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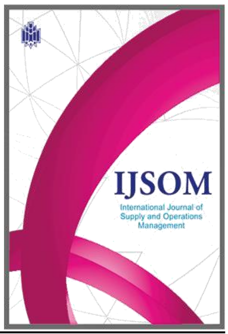

A Cuckoo Search Algorithm Approach for Multi- Objective Optimization in Reverse Logistics Network under Uncertainty Condition

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Abstract

In this study, an efficient logistics network was designed to optimize both time and cost as the most effective factors using a mathematical model (two-objective fuzzy optimization) in a reverse logistics system. This paper attempted to determine the value of goods sent between return processing centers in any period of time in order to minimize the total cost and time of delay within supply chain. The fuzzy approach was adopted in order to consider uncertainty in reverse logistics network. The validity of model was measured through a model proposed by Azar Resin Chemical Industrial Company and then implemented and solved by GAMS software. According to the previous studies that implemented the model at a smaller scale, the problem revolved around designing NP-hard logistics network. Hence, exact methods cannot solve these problems on a large scale. Therefore, for solving the problem, Meta-Heuristic algorithms was used in this study. Because Cuckoo search algorithm has a high efficiency in comparison to other algorithms. In order to validate the newly proposed algorithm, the results were compared against the exact solution. The findings suggested that the proposed Cuckoo algorithm was sufficiently accurate to solve the problem and achieve values similar to exact solution.

Keywords: Reverse logistics; Optimization; Fuzzy; Cuckoo algorithm; Mixed integer linear programing (MILP).

1. Introduction

Reverse supply chain management (RSCM) is for all operations related to reuse and reprocessing of products and materials. According to Blackburn et al. (2004) It is"the process of moving goods from their typical final destination for the purpose of recycling and proper use of goods". Reverse logistics management 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 reverse logistics network (Ozceylan et al., 2014). As a part of supply chain, reverse logistics network can be defined as accurate, timely and appropriate transport of usable and unusable materials, items and goods from distal end point and end-users through supply chain to appropriate unit. In other words, reverse logistics is the process of moving and transporting goods and products which can be returned to supply chain. Designing and implementing reverse logistics network for product returns will not only curtail inventory and transportation costs, but will also increase customer loyalty (Lee et al., 2009). This being the case, environmental regulations and economic interests, consumer awareness, and social responsibility toward the environment are essential driving forces (Bagheri et al., 2013). In laws recently enacted in different countries, particularly in European Union, companies are responsible for collecting scrap and recycle their products. If companies fail to collect, recover, recycle, or destroy their products, there will endanger the natural environment (Meade et al., 2007). In recent decades, many important companies such as Dell, General Motors, Kodak, and Xerox have paid special attention to rebuilding, repairing, and recovery of their products (Keskin et al., 2007). In this context, it is crucial to design logistics network as a part of supply chain planning. Therefore, an appropriate network design can play a positive role in meeting the objectives of supply chain, particularly cost reduction, accountability, and efficiency (Chopra et al., 2003). Due to its potential for recovering the value of returned and used products, reverse logistics has attracted a great deal of attention and become a key element in supply chain. Competitive marketing, strategic issues and improvement

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of customer loyalty, and subsequent sales are considered as the incentives to the adoption of reverse logistics (Cruz and Ertel, 2009; Kannan, 2009). Moreover, an efficient supply chain design will guarantee sustainable competitive advantages for companies (Pishvaee et al., 2010). The reverse logistics network design covers a wide range of applications from linear models to complex non-linear models, minimizing cost of shipping in complex multi-objective optimization problems (Altiparmak et al., 2006). In a quantitative approach, integrating RL in the design of green and sustainable supply chains can be done by adding some decision variables, objective functions, and constraints to mathematical models (Govindan et al., 2015). According to Liao (2018), Reverse logistic (RL) which originates from a waste management point of view is an important factor to increase customer satisfaction.

Therefore, to the present study addresses the time of reverse supply chain (delivery time from return to processing and from processing center to manufacturer) as one of the managers' main concerns as it always causes customers' dissatisfaction and there is a call for taking it into account in an in-depth research study. Also, in this study, in addition to investigating 'cost' as a variable, we tried to examine fixed costs. Accordingly, the two objectives functions of operation time and cost are taken into consideration in this paper. Since the design and deployment of logistics network are strategic decisions, their effect may last several years during which demand parameters and customer returns might vary in an uncertain trend. Hence, it is essential to design an efficient logistics network responsive to uncertainty. In this paper, fuzzy theory is employed to consider uncertain parameters, i.e. fuzzy numbers. The rest of paper is organized as follows. Section (2) reviews the related literature and explains our contribution in detail. Section (3) refers to proposed mathematical model under uncertainty conditions. Section (4) reviews a case study in Azar Resin Chemical Industrial Company and the implications for academic and practitioner, and finally, Section (5) summarizes and discusses the main results obtained using fuzzy objectives, and provide conclusions and recommendations for future research studies.

