is equal to the flow exiting from it to the second customer:

$$\sum_{f=1}^{F} \sum_{r1=1}^{R1} Q_{(f)(r1)(t)} + \sum_{r1=1}^{R1} \sum_{d1=1}^{D1} Q_{(r1)(d1)(t)} = \sum_{d1=1}^{D1} \sum_{c2=1}^{C2} Q_{(d1)(c2)(t)}, \ \forall\, t \in \{1,2,...,T\} \qquad \dots (26)$$

13) The flow entering the second customer zone from the redistribution center does not exceed the second customer demand for a particular period:

$$\sum_{d1=1}^{D1} Q_{(d1)(c2)(t)} \leq D_{(c2)(t)}, \quad \forall t \in \{1,2,..T\}, c2 \in \{1,2,..,C2\} \qquad \ldots (27)$$

b. Constraints for transportation path

Visit all the locations exactly once as per route assumed and should leave from a particular location after entry.

1)   Transport Depot to Supplier path

$$\sum_{i=1,i \neq j}^{T1+S} x_{ij} = 1, \forall j \in \{1,2,....,S\} \qquad \ldots (28)$$

$$\sum_{j=1,i \neq j}^{T1+S} x_{ij} = 1, \forall i \in \{1,2,....,T1\} \qquad \ldots (29)$$

2)   Supplier to Facility path

$$\sum_{i=1,i \neq j}^{S+F} x_{ij} = 1, \forall j \in \{1,2,....,F\} \qquad \ldots (30)$$

$$\sum_{j=1,i \neq j}^{S+F} x_{ij} = 1, \forall i \in \{1,2,....,S\} \qquad \ldots (31)$$

3)   Facility to Facility Store Path

$$\sum_{i=1,i \neq j}^{F+F1} x_{ij} = 1, \forall j \in \{1,2,....,F1\} \qquad \ldots (32)$$

$$\sum_{j=1,i \neq j}^{F+F1} x_{ij} = 1, \forall i \in \{1,2,....,F\} \qquad \ldots (33)$$

4)   Facility Store to Distributor Path

$$\sum_{i=1,i\neq j}^{F1+D} x_{ij}=1, \forall j \in \{1,2,...,D\} \qquad \text{... (34)}$$

$$\sum_{j=1,i\neq j}^{F1+D} x_{ij}=1, \forall i \in \{1,2,...,F1\} \qquad \text{... (35)}$$

5)   Distributor to Customer Path

$$\sum_{i=1,i\neq j}^{D+C1} x_{ij}=1, \forall j \in \{1,2,...,C1\} \qquad \text{... (36)}$$

$$\sum_{j=1,i\neq j}^{D+C1} x_{ij}=1, \forall i \in \{1,2,...,D\} \qquad \text{... (37)}$$

6)   Customer to Disassembly Location path

$$\sum_{i=1,i\neq j}^{C1+L} x_{ij}=1, \forall j \in \{1,2,...,L\} \qquad \text{... (38)}$$

$$\sum_{j=1,i\neq j}^{C1+L} x_{ij}=1, \forall i \in \{1,2,...,C1\} \qquad \text{... (39)}$$

7)   Disassembly Location to Disposal Location Path

$$\sum_{i=1,i\neq j}^{L+G} x_{ij}=1, \forall j \in \{1,2,...,G\} \qquad \text{... (40)}$$

$$\sum_{j=1,i\neq j}^{L+G} x_{ij}=1, \forall i \in \{1,2,...,L\} \qquad \text{... (41)}$$

8)   Disassembly Location to Recycling & Repair Center Location Path

$$\sum_{i=1,i\neq j}^{L+R1} x_{ij}=1, \forall j \in \{1,2,...,R1\} \qquad \text{... (42)}$$

$$\sum_{j=1,i\neq j}^{L+R1} x_{ij}=1, \forall i \in \{1,2,...,L\} \qquad \text{... (43)}$$

9)   Repair Center Location to facility path

$$\sum_{i=1,i\neq j}^{R1+F} x_{ij} =1, \forall j \in \{1,2,...,F\} \qquad \text{... (44)}$$

$$\sum_{j=1,i\neq j}^{R1+F} x_{ij} =1, \forall i \in \{1,2,...,R1\} \qquad \text{... (45)}$$

