Optimization Multi-Objective Cost and Delay Rate in Delivering Orders in the Three- Echelon Reverse Supply Chain Based On Cost Management

Morteza Ghahremani
Ph.D. Student, Department of Industrial Management, Qazvin Branch, Islamic Azad University, Qazvin, Iran.

Reza Ehtesham Rasi
Department of Industrial Management, Qazvin Branch, Islamic Azad University, Qazvin, Iran.
(Corresponding Author)
ehteshamrasi@qiau.ac.ir

Sadegh Abedi
Department of Industrial Management, Qazvin Branch, Islamic Azad University, Qazvin, Iran.

Submit: 19/01/2021 Accept: 29/05/2022

ABSTRACT

At present, the domestic costs of most construction companies are relatively scattered with the cost data of various business agents. Unless it is controlled by an experienced manager, decision-makers cannot have the real-time dynamic cost of a project. In the information age, it is of vital importance to use the information to control the cost of supply chain dynamically. Cost management and the establishment of an information platform are ways to control the platform integrated cost data, and corresponding method information, and its core is cost data information in the supply chain. The place for financial cost analysis and decision making is a conceptually rich field where information and delivery time is a commercial product which is complicated and extensive. The objective of this research is to define the number of returned products to minimize total cost and delay time of reverse logistics. In this research, a fuzzy bi-objective optimization model was introduced in the reverse logistics system. And determine the number of returned products that should be delivered to be recovered, processed and re manufactured in different time periods so that the total cost of reverse logistics and delay time to be minimized based on cost management. To deal with ambiguity in the reverse logistics network, a fuzzy approach has been applied. To solve the problem in large scale, meta-heuristic algorithms of Cuckoo and Genetic were employed by applying MATLAB software. In order to compare two optimization algorithms, a series of sample problems have been generated then the results of the two algorithms were compared and superiority of each of them was discussed.

Keywords:

Reverse Logistics, Optimization, Fuzzy, Metaheuristic Algorithms, Cost management.

1. Introduction

In today's highly volatile and unpredictable environment, the success of an enterprise depends on its ability to coordinate in a complex communication network among members of the supply chain (SC) (Mena et al., 2013).According to Abidi et al (2017) the focus of doing business has been changed to integration and collaboration with a greater emphasis on handling supply chains by managers. Integration of business activities and collaboration with upstream and downstream partners has become an integral part of doing business. Today, the volume of manufactured and used products leave significant damage to the environment and consumers are concerned about the environmental situation (Percival et al., 2017). The reverse logistics management is an important part of today’s supply chains that allow firms to return the raw materials and goods to suppliers and utilize methods of making goods and items usable in order to decrease total costs (Cullinane et al., 2010). Cost management (CM) is the control of actual or forecasted costs incurred by a supply chain. It is essential for a company to employ proper cost management, or else it will have difficulty consistently generating a profit. This concept is best applied as a formalized process, using some or all of steps. If a business is trying to manage costs associated with future activities (such as the design of a new product or the construction of a new headquarters building) then the cost management activities are somewhat different. Any of the following activities could be followed:

- Use target costing to continually estimate costs as features are added to or subtracted from a project (usually a new product).
- Use milestone reviews to compare the costs originally estimated to be incurred to actual costs incurred. These reviews can sometimes result in the outright cancellation of projects prior to their completion (Agrawal et al., 2016).

Reverse logistics (RL) is particularly popular due to the many competitive advantages such as environmental and economic benefits. Reverse supply chain management (RSCM) is for all operations related to reuse and reprocessing of products and materials (Rasi, 2018). RL and closed-loop supply chains constitute one of the important aspects of any business involving manufacturing, distribution and support services of any type of products. Due to its importance, many researchers have focused on the design of the reverse logistics network (Ozceylan et al., 2014). Consumer awareness towards the environment and social responsibility are key drivers of this area (Keskin & Üster, 2007; BAGHERI et al., 2013). In this regard, development of a logistics network as part of the supply chain planning has particular importance. Therefore, the proper development of this network can have a positive effect on supply chain objectives especially cost reduction, accountability level and efficiency (Chopra, 2003). RL network development models include a wide range of linear and nonlinear models from minimizing cost of sending a product to complex multi-objective optimization problems (Altiparmak et al., 2006). In real-world decision makers should consider several objectives at the same time for the efficient decision-making process. Also, ambiguity is another real-world consideration that should be taken into account. Consumer utility is not static and change over time, when consumer purchase a unique product. This shows that suppliers should dynamically adjust the product orientation and pricing decisions. It is still not clear that when and why the firm adopts what degree of the product greenness if consumer changes his utility (Zhang & Wang, 2019).Considering the points mentioned about the importance of RL and its role in the supply chain, this paper strives to develop a logistic network considering different objective functions in a RLs problem. Today, organizations are not just simply seeking to minimize their reverse logistics costs, as many firms are seeking to improve their recoveries on goods at the end of the flip side of the supply chain. In supply chain networks, materials flow from suppliers through to end customers. Supply chain executives measure the effectiveness that flow using the on-time delivery (OTD) metric. It’s a common supply chain measurement focused on ensuring delivery to the end customer is fast and efficient from the time the customer puts his or her order in place (forward and reverse supply chain). There are 4 metrics to monitor reverse flow in each supply chain as following: Volume of returns; type/condition of returned product; dollar value and percent of sales. Accordingly, two objectives function of time & cost of operation are considered to maximize the revenue of organizations base on cost management approach. In the real world, there exists much fuzzy knowledge (i.e. vague, uncertain inexact etc.). Human thinking and reasoning (analysis, logic, and interpretation) frequently involved fuzzy information. Due to the ambiguity of parameters and variables in the real world, we assumed that time and cost are not certain and then we decided to use fuzzy. In contrast, an efficient logistics network should be developed in a manner that can respond to the fuzziness of the environment. Therefore, in this study, the fuzzy theory is used to consider uncertain parameters. In order to achieve the purpose of cost reduction and efficiency increase, enterprises have adopted the model of financial sharing service center, but the cost management of enterprises faces new challenges. Cost management is an important part of enterprise management, including cost accounting, analysis, and control. The traditional cost management mainly relies on the collaboration between labor and enterprise financial management software. It is easy to generate problems such as heavy manual data collection, high error rate and untimely information(Jingshan eta.,2018). This paper has been structured as follows. In the second part, the literature on the subject of this research is examined. In the third section, the problem of fuzzy cost and time optimization is introduced in the reverse logistics network, parameters, objective functions and related restrictions also will be explained in this section. In Section 4, fuzzy bi-objective modeling is developed. The meta-heuristic cuckoo and genetic algorithms are discussed in Section 5. In Section 6, the computational results related to the solution of two meta-heuristic algorithms and their comparison are reported. Managerial implication has been explained in section 7 and the conclusions and suggestions for future work are expressed in Section 8.