2. The Review of the Related Literature

In recent years, most of companies have probably spent lots of time and money to fine-tune their supply chains. Previously, several studies have been done in field of reverse supply chain. RL includes various activities, such as return products to supplier, resell, sell-via-outlet, reconditioning, etc. In fact, both RSC and RL definitions are rather broad and similar. However, Prahinski and Kocabasoglu (2006) noted that while RL focuses on the movement and storage of returns, i.e. transportation, warehousing, and inventory management activities, the concept of RSC is boarder – it requires the holistic view on reverse supply chain business processes, network design, relationships, and coordination between RSC members. Along with the increasing concerns about environmental laws, there has been greater attention to reverse logistics. According to Kumar and Putman (2008), the European Union is developing regulations such as End-of-Life Vehicles (ELV) directive, Waste Electrical and Electronic Equipment (WEEE) directive, Restriction of Use of certain Hazardous Substances (RoHS) directive, and packaging and packaging waste directive.

Murphy (1986) carried out a case study to obtain information about transportation and warehousing issues in product recall procedures. Min (1989) proposed a goal programming model to select shipping method that minimizes costs of transportation and reverse distribution against time of product shipping under recall circumstances. However, this model was only capable of solving small-scale problems. In the last few years, environmental issues and the availability of greater opportunities to save money and resources or increase revenue through product return have encouraged researchers to examine the reverse logistics. In logistics network design, including optimization and facility location models based on mixed integer programming, there have been many studies discussed as follows. The reverse logistics models have been evaluated from three perspectives of modeling for reuse, waste, and reproduction. Kroon and Vrijens et al. (1995) proposed a MILP model for reusable products. The proposed location had no capacity constraint designed for a case study on portable and reusable boxes. Del Castillo and Cochran (1996) examined integrated planning of production, distribution, and collection of containers for reuse and distribution of products. Fleischmann et al. (1997) considered the quantitative models of recovery, production planning, and inventory control. They divided reverse logistics into three main areas of distribution planning, inventory control, and production planning. They also pointed out the lack of an overall framework and mathematical model for reverse logistics. Barros et al. (1998) offered MILP model for reverse logistics network design for two-echelon with limited capacity of stone recovery. In this study, an innovative approach was developed to determine and optimized the capacity of warehouses. Jayaraman et al. (1999) proposed MILP model for reverse logistics network design, serving to minimize costs. This study only covered activity related to the recovery of the returned products. Krikke et al. (1999) proposed two-level complex linear programming model for reverse logistics network design dedicated to photo-copier manufacturers. In this model, cost of processing the returned products and inventory were taken into account in the objective function. Louwers et al. (1999) discussed the launching of a carpet recycling network for part of Europe. Fleischmann et al. (2000) categorized the recovery process into collection, inspection/separation, reprocessing, disposal, and re-distribution. There have been numerous analytical and quantitative approaches proposed for different problems, such as forecasting, production planning, inventory control, management, and location. Fleischmann et al. (2001) combined design forward and reverse supply chain in a sequence. They found that when the rate of return is high and the price difference between forward and reverse supply chains is small and simultaneous, the design is recommended. In a case study on reproduction, Kerr and Ryan (2001) attempted to demonstrate the benefits of achieving reproducibility in production systems. They found if the product is designed to be dismantled and rebuilt, reproduction could reduce resource consumption. De Koster (2002) comparatively evaluated transport mechanisms in 3 levels of retailers, 3 sectors of supply chain, and 3 mail-order companies. Jayaraman et al. (2003) proposed a comprehensive model of mixed integer programming for the reverse distribution problem. They proposed MILP model for reverse logistics network design. This model was based on a strategic level and determined which reproduction centers should be constructed based on returned products. Lee et al. (2009) proposed three-echelon reverse logistics network through an integer programming model aimed at minimizing costs of reverse logistics. Min et al. (2005) suggested MILP model to minimize costs of reverse logistics. In order to solve proposed model, a genetic algorithm was developed based on binary approach. Üster et al. (2007) developed semi-integrated network, where return and recovery centers were localized in reverse logistics and direct streams were optimized simultaneously. In this study, an exact solution was developed based on analysis. Frota Neto et al. (2008) developed a framework for the design and evaluation of sustainable reverse logistics networks based on data envelopment analysis (DEA) and multi-objective programming. In this study, new model was validated by implementing it in European pulp and paper industry. Two objectives of this study were the minimization of costs and the environmental impact in logistics network design. Pati et al. (2008) proposed MILP model ideal for solving problem and examining the relationship between objectives in paper distribution network. One of the objectives of this study was to curtail reverse logistics costs. A few models have focused on simultaneous design of forward and reverse supply chains. Faizul et al. (2010) examined the relevant literature to add up costs of distribution, operations, retail, storage, and service levels to the above costs. Pishvaee et al. (2010) proposed two-objective MILP model for direct logistics network design. In order to solve new model, they developed multi-objective memetic algorithm with dynamic local search mechanism to find a set of superior solutions. Dat et al. (2012) proposed a multilevel reverse logistics network design model composed of collecting, disassembly , treatment (recycling and repair of equipment), and the final sites (disposal of facilities, primary and secondary markets).When it comes to reverse logistics design supply chain, time and cost of products recovered from customers are considered as the two key factors. Moreover, inventory control and distribution planning are the basic processes supporting the total cost of supply chain and customer service levels (Farahani and Elahipanah, 2008). Eskandarpour et al. (2014) provided MILP to determine the proper collection and recycling centers for whole of supply chain i.e. the reverse and forward logistics. Liao (2018) developed a generic mixed integer nonlinear programming model (MINLP) for reverse logistics network design. His model maximized total profit by handling products returned for repair, remanufacturing, recycling, reuse, or incineration/landfill, where a hybrid genetic algorithm (GA) was proposed to solve the problem.