10)   Facility location to Redistributor location path

$$\sum_{i=1,i\neq j}^{F+D1} x_{ij} =1, \forall j \in \{1,2,...,D1\} \qquad \text{... (46)}$$

$$\sum_{j=1,i\neq j}^{F+D1} x_{ij} =1, \forall i \in \{1,2,...,F\} \qquad \text{... (47)}$$

11)   Redistributor location to Secondary Customer location path

$$\sum_{i=1,i\neq j}^{D1+C2} x_{ij} =1, \forall j \in \{1,2,...,C2\} \qquad \text{... (48)}$$

$$\sum_{j=1,i\neq j}^{D1+C2} x_{ij} =1, \forall i \in \{1,2,...,D1\} \qquad \text{... (49)}$$

The next section provides an overview of the algorithms in detail.

4.   Algorithm Description

Solving the proposed model using conventional combinatorial techniques would be very difficult and hence this study aims to use evolutionary techniques to solve the model. Evolutionary techniques are known for resolving NP-hard combinatorial problems. Two popular evolutionary algorithms Artificial Immune System (AIS) and Particle Swarm Optimization (PSO) were applied to find solutions to the proposed model. We intend to compare the performance of these two algorithms in resolving the model, and seek to investigate which algorithm can solve the

model in a lesser time. The upcoming section provides an overview of the two algorithms in detail.

4.1 Artificial Immune System (AIS) Algorithm

Algorithms play an important role in resolving complex mathematical problems in operations research. Over the years a number of algorithms have been proposed and applied to a wide range of industrial problems. Nature has always inspired researchers and this inspiration and understanding have led to the development of number of nature inspired algorithms, also known as evolutionary algorithms that have been used to resolve complex optimization problems. Among these are: Genetic Algorithms (GA), Ant Colony Optimization Algorithms (ACO), Particle Swarm Optimization (PSO), Bee Colony Optimization (BCO) and Artificial Immune System (AIS) based algorithms (Kennedy, 2010; Kumar *et al.*, 2011; Moslehi and Mahnam, 2011). Each algorithm is inspired by a different natural activity, for example the Particle Swarm Optimization Algorithm (Kennedy, 2010) emulates the real behavior of flocks of birds whereas Bee Colony Optimization (Teodorović *et al.*, 2006) is inspired by the way in which bees in nature search for food. For large supply chain problems, classical optimization techniques such as mixed integer linear programming might face oscillatory problems leading to a slower solution time. However, evolutionary algorithms have been quite successful in resolving complex optimization problems (Shahsavar, Najafi, & Niaki, 2015; Chiang and Lin, 2013; Ko and Evans, 2007; Chan *et al.*, 2006). In this paper, a comparison study has been performed between Artificial Immune System and Particle Swarm Optimization to solve the logistics problem considered in this paper.

The Artificial Immune System (AIS) algorithm, inspired by nature's biological immune system was proposed by De Castro et al. (2001; 2002). The prime function of an immune system is to protect the body from unfamiliar invaders. To accomplish this task the body produces a number of antigenic receptors that combat the attacking antigens. The cells that belong to our body and which are harmless, are termed Self Antigens whereas, the disease causing cells are referred to as Nonself Antigens (Kumar *et al.*, 2006; Chan *et al.*, 2006). The cells and molecules of the immune system maintain constant surveillance for infecting organisms. They recognize an almost limitless variety of infectious cells and substances distinguishing them from native noninfectious cells. When a pathogen enters the body it is detected and mobilized for

elimination. The system is capable of remembering each infection so that a second exposure to the same pathogen is dealt with more efficiently (Janeway, 1992). Based on this theory algorithms are developed which can be used to tackle problems of pattern recognition, memory acquisition and optimization.

CLONALG was developed to perform pattern recognition and optimization (De Castro *et al.*, 2001; White and Garrett, 2003; Diana *et al.*, 2015; Pérez-Cáceres and Riff, 2015). This specific algorithm is presented in this paper. The elements that can be detected by the immune system are termed Antigens (Ag's). To counter these, our body produces a number of antigenic receptors that fight against attacking antigens. These molecules that protect the body from the foreign invaders are known as Antibodies (Ab's). When an antigen is noticed the antibody, produced from the B-Lymphocytes, which recognize an antigen will grow by cloning. In AIS, 'Ag's' are the optimal points of an objective function, while 'Ab's' are the test configurations. The optimization search is carried out by modifying 'Abs' in order to have a better affinity that yields a greater value of the objective function. The next subsection shows the pseudo code of the algorithm.