2. Literature review

Cost management is the process of planning and controlling the budget of a business. Having a good cost management system in place will allow organizations to better estimate and allocate budget. Cost management is a form of management accounting that allows a business to predict impending expenditures to help reduce the chance of going over budget. Many businesses employ cost management tactics for specific projects, as well as for the over-all business model. When applying it to a project, expected costs are calculated while the project is still in the planning period and is approved beforehand. During the project, all expenses are recorded and monitored to make sure they stay in line with the cost management plan. After the project is finished, the predicted costs and actual costs can be compared and analyzed, helping future cost management predictions and budgets (Rasi, 2014). The main objective of each supply chain is to meet customer needs with the highest possible performance and low cost (Stadtler et al., 2015). In fact, the supply chain is a network of parties that each one contributes to meet the final customer's needs (Christopher, 2016). In this regard, reverse logistics involves the process of returning goods and the proper handling of these items and all operations related to re-use of goods and materials in order to increase the productivity, profitability, and efficiency of the logistics organization (Shakourloo et al., 2016). In recent years, many studies have been presented models to optimize reverse logistics costs. Jayaraman et al. (2003) presented a mixed integer linear programming model to develop a reverse logistics networks, this model is based on a strategic level and determines which reproduction centers to be constructed with respect to returned products. Min et al. (2005) developed a mixed integer nonlinear programming model aimed at minimizing costs in the reverse logistics network. In order to solve the proposed model, a genetic algorithm was developed and a binary approach was applied. Lee and Dong (2009) presented a three-echelon reverse logistics network by using an integer programming model that their aim is to minimize logistics costs. Pishvaee and Torabi (2010) presented a mixed integer bi-objective non-linear programming model to develop an integrated direct and reverse logistics network. In order to solve the proposed model, the multi-objective memetic algorithm was applied with a dynamic local search mechanism to find a set of inappropriate solutions. In order to deal with solving problems with great complexity, various meta-heuristic methods have been proposed. One of the newest methods is Cuckoo optimization algorithm which has be used in several studies (Akbari & Rashidi,2016, Amiri & Mahmoudi,2016,W ood,2016).Jayaraman and Pirkul (2001) presented a mixed integer linear programming model for a multi-product and four-rank logistics network; this model is one of few models that make the decision about the supplier rank. Melachrinoudis et al. (2005) used a multi-objective physical methodology to redesign the structure of warehouses network in order to reduce cost. Listeş and Dekker (2005) presented a mixed integer linear programming model to design direct logistics in a periodic chain to minimize the cost. Jayaraman et al. (1999) presented a mixed integer linear programming model for designing a reverse logistics network to minimize the cost. This is one of the few articles that have been designed a reverse logistics traction system based on customer demand for recovered products. To design the closed-loop logistics network of third-party logistics services suppliers, Du and Evans (2008) presented an advanced bi-objective integrated integer programming model by integrating distribution centers, collecting centers and recovery centers. The objective of this model is to minimize cost and time of delivery to customers. In other studies, the mathematical modeling of the logistics network has been evaluated. Ülkü & Bookbinder (2012) studied the effects of different cost scenarios in the logistics network design. They obtained multiple optimal solutions for cost and delivery time to maximize the supplier profit. Some studies modeled reverse logistics activities at the end of the vehicles' life cycle, reverse logistics design for electronic equipment wastes and outsourcing reverse logistics activities (Demirel et al., 2016; Kilic et al., 2015; Agrawal et al., 2016). Some researchers explored forward and backward logistics and closed-loop supply chain structural design for new products (Pedram et al., 2017; Gaur et al., 2017). In this study, the creditability approach is used for fuzzification. Cuckoo optimization algorithm has been also used to solve the problem in large dimensions to optimize time and cost in the reverse logistics network at three-echelon of recovery, processing and producing centers. Finally, we compared GA and Cuckoo algorithms to find the best solution. RL operations for companies engaged in manufacturing operations pose a new line of operations and business. The cost-benefit analysis poses one of the most important issues that determines the effectiveness and viability of RL systems. The cost-benefit analyses have to be performed in order to determine the returned products' values and operating costs associated with remanufacturing or recycling them (Stock 2001). Chan (2007) stated that one of the driving forces for companies to adopt RL is cost savings from RL activities. The author reported a case study of using returnable packaging materials between a manufacturer and an original equipment manufacturer (OEM) supplier. This case study showed how it is possible for an OEM to obtain a stable reverse flow over the life cycle of the product so as to guarantee a stable recovery process.This paper describes a multi-stage network-based model to minimize the overall cost for the reverse logistics management of inert construction waste across its entire life cycle. This model takes a unique two-type costing approach to overcome the ambiguities and deficiencies existing in previous models. Type-I cost refers to the facility-based costing (FBC) and Type-II cost refers to non-facility based costing (NFBC). Of course hidden costs, if you can find them, mean hidden opportunities. In the management of returns, costs you can look for and aim to eliminate or reduce include the following:

- Labor costs associated with customer relations (where there is a return, there may be an unhappy customer who must be appeased);
- Customer service labor costs (identifying warranty eligibility, determining what return and credit rules apply in each individual case);
- Transaction costs;
- Transport and shipping costs;
- Warehouse and storage costs;

If you can identify the costs which lie hidden in these elements of reverse logistics, and take steps to minimize them, the savings may make a meaningful contribution to overall supply chain cost reduction. Much depends upon the nature of your supply chain operation of course. Some industries experience more returns than others. The impact of returns too, can differ from one industry or organization to another. That's why the most important first step in improving reverse logistics management is to dig down and understand the true costs of product returns in your operation.

3. Problem statement

Today, one of the important issues in the field of logistics and SCM in different industries is reverse logistics. This issue has not been seriously considered in various industries so far. Over the past two decades, many companies and industries have begun implementing research in this area and have considered reverse logistics as one of the important processes in their supply chain. When reverse logistics design is proposed, two time and cost factors are considered as key factors for the products recovery process. Additionally, inventory control and distribution planning are essential supporting processes that affect the total cost of the supply chain and customer service level (Farahani & Elahipanah,2008).In this study, a reverse logistics network with objectives of minimizing time and cost was designed with the fuzzy approach. In this network, there is a customer area several recovery centers, several processing centers and a manufacturer that delivers the recovered products to customers through the reverse logistics process. If the recovered products are delivered to customers at the expected time, service will be satisfactory. In the design of the reverse logistics network, there should be a balance between total cost and delayed delivery time base on cost management. For example, in some cases, the company may use more processing centers to reduce delayed delivery and meet the maximum customer satisfaction and as result, there would be more fixed reopening cost. As mentioned, in order to consider uncertainty in the reverse logistics network has been used fuzzy approach.