4.2 Particle Swarm Optimization (PSO)

Kennedy and Eberhart (1995) developed this technique inspired by the social behavior of bird flocking. In this technique, particles are generated with their positions and velocities. These velocities change the particle positions. Each particle velocity is updated based on the performance of fitness function. In every iteration, particles are updated with their local best (pbest) and global position (gbest) of their positions and velocities.
A population is initialized with some fixed number of particles with respective position (x_t) and velocity vector (v_t). Fitness value is calculated for each and every iteration for every particle. For every iteration, individual best of the particle (pbest) and global best (gbest), i.e. best of all particles, are recorded. With respect to global best, every particle's velocity and position are updated as given below:

$$V(t+1) = w \ x \ v(t) + c_1 \ x \ r_1 x (pbest-x(t)) + c_2 \ x \ r_2 x \ (gbest-x(t))$$
$$X(t+1) = x(t)+v(t+1)$$

where c_1 and c_2 are acceleration factors, and r_1 and r_2 are random factors whose values lie between 0 and 1.

4.3 Pseudo Codes of both (AIS and PSO) Algorithms

Artificial Immune System	Particle Swarm Optimization
Initialize AB, select_n, β, p (decay)	*Define Swarm Size(M), Max Iteration(N)*
for k = 1 to AB do	*Initialize Swarm population with position vector(x(t)) and velocity vectors(v(t))*
Initialize to random array values	
end	*for m=1 to M do*
for m = 1 to maxim_gen do	*fitness(f) = f(x_i(t))*
for k = 1 to AB do	*gbest = max(x(t) for which fitness value is higher)*
affinity (l) = f(x_i)	
end	*end*
sort (affinity)	*do iteration t*
Select_ab = x (index (1 to n))	*for m=1 to M(iteration number =1)*
Sum=0	*select position best = current position vector;*
for k = 1 to_n do	*global best = position vector(gbest)*
NC(k) = round (β AB/k)*	*end*
for l = 1 to NC(k) do	*for m to M(iteration number >1)*
*MC(sum+) = Select_ab (k)+ exp(p)*tan(random term)*	*x(t+1) = x(t)+v(t+1);*
	and
Affinity_MC(sum+l)= f(MC(sum+l))	*v(t+1) = w x v(t) + c_1 x r_1x(pbest-x(t)) + c_2x r_2x (gbest-x(t));*
end	
sum=sum+NC(k)	*end*
end	*end*
In AB, last d antibodies are replaced with new mutated child	*Select x(gbest) as the optimal value.*
end	
Result = f (sort (AB (1)))	

5. Results and Discussions

To solve the problem studied in this research, we considered a network showing one transport depot, two suppliers, one facility, one facility store, two distributors, three customers, one disassembly location, one disposal yard, one recycling center, one redistributor and one customer zone. The values of demand at customer zones and second customer zones are assumed to be deterministic. A comparison between the algorithms has been shown in graphs section below. Our findings indicate that using AIS algorithm, results are better as it resulted in optimal value with less number of iterations. The value of expected profit obtained from the AIS algorithm is $22, 7730. The values assumed for costs and sales are given in table 1. The optimal path obtained from the AIS algorithm for the optimum profit was found to be: transport depot (1) – supplier (3) - supplier (2) - facility (4) - facility store (5) - distributor (6) - distributor (7) -customer zone (10) - customer zone (8) - customer zone (9) - disassembly location (11) - recycling and repair center (13) - facility (4) - re-distributor (14) - secondary customer zone (15). The path of the vehicle is shown in Figure 2 with circled numbers indicating respective locations in the chain.

[Insert Figure 2 here]

The distance between different points assumed in the code by AIS algorithm and PSO algorithm is a random number; therefore the path will differ from one run to another, as also will the amount of goods moving from one location to another. Customer demands are satisfied as shown in the graph for two periods. Demand at customer locations is considered to be 500 units per location per period. The graphs show that demand levels are nearly satisfied by the firm. The graphs shown below are the optimal values obtained by AIS algorithm.

Period 1:

[Insert Figure 3 here]

Period 2:

[Insert Figure 4 here]

The quantity supplied for second customer locations is given in figure 5. Demand levels are assumed to be 225 units per period.

[Insert Figure 5 here]

The programming code for AIS algorithm was run for 300 iterations and at a parameter setting of p = 0.005 and β = 4. The calculations were carried out using MATLAB 2007. The change in total expected profit with each iteration is shown in Figure 6.