3.1. Research assumptions

The assumptions related to bi-objective (time and cost) fuzzy mathematical programming model in the reverse logistics system are described as following:

- The reverse logistics network includes three-echelon of recovery, processing and manufacturing centers;
- In order to consider uncertainty, the input parameters of the problem are fuzzy numbers;
- Only one type of product is considered;
- The amount of manufacturer demand and amount of end-of-life products that should be collected in each period is specified at beginning of the period;
- Reopening the centers has fixed cost.

3.2. Problem Indicators

I= number of recovery centers
M= number of manufacturer
J= number of processing centers
T= time horizontal

3.3. Parameters and variables

b_j = capacity of center j

c_{jM} = the cost of transportation from processing center j to manufacturer M

c_j^H =inventory maintenance cost in processing center j in each period

c_{ij} = cost of transportation from recursive center i to processing center j

c_j^{op} = fixed cost of re-opening processing center j

d_{ij} = delivery time from recursive center i to processing center j

d_{jM} = delivery time from processing center j to manufacturer M

$d_M(t)$ = demand of manufacturer M in period t

p_j = time of the of operation in center j

t_E = expected delivery time by customer

$r_i(t)$ = product recovery rate in recursive center i at period t

$x_{ij}(t)$ = amount of delivered products from recursive center i to processing center j at period t

$x_{jM}(t)$ = amount of delivered products from processing center j to manufacturer M at period t

$y_j^H(t)$ = amount of delivered products to processing center j at period t

$$z_j = \begin{Bmatrix} 0 \\ 1, if\ processing\ center\ is\ used \end{Bmatrix}$$

3.4. Mathematical model

The first objective function is to minimize the total cost of reverse logistics network which includes fixed cost of reopening the processing centers, the cost of transport between centers and maintaining the cost of inventory. The second objective function is to minimize the time of delay in delivering customer orders. In reverse logistics, meeting customer's delivery schedule is much more difficult than direct logistics because of uncertainty in a number of returned products. In order to solve this problem, total delivery delay time should be minimized.

$$Min\ f_1 = \sum_{t=0}^{T}[\sum_{j=1}^{J} c_j^{op} z_j + \sum_{i=1}^{I}\sum_{j=1}^{J} c_{ij}x_{ij}(t) + \sum_{j=1}^{J} c_{jM}x_{jM}(t) + \sum_{j=1}^{J} c_j^H y_j^H(t)]$$

$$Min\ f_2 = \sum_{t=0}^{T}[\sum_{i=1}^{I}\sum_{j=1}^{J} d_{ij}x_{ij}(t) - t_E d_M(t) + \sum_{j=1}^{J}(d_{jM} + p_j)x_{jM}(t)]$$

$$\sum_{j=1}^{J} x_{ij}(t) \le r_i(t) \quad \forall i, t$$

$$\sum_{i=1}^{I} x_{ij}(t) + y_j^H(t-1) \le b_j z_j \quad \forall j, t$$

$$\sum_{j=1}^{J} x_{jM}(t) \le d_M(t) \quad \forall t$$

$$y_j^H(t-1) + \sum_{i=1}^{I} x_{ij}(t) - x_{jM}(t) = y_j^H(t) \quad \forall j, t$$

$$x_{ij}(t),\ x_{jM}(t),\ y_j^H(t) \ge 0 \quad \forall i, j, t$$

$$z_j \in \{0,1\} \quad \forall j$$

Constraint (3) indicates that the maximum amount of products sent from the recovery center i to the processing center j at period t are equal with the amount of recovered returned products in the recursive center i at period t. Constraint (4) and (5) represent the capacity of processing center and manufacturer respectively. Constraint (6) control amount of inventory at each processing center. Constraints (7) show those decision variables and are non-negative and constraint (8) ensures that the variable is a binary variable.

4. Fuzzy bi-objective modeling

In this study, the fuzzy theory is used for modeling the problem. Most of the traditional tools for formal modeling are crisp, deterministic and precise in character. Crisp means dichotomous that is yes-or-no type rather than more-or-less type. Precision assumes that the parameters of a model represent exactly the real system that has been modeled. When the parameters of the problem are uncertain, the presentation of the fuzzy scheduling algorithm creates a flexible system (Behnamian & Ghomi, 2014). In addition, the computational complexity of fuzzy modeling is far less than other approaches (Sowinski & Hapke, 2000). Fuzzy logic starts with and builds on a set of user-supplied human language rules. The fuzzy systems convert these rules to their mathematical equivalents. This simplifies the job of the system designer and the computer and results in much more accurate representations of the way systems behave in the real world. Additional benefits of fuzzy logic include its simplicity and flexibility. Fuzzy logic can handle problems with imprecise and incomplete data and it can model nonlinear functions of arbitrary complexity. Considering the expressed features and the nature of the problem in this study, it seems that the fuzzy approach will have a great contribution to uncertainty. In a fuzzy approach, we can use different fuzzy numbers such as triangular fuzzy numbers or trapezoidal fuzzy numbers. In a triangular fuzzy number, for the value of parameters, the highest confidence level is obtained while in the trapezoidal number, for an interval of one parameter a maximum value is obtained. In this case, the risk of decision making is reduced and they accept uncertainty in real conditions with higher confidence. In this study, considering the nature of the problem and its complexity, decision makers prefer to obtain the highest confidence per interval for each parameter. The fuzzy set of the reference X is a set of ordered pairs written in the form of equation (9) (Zadeh, 1999).

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in X\} \qquad)9($$

Where $\mu_{\tilde{A}}(x)$ is obtained from equation (10).

$$\mu_{\tilde{A}}(x): X \to [0,1] \qquad)10($$

Given the above equation, we can say that the membership function relates to each member of the set X to the interval [0, 1]. The most common fuzzy numbers used in researches are trapezoidal and triangular fuzzy numbers. In this study, trapezoidal numbers are fourfold; its representation is according to Fig. 1 and its membership function is in the form of equation (11).

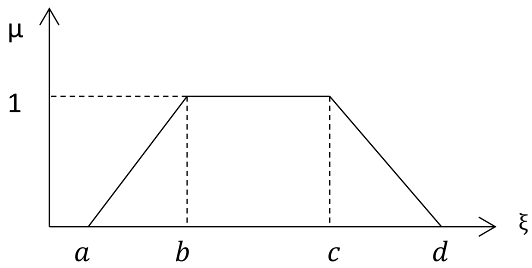

Figure 1. Trapezoidal Fuzzy Number

$$\mu(x) = \begin{cases} \frac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \frac{d-x}{d-c} & c \le x \le d \\ 0 & O.W. \end{cases} \quad (11)$$

possibility module is determined by a possibility distribution function that has been defined as follows (Zadeh, 1999).

$$Pos(x): P(x) \to [0,1] \quad (12)$$

Possibility criterion is shown through Equation (13):

$$Pos(\xi \le r) = sup_{\xi \le r} \quad \mu_{\tilde{A}}(x) \quad (13)$$

Also, another collective criterion possibility is defined by (13), which indicates the necessity of occurrence of a fuzzy event called as necessity criterion and is expressed in the form of equation (14).

$$Nec(A) = 1 - Pos(A^c) = 1 - sup_{\xi > r} \quad \mu_{\tilde{A}}(x) \quad (14)$$

Equation (14) states that if the possibility of occurrence of event A is low, the necessity of event A is raised. In order to determine a dual standard, Liu and Liu (2002) introduced the concept of credibility. In addition, adequate prerequisites for the credibility criterion were presented by Li & Liu (2006). The definition of the credibility criterion is in accordance with the criteria of possibility and necessity in form of equation (15) (Mehlawat & Gupta, 2014; Zhang et al., 2015).

$$Cr(A) = \frac{1}{2}\{Pos(A) + Nec(A)\} \quad)15($$

The value of the possibility has been defined a trapezoidal fuzzy variable according to equation (16):

$$pos\{\xi \le r\} = \sup \mu_x(x) = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a \le x \le b \\ 1 & x \ge b \end{cases} \quad)16($$

In addition, necessity value is trapezoidal which is defined by Equation (17).

$$= \begin{cases} 0 & x \le c \\ 1 - \frac{d-x}{d-c} = \frac{x-c}{d-c} & c \le x \le d \\ 1 & x \ge d \end{cases} \quad (17)$$

According to above cases and definition of Cr, credibility function of the trapezoidal fuzzy number will be according to equation (18):

$$Cr\{\xi \le r\} = \frac{1}{2}\{pos\{\xi \le r\} + Nec\{\xi \le r\}\}$$

$$= \begin{cases} 0 & x \le a \\ \frac{x-a}{2(b-a)} & a \le x \le b \\ \frac{1}{2} & b \le x \le c \\ \frac{1}{2}(1 + \frac{x-c}{d-c}) & c \le x \le d \\ 1 & x \ge d \end{cases} \quad (18)$$

According to the definitions, the α-optimistic value indicated by the symbol$\xi(\alpha)_{sup}$which for $\alpha > \frac{1}{2}$ is calculated as follows.

$$\xi(\alpha)\ sup\{x | Cr\{\xi \ge x\} \ge \alpha\}_{sup} \quad (19)$$

Similarly, the α-pessimistic value indicated by the symbol$\xi(\alpha)_{inf}$ is calculated for $\alpha > \frac{1}{2}$and it equals to:

$$\xi(\alpha)\ inf\{x | Cr\{\xi \le x\} \ge \alpha\}_{inf} \quad (20)$$

In equation (20), the subset of elements of the fuzzy set A which its degree of membership is at least equal to α (α> 0) is called alpha cut A. The most important use of the alpha cut is the transformation of the fuzzy set to certain set. In general, the fuzzy linguistic approach can consider optimistic or pessimistic in decision making, triangular fuzzy numbers are recommended for evaluating priorities rather than conventional numerical equations. In this section, two optimistic or pessimistic approaches (left and right extensions) have been used to assign numbers to α. According to definitions, in order to defuzzification of parameters that are considered as fuzzy in the objective function, the mean of four fuzzy numbers according to equation (21) is used and to defuzzification of the parameters that are in the problem limitations, two equations (22) and (23) are used (Liu & Liu, 2002, Pishvaee et al., 2012, Lu et al., 2016).

$$\xi = \frac{(a+b+c+d)}{4} \tag{21}$$

$$Cr\{\xi \leq x\} \geq \alpha \Leftrightarrow x \geq (2-2\alpha)c + (2\alpha-1)d \tag{22}$$

$$Cr\{\xi \geq x\} \geq \alpha \Leftrightarrow x \leq (2\alpha-1)a + (2-2\alpha)b \tag{23}$$

Since in the right side, limits are fuzzy according to the nonlinear fuzzy programming method each function is solved with a highest then with the lowest limit of the fuzzy number. At this stage, we must solve a certain multi-objective model. For this purpose, various methods have been presented and in this research fuzzy logic method based on the degree of the membership function of objectives have been applied. First, the maximum and minimum values of each of the objectives will be determined then the amount of α that is the same degree with the realization of objectives is obtained (Pishvaee et al., 2012). In order to develop a more realistic model, all parameters of the problem are considered uncertain by applying trapezoidal fuzzy number type. Thus, the proposed bi-objective fuzzy mathematical model will be as follows:

$$Min\ f_1 = \sum_{t=0}^{T}[\sum_{j=1}^{J}\tilde{c}_j^{op}z_j + \sum_{i=1}^{I}\sum_{j=1}^{J}\tilde{c}_{ij}x_{ij}(t) + \sum_{j=1}^{J}\tilde{c}_{jM}x_{jM}(t) + \sum_{j=1}^{J}\tilde{c}_j^{H}y_j^{H}(t)]$$

$$Min\ f_2 = \sum_{t=0}^{T}[\sum_{i=1}^{I}\sum_{j=1}^{J}\tilde{d}_{ij}x_{ij}(t) - t_E\tilde{d}_M(t) + \sum_{j=1}^{J}\left(\tilde{d}_{jM} + \tilde{p}_j\right)x_{jM}(t)]$$

$$\sum_{j=1}^{J} x_{ij}(t) \leq \tilde{r}_i(t) \quad \forall i,t$$

$$\sum_{i=1}^{I} x_{ij}(t) + y_j^H(t-1) \leq \tilde{b}_j z_j \quad \forall j,t$$

$$\sum_{j=1}^{J} x_{jM}(t) \leq \tilde{d}_M(t) \quad \forall t$$

$$y_j^H(t-1) + \sum_{i=1}^{I} x_{ij}(t) - x_{jM}(t) = y_j^H(t) \quad \forall j,t$$

$$x_{ij}(t),\ x_{jM}(t),\ y_j^H(t) \geq 0 \quad \forall i,j,t$$

$$z_j \in \{0,1\} \quad \forall j$$

Regarding the defuzzification method presented in the previous section, equations (21) to (23) are used to change objective functions of time and cost as follows:

$$Min\ f_1 = \sum_{t=0}^{T}[\sum_{j=1}^{J}\left(\frac{c_{j1}^{op}+c_{j2}^{op}+c_{j3}^{op}+c_{j4}^{op}}{4}\right)z_j + \sum_{i=1}^{I}\sum_{j=1}^{J}\left(\frac{c_{ij1}+c_{ij2}+c_{ij3}+c_{ij4}}{4}\right)x_{ij}(t) + \sum_{j=1}^{J}\left(\frac{c_{jM1}+c_{jM2}+c_{jM3}+c_{jM4}}{4}\right)x_{jM}(t) + \sum_{j=1}^{J}\left(\frac{c_{j1}^{H}+c_{j2}^{H}+c_{j3}^{H}+c_{j4}^{H}}{4}\right)y_j^H(t)]$$