[Insert Figure 6 here]

A similar test was performed using the PSO algorithm that also was run for 300 iterations using MATLAB 2007. The change in expected profit with each iteration is shown in Figure 7.

[Insert Figure 7 here]

From the analysis it is evident that AIS performs better than PSO for the model studied in this paper.

6. Concluding Remarks, Limitations and Further Research

This paper highlights the significance of the green supply chain and of reverse logistics programs in manufacturing organizations. Discussion in the literature shows that there is a growing interest among the research community to address reverse logistics issues. Rising environmental awareness and changing regulations has forced manufacturing industries to focus on green sustainable practices. As a result, the manufacturing industry is emphasizing the efficient handling of their reverse logistics operations while aiming at simultaneously minimizing their costs and increasing their profitability. This study therefore addresses this issue by particularly focusing on and proposing a forward and reverse logistics model based on the optimum routing of vehicles. In particular, this paper puts forward a model of a multi-period, multi-echelon, vehicle routing, forward-reverse logistics system. The network considered in the model assumes a fixed number of suppliers, facilities, distributors, customer zones, disassembly locations, re-distributors and second customer zones. The demand levels at customer zones are assumed to be deterministic. The proposed model has proved to be useful in obtaining the route of the vehicle, maximizing the profit and providing information to the firm about the quantities to be produced

at the facility and amount of goods to be obtained from the supplier. This study applies the AIS and PSO algorithms to determine the optimal route and quantity produced more efficiently. This paper also shows that for the considered model, AIS works better than the PSO.

Therefore, from a theoretical perspective this paper contributes to the limited literature on reverse logistics that considers costs, profit as well as vehicle route management. Additionally, the paper shows the efficacy of the AIS over PSO in resolving the forward reverse logistics model, thus suggesting that researchers should seek further evidence to see if this applies for other models. These contributions are beneficial for manufacturing organizations that are engaged in reverse logistics operations. For example, relevant managers in these organizations can learn from the proposed model and use it as a reference to optimize the reverse operations of their organizations. In particular, the proposed model can help managers to have better visibility of the demand and supply while also efficiently managing the vehicle routing. This can effectively lead to a maximization of the organization's profits. Due to the high relevance of reverse logistics and the growing attention paid to this type of operation, other industries where this approach has been applied, for example repair service (Amini *et al.*, 2005), post-service (Du and Evans, 2008) and healthcare (Ritchie *et al.*, 2000), are also likely to benefit from this research and the proposed model. All these sectors are under constant pressure to operate competitively and the effective implementation and optimization of reverse logistics operations provide them with this opportunity.

Like all researches, this paper has a number of limitations. For instance, the values of the parameters used to test the model in this paper are assumed deterministic values. Therefore, future research studies should aim at empirically testing the model and algorithm in a realistic industrial scenario. Working closely with some manufacturing organizations, collecting real data and testing should be an interesting area for future investigation. This model can be further extended to a stochastic model by considering mean and variance of demand at different customer locations. Therefore, the research has adequate scope for further extension. Some parameters were considered to be fixed to ease the solution method in this research; future work may involve testing the model by randomly generating the parameters. Vehicle routing can also be extended by considering capacity constraints for vehicle. Although this study tested the model using two evolutionary algorithms where AIS emerged as a better alternative, future work may

also involve testing the model using other evolutionary algorithms and comparing the solutions with hybrid algorithms.

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Table 1: Assumed parameters and their respective values

Parameters	Description	Value ($)
P_c	Price of product at first customer zone	100
P_k	Price of product at second customer zone	80
MC	material cost for suppliers	20
FC	manufacturing cost for facility	20
RC	recycling cost at recycling and repair center	5
SC	shortage cost	10
PC	purchasing cost of used products from first customer zones	5
DAC	disassembly costs at disassembly location	3
RMC	remanufacturing costs for facility	10
RDC	redistribution costs	1
DC	disposal costs	2
FH	holding costs for holding at facility store	5
DH	holding costs for holding at distribution location	5
RR	return ratio at the first customers	0.4
Rc	recycling ratio	0.3
RM	remanufacturing ratio	0.3
Rd	redistribution ratio	0.3
RD	disposal ratio	0.1
$C_{(i)(j)}$	Distance from location 'i' to location 'j'	20*rand( ) in

| | | distance units |