$$
\begin{aligned}
&Min\ f_2 \\
&= \sum_{t=0}^{T}\left[\sum_{i=1}^{I}\sum_{j=1}^{J}\left(\frac{d_{ij1}+d_{ij2}+d_{ij3}+d_{ij4}}{4}\right)x_{ij}(t)\right. \\
&+ \sum_{j=1}^{J}(\left(\frac{d_{jM1}+d_{jM2}+d_{jM3}+d_{jM4}}{4}\right) \\
&+ \left(\frac{p_{j1}+p_{j2}+p_{j3}+p_{j4}}{4}\right))x_{jM}(t) \\
&- t_E\left(\frac{d_{M1}(t)+d_{M2}(t)+d_{M3}(t)+d_{M4}(t)}{4}\right)]
\end{aligned}
$$

$$\sum_{j=1}^{J} x_{ij}(t) \le [(2\alpha-1)r_{i1}(t)+(2-2\alpha)r_{i2}(t)] \quad \forall i,t \tag{34}$$

$$
\begin{aligned}
&\sum_{i=1}^{I} x_{ij}(t) + y_j^H(t-1) \\
&\le z_j\left[(2\beta-1)b_{j1}+(2-2\beta)b_{j2}\right] \quad \forall j,t
\end{aligned} \tag{35}
$$

$$\sum_{j=1}^{J} x_{jM}(t) \le [(2\gamma-1)d_{M1}(t)+(2-2\gamma)d_{M2}(t)] \ \ \forall t \tag{36}$$

Two meta-heuristic algorithms have been developed to solve the proposed model and their results are examined and compared for a set of problems.

6. Proposed Meta-heuristic Algorithms

Since most of the logistics network design problems are NP-hard (Altiparmak et al., 2006, Lee & Dong, 2009, Pishvaee et al., 2010), accurate methods do not have the capability to solve such problems at large dimensions. Therefore, heuristic and meta-heuristic methods have been developed to solve problems with large dimensions. In this section, each algorithm and its operation are summarized.

6.1. Cuckoo Search Algorithm

In this study, Cuckoo search algorithm was developed to optimize time and cost by fuzzy multi-objective model. Some birds abandoned the trouble of any nesting and parenting duties and used their cleverness to grow their own chickens. These birds never nest for themselves and instead put their eggs in the nest of other types of birds and wait for them to look after their eggs. Cuckoo chickens come out of egg faster than eggs of host bird and grow faster (Payne & Sorensen, 2005).

Figure (2) illustrates the flowchart of the cuckoo optimization algorithm (Rajabioun, 2011). In nature, each cuckoo lays egg between 5 and 20. These numbers are used as the upper and lower limits for allocation of eggs to each cuckoo in different repetitions. Another habit of each cuckoo is that they are laying their own eggs in a given radius which is called egg-laying radius (ELR) (Akbari & Rashidi, 2016). The maximum egg laying radius is determined based on the total number of eggs. The current number of eggs of the cuckoo and the upper and lower limit of the variables of the problem according to equation (37).

$$ELR = \alpha \times \frac{Number\ of\ current\ cuckoo's\ eggs}{Total\ number\ of\ eggs} \times (\mathrm{var}_{hi} - \mathrm{var}_{low}) \tag{37}$$

In the above equation, there is the parameter to maximize ELR value which is adjustable. Additionally, there are an upper limit and the lower limit of variables respectively. After each laying, P% of all eggs (usually 10%) that have least profit functions is eliminated. The remaining chickens are fed and grown in host nests. After the formation of cuckoo groups, the group with the highest average profit (optimism) is selected as the target group and the other groups migrate to it. When migrating to the destination, cuckoos do not pass through the all path to the destination. They pass through only a part of the path and have a deviation in the path. This mode of movement is clearly seen in Fig (2). Each cuckoo only passes through only λ% of the total path to the current ideal objective and has a radian deviation φ. These two parameters help cuckoos search more environments (Rajabioun, 2011). In order to design a cuckoo optimization algorithm in this research, λ is a random number generated between 1 and 0 and φ is also a number between 0 and1. The upper and lower limits of the variable in the calculation of ELR are considered to be 0 and 1 respectively. Other control parameters of the cuckoo algorithm are presented in the next section.

5.2. Genetic Algorithm

Since 1960, imitation of living organisms has been considered for use in powerful algorithms for optimization problems called "evolutionary calculation techniques". The Genetic Algorithm was firstly proposed by John Holland and his colleagues at the University of Michigan in 1962. In their research, they made an effort for the process of adaptation in artificial systems that should have the capabilities of natural systems. The result of these efforts was the emergence of a genetic algorithm.

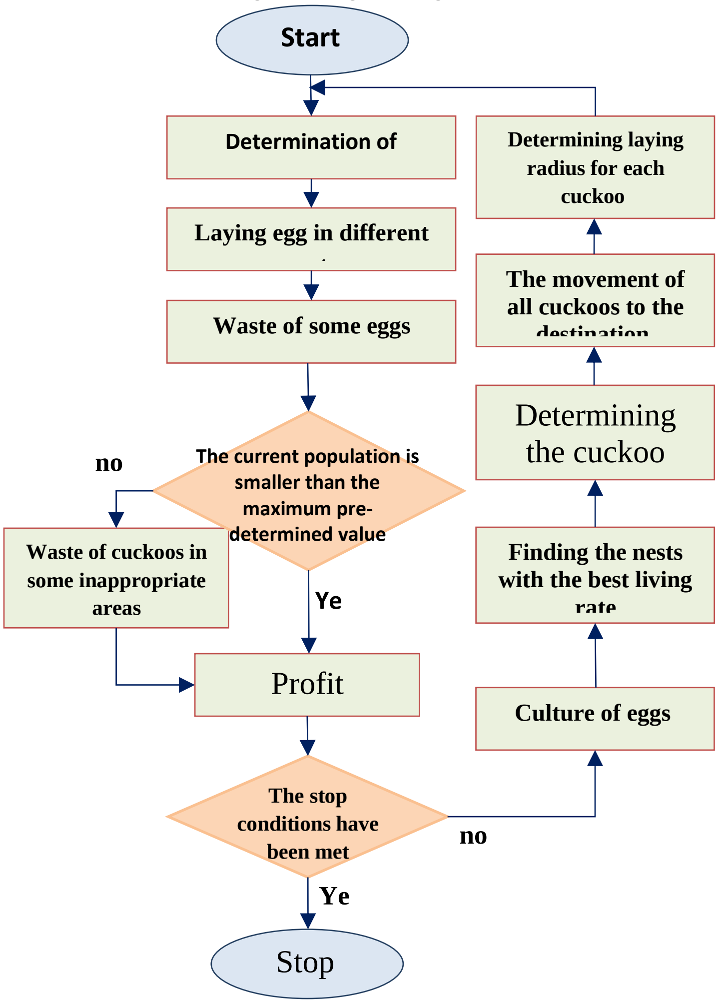

Figure 2. Cuckoo Flowchart Algorithm

Mathematical foundations were published in the book titled "Adaptation in the Natural and Artificial System" by Holland and Goldberg developed it in 1986. Most of the traditional methods of optimization have this major disadvantage that they stop as soon as it reaches the first "local optimal" point and did not have the ability to exit from this point and move to "globally optimal " point. Known methods in this area include the descending slope method developed by Kushi used to solve optimization problems without limitation and the "Lagrange coefficient" method for solving problems with equal limitation. Various other techniques have been developed for optimization search and problems including random searching, gradient method, elemental simulation and random algorithms. Among the random algorithms, the genetic algorithm (GA) has high efficiency. One of the most important applications of the genetic algorithm is the optimization of design parameters in different systems. Genetic actions imitate the inherited gene transfer process for the creation of new descendants in each generation. An important part of the genetic algorithm is the creation of new chromosomes called descendants through some of the old called parental chromosomes. This important process is carried out by genetic actions. In general, these actions are performed by two crossover and mutation operators. The crossover operator is applied on two chromosomes at a moment and two newborns are created by combining the structure of two chromosomes. An important concept associated with this operator is the crossover rate. Crossover rate is the ratio of the number of newborn babies produced in each generation to the size of the main population. This rate determines the expected number of chromosomes that are altered by the mentioned operator. The larger crossover rate allows a wider segment of the search space to be searched. If the crossover rate is too large, it will waste time to visit unreliable areas of the solution. The mutation operator in different chromosomes generates unplanned random changes and enters the genes that did not exist at the beginning of the population. An important concept in this operator is called the mutation rate. The mutation rate is the percentage of the total number of existing genes that are changed. If the mutation rate is very small, many genes that can be useful would have not been tested but if the mutation rate is very high, a random disturbance occurs and the babies lose their resemblance to the parent which leads to the loss of the historical memory of the algorithm. Therefore, the optimal mutation rate should be chosen. Obviously, an index is required for detection of the more appropriate chromosome. On the issue of optimization of functions, this index is usually problem objective function that is each chromosome will be converted to the corresponding solution and placed in the objective function. Any chromosome whose value is better than its objective function will be more appropriate. However, in the case of some more complex problems, it is necessary to define the fitness function. In order to select the best solutions for the reproduction of the new population, a method should be used that will even choose the best solution. Two commonly used methods include random selection by roulette wheel and racing selection method. The problem-solving process by a genetic algorithm is illustrated in Figure (3) in the form of a flowchart.

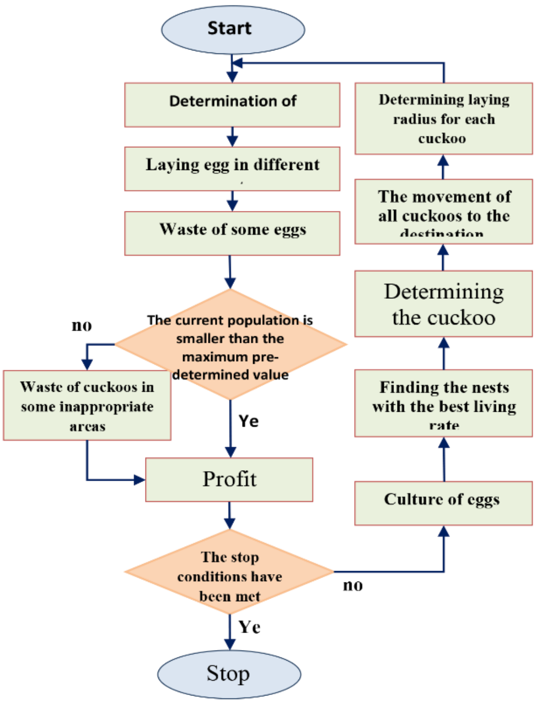

Figure 3. Flowchart of Genetic Algorithm

6. Evaluation of Developed Algorithms

In order to evaluate the quality and dispersion of Meta-heuristic algorithms, the relative percentage of deviation (RPD) and computational time have been used. In order to make these comparisons, 18 test problems with different values for the number of recursive centers and processing centers in different time horizons have been solved and the results are presented in Table (1).In order to generate input data, we used data base on fuzzy numbers. Four random numbers are firstly generated by deploying random uniform distributions then they are arranged in ascending form and used as input data. The proposed algorithms were implemented in the computer with Intel (R) Core (TM) i7-5500U CPU with 4.4 GHz specification with 8 GB of memory by applying the MATLAB R2016a software.

Table 1- Input data values for experimental

U ~ [3 10]	b_j
U ~ [30 50]	$d_M(t)$
U ~ [20 50]	$r_i(t)$
U ~ [10 25]	c_{ij}
U ~ [10 25]	c_{jM}
U ~ [10 25]	c_j^{op}
U ~ [10 25]	c_j^H
U ~ [5 20]	d_{ij}
U ~ [10 25]	d_{jM}
U ~ [10 20]	p_j
10	t_E

Each of the control parameters considered for algorithms has a significant impact on the quality of solution and computational time. For example, increasing the population in the genetic algorithm may increase the computational load of the algorithm and consequently its inefficiency. To adjust the parameters of the algorithm, each algorithm was implemented several times and finally the best combination of algorithm parameters was obtained as shown in the Table (2).

Table 2- Parameters of Genetic and Cuckoos Algorithms

GA		COA	
Value	Parameter	value	Parameter
200	max_{it}	10	$initial_{Cuckoo}$
100	n_{pop}	100	$N_{MaxCuckoo}$
0.8	P_c	50	max_{Gen}
0.3	P_m	2	$N_{Cluster}$

6.1. RPD (Relative Percentage Deviation) criterion

The relative percentage deviation shows the degree of deviation of algorithms to best value of the objective function. As a result, the lower this value indicates that the algorithm is performing better. The way to calculate it as follows:

$$RPD = \frac{sol - Bestsol}{Bestsol} * 100 \qquad (38)$$

In which sol is the solution obtained from the implementation of the algorithm and Best sol is the best solution obtained from algorithms. For small size problems, 18 types of problems are generated and executed 10 times in order to reduce the error of random numbers. Then, averages of results are reported. Table (3) gives the average of the obtained results for small problems. The first item of the second column(I) gives the number of recovery centers and the second item(J) gives the number of processing centers and the third (time horizontal). The next columns give the results and times of the algorithms. Above the results of the implementation of algorithms for hypothetical problems are reported. Table (3) comprises two algorithms by RPD and time indexes and suggests that although cuckoo algorithm performs better in all proposed cases. In terms of time of algorithm implementation, it spends the much computational time required to achieve the solution in all cases. In addition, when dimensions of the problem increase, it will cause to increase the computational time of achieving an optimal solution. Using the multi-objective model under uncertainty by fuzzy parameters in this study provides an easier way to address the complexity of the decision-making problems better.

Table 3- Computational results for proposed problems

	J	I	T	RPD		Time	
				GA	COA	GA	COA
1	4	3	5	137/86	0	26.61	34.2
2	5	4	5	131/42	0	37.32	48.67
3	7	5	6	202/80	0	68.80	89.48
4	8	5	6	229/12	0	78.33	102.77
5	10	7	8	285/50	0	161.69	205.81
6	12	8	8	226/16	0	213.30	273.38
7	13	8	9	323/70	0	262.11	331.63
8	14	10	10	403/22	0	385.44	473.89
9	15	12	10	412/60	0	477.54	597.45
10	16	12	12	471/12	0	608.54	726.32
11	18	12	12	477/58	0	686.11	844.70
12	20	12	12	479/22	0	757.06	953.91
13	21	13	12	494/85	0	830.63	1035.21
14	22	15	15	638/91	0	1352.67	1624.86
15	24	17	15	631/59	0	1562.65	1925.78
16	26	19	17	741/87	0	2059.28	2639.20
17	28	21	20	877/29	0	2864.03	3978.73
18	30	23	22	967/15	0	4335.88	4631.85

7. Managerial Implication

It is recommended that managers, according to the research findings try to reduce costs and delay orders in industrial factories base on cost management. Managers in order to achieve the above objectives in long term, they should study parameters of industrial i.e. the number of processing centers, the centers of return, etc. According to findings, we suggest managers monitor the quantity of returned products in the supply chain in uncertainty condition to ensure of increasing profit in all of the levels.

8. Conclusion and Discussion

In this research, a fuzzy bi-objective optimization model was introduced in the reverse logistics system. The aim of this research is to determine the number of returned products that should be delivered to be recovered, processed and re manufactured in different time periods so that the total cost of reverse logistics and delay time to be minimized. Additionally, in order to consider the uncertainty in the reverse logistics network, a fuzzy approach has been used. Finally, a mathematical programming model was presented. To solve the problem at high dimensions, the cuckoo, and genetic algorithm was implemented in MATLAB software. Then, by designing a number of sample problems in different dimensions results were compared. This problem was solved using CA Optimization algorithm in 21 seconds and the value of the target function is 6496.958. The value of the target function cost is USD 10074.29 and the delayed payment is equal to USD 2919.625. It is observed that the value of the objective function decreases with increasing number of repetitions. On the other hand, the value of the objective function in several first repetitions is the order decreases and this value remains constant after duplicate, which also indicates the good performance of the algorithm. The cuckoo is proposed because it converges to a small number of repetitions.

The computational results showed that cuckoo algorithm (CA) has a better performance in finding a better solution than the genetic algorithm (GA) although will take more time. In the reverse supply chain, there are other influential components, such as pollutants which can be investigated in order to protect the environment. Additionally, another echelon of the supply chains such as recovery, repair, disposal, and reuse will also be added to the problem. Further, other new meta-heuristic methods such as weed algorithm and droplet evaporation algorithm can be used. Finally, the uncertainty in the problem was considered in this study using the fuzzy approach. In this regard, we can use other approaches, such as possibility approaches and scenario-based solutions. For future researches, we suggest to consider truck movement between difference centers i.e. processing and return finished and WIP products or raw material.

References

1) Abidi, Naseem. Bandyopadhayay, Asit. Gupta, Vishal.2017. Sustainable Supply Chain Management:
2) A Three Dimensional Framework and Performance Metric for Indian IT Product Companies. International Journal of Information Systems and Supply Chain Management,10(1),29-52.
3) AGRAWAL, S., SINGH, R. K. & MURTAZA, Q. 2016. Outsourcing decisions in reverse logistics: sustainable balanced scorecard and graph theoretic approach. Resources, Conservation and Recycling, 108, 41-53.
4) AKBARI, M. & RASHIDI, H. 2016. A multi-objectives scheduling algorithm based on cuckoo optimization for task allocation problem at compile time in heterogeneous systems. Expert Systems with Applications, 60, 234-248.
5) ALTIPARMAK, F., GEN, M., LIN, L. & PAKSOY, T. 2006. A genetic algorithm approach for multi-objective optimization of supply chain networks. Computers & industrial engineering, 51, 196-215.
6) AMIRI, E. & MAHMOUDI, S. 2016. Efficient protocol for data clustering by fuzzy Cuckoo Optimization Algorithm. Applied Soft Computing, 41, 15-21.
7) BAGHERI, N. R., BARADARANKAZEMZADE, R. & ASADI, R. 2013. IDENTIFYING AND RANKING OF THE SUCCESS FACTORS IN AUTOMOTIVE REVERSE LOGISTICS THROUGH INTERPRETIVE STRUCTURAL MODELING (ISM).
8) BEHNAMIAN, J. & GHOMI, S. F. 2014. Multi-objective fuzzy multiprocessor flowshop scheduling. Applied soft computing, 21, 139-148.
9) CHOPRA, S. 2003. Designing the distribution network in a supply chain. Transportation Research Part E: Logistics and Transportation Review, 39, 123-140.
10) CHRISTOPHER, M. 2016. Logistics & supply chain management, Pearson UK.
11) Chan, H.K., 2007. A pro-active and collaborative approach to reverse logistics – a case study.
12) Production Planning & Control, London 18 (4), 350–360.
13) CULLINANE, S., BROWNE, M., WHITEING, A. & MCKINNON, P. A. 2010. Green Logistics: improving the environmental sustainability of logistics, Kogan Page.
14) DEMIREL, E., DEMIREL, N. & GÖKÇEN, H. 2016. A mixed integer linear programming model to optimize reverse logistics activities of end-of-life vehicles in Turkey. Journal of Cleaner Production, 112, 2101-2113.
15) DU, F. & EVANS, G. W. 2008. A bi-objective reverse logistics network analysis for post-sale service. Computers & Operations Research, 35, 2617-2634.
16) FARAHANI, R. Z. & ELAHIPANAH, M. 2008. A genetic algorithm to optimize the total cost and service level for just-in-time distribution in a supply chain. International Journal of Production Economics, 111, 229-243.
17) GAUR, J., AMINI, M. & RAO, A. 2017. Closed-loop supply chain configuration for new and reconditioned products: An integrated optimization model. Omega, 66, 212-223.
18) Jingshan, Q. hao, W. Bo, L.(2018).Analysis on the Construction of Enterprise Financial Shared Service Center System . China Business Theory.22: 119-120.
19) JAYARAMAN, V., GUIDE JR, V. & SRIVASTAVA, R. 1999. A closed-loop logistics model for remanufacturing. Journal of the operational research society, 50, 497-508.
20) JAYARAMAN, V., PATTERSON, R. A. & ROLLAND, E. 2003. The design of reverse distribution networks: Models and solution procedures. European journal of operational research, 150, 128-149.
21) JAYARAMAN, V. & PIRKUL, H. 2001. Planning and coordination of production and distribution facilities for multiple commodities. European journal of operational research, 133, 394-408.
22) KESKIN, B. B. & ÜSTER, H. 2007. Meta-heuristic approaches with memory and evolution for a multi-product production/distribution system design problem. European Journal of Operational Research, 182, 663-682.
23) KILIC, H. S., CEBECI, U. & AYHAN, M. B. 2015. Reverse logistics system design for the waste of electrical and electronic equipment (WEEE) in Turkey. Resources, Conservation and Recycling, 95, 120-132.
24) LEE, D.-H. & DONG, M. 2009. Dynamic network design for reverse logistics operations under uncertainty. Transportation Research Part E: Logistics and Transportation Review, 45, 61-71.

25) LI, X. & LIU, B. 2006. A sufficient and necessary condition for credibility measures. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 14, 527-535.
26) LISTEȘ, O. & DEKKER, R. 2005. A stochastic approach to a case study for product recovery network design. European Journal of Operational Research, 160, 268-287.
27) LIU, B. & LIU, Y.-K. 2002. Expected value of fuzzy variable and fuzzy expected value models. IEEE transactions on Fuzzy Systems, 10, 445-450.
28) LU, H., DU, P., CHEN, Y. & HE, L. 2016. A credibility-based chance-constrained optimization model for integrated agricultural and water resources management: A case study in South Central China. Journal of hydrology, 537, 408-418.
29) MEHLAWAT, M. K. & GUPTA, P. 2014. Credibility-based fuzzy mathematical programming model for portfolio selection under uncertainty. International Journal of Information Technology & Decision Making, 13, 101-135.
30) MELACHRINOUDIS, E., MESSAC, A. & MIN, H. 2005. Consolidating a warehouse network:: A physical programming approach. International Journal of Production Economics, 97, 1-17.
31) MENA, C., HUMPHRIES, A. & CHOI, T. Y. 2013. Toward a theory of multi-tier supply chain management. Journal of Supply Chain Management, 49, 58-77.
32) MIN, H., KO, H. & PARK, B. 2005. A Lagrangian relaxation heuristic for solving the multi-echelon, multi-commodity, closed-loop supply chain network design problem. International Journal of Logistics Systems and Management, 1, 382-404.
33) Rasi,E.R.2015.Identify and prioritize the factors affecting Quality costs of automotive products in mass production phase (Case study: Iran Khodro and Saipa). Journal of Management Accounting and Auditing Knowledge,4(14),75-86.
34) PAYNE, R. B. & SORENSEN, M. D. 2005. The cuckoos, Oxford University Press.
35) PEDRAM, A., YUSOFF, N. B., UDONCY, O. E., MAHAT, A. B., PEDRAM, P. & BABALOLA, A. 2017. Integrated forward and reverse supply chain: A tire case study. Waste Management, 60, 460-470.
36) PERCIVAL, R. V., SCHROEDER, C. H., MILLER, A. S. & LEAPE, J. P. 2017. Environmental regulation: Law, science, and policy, Wolters Kluwer Law & Business.
37) PISHVAEE, M. S., FARAHANI, R. Z. & DULLAERT, W. 2010. A memetic algorithm for bi-objective integrated forward/reverse logistics network design. Computers & operations research, 37, 1100-1112.
38) PISHVAEE, M. S. & TORABI, S. A. 2010. A possibilistic programming approach for closed-loop supply chain network design under uncertainty. Fuzzy sets and systems, 161, 2668-2683.
39) PISHVAEE, M. S., TORABI, S. A. & RAZMI, J. 2012. Credibility-based fuzzy mathematical programming model for green logistics design under uncertainty. Computers & Industrial Engineering, 62, 624-632.
40) Ozceylan.E, T. Paksoy, T. Bektas.(2014). Modeling and optimizing the integrated problem of closed-loop supply chain network design and disassembly line balancing. Transportation Research Part E: Logistics and Transportation Review, 61,3, 142–164.
41) RAJABIOUN, R. 2011. Cuckoo optimization algorithm. Applied soft computing, 11, 5508-5518.
42) Rasi,Ehtesham.R.2018. A Cuckoo Search Algorithm Approach for Multi- Objective Optimization in Reverse Logistics Network under Uncertainty Condition. International Journal of Supply and Operations Management, 5, 1, 66-80.
43) Stock, J.R., 2001. The 7 deadly sins of reverse logistics. Material Handling Management, 56 (3), MHS5–MHS11.
44) SHAKOURLOO, A., KAZEMI, A. & JAVAD, M. O. M. 2016. A new model for more effective supplier selection and remanufacturing process in a closed-loop supply chain. Applied Mathematical Modelling, 40, 9914-9931.
45) SOWINSKI, R. & HAPKE, M. 2000. Scheduling under fuzziness, Physica-Verlag.
46) STADTLER, H., KILGER, C. & MEYR, H. 2015. Supply chain management and advanced planning. Springer Berlin Heidelberg.
47) ÜLKÜ, M. A. & BOOKBINDER, J. H. 2012. Optimal quoting of delivery time by a third party logistics provider: The impact of shipment consolidation and temporal pricing schemes. European Journal of Operational Research, 221, 110-117.
48) WOOD, D. A. 2016. Hybrid cuckoo search optimization algorithms applied to complex wellbore trajectories aided by dynamic, chaos-enhanced, fat-tailed distribution sampling and metaheuristic profiling. Journal of Natural Gas Science and Engineering, 34, 236-252.
49) ZADEH, L. A. 1999. Fuzzy sets as a basis for a theory of possibility. Fuzzy sets and systems, 100, 9-34.
50) ZHANG, Y., HUANG, G., LU, H. & HE, L. 2015. Planning of water resources management and pollution control for Heshui River watershed, China: a full credibility-constrained programming

approach. Science of The Total Environment, 524, 280-289.

51) Zhang,YuHang.Wang,Ying.2019. Supply Chain Decisions Considering Heterogeneous Consumer Greenness Preference and Reservation Utilities. International Journal of Information Systems and Supply Chain Management,12(1),1-21