In this paper, a reverse logistics network is designed and a MILP is developed to optimize the two objectives i.e. cost and time by a new fuzzy approach. In Figure 1, there are one customer's area, several recovery centers, several processing centers, and one manufacturer in network, which offers back to customer recovered products through reverse logistics. This study attempts to determine the value of goods sent between centers in any time period so that the total cost of reverse logistics and time are minimized.

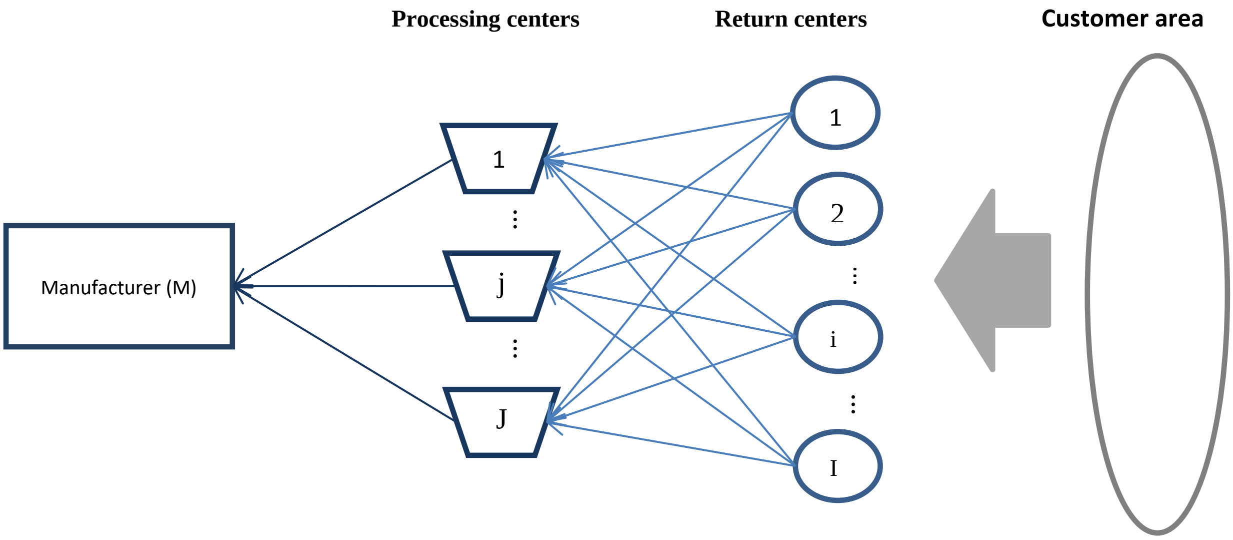

Figure 1. The newly proposed reverse logistics network model

If the recovered products are delivered to customers timely, service will be satisfactory. Otherwise, customers will not be satisfied with service delivery. In the reverse logistics network design, there is a balance between total cost and shipment delay. For example, the company in some cases may have to employ more processing centers to reduce the delay and meet maximum customer satisfaction. This in turn can lead to more opening fixed costs. Moreover, the fuzzy approach is adopted to cover uncertainty in the reverse logistics network.

In many previous studies, it is assumed that important parameters, such as demand and return are certain, whereas the logistics network design and deployment are strategic decisions whose effect will remain for several years. The parameters of customer return and demand during this period may change. Hence, an efficient logistics network should be designed in a way to be responsive to the uncertainty. Furthermore, since time and cost are the most influential factors in design of reverse logistics, it intends to develop two-objective mathematical model to optimize time and cost through metaheuristics Cuckoo search algorithm as follows:

- Providing a mathematical model for the reverse supply chain, taking into account the objective functions of time and cost
- Applying fuzzy theory to incorporate uncertainty in the problem
- Optimization of the mathematical model through Cuckoo search algorithm

3. Proposed mathematical model

In this paper, new two-objective fuzzy mathematical model is proposed for reverse logistics system. This section first explores the assumptions about two-objective fuzzy mathematical programming in reverse logistics system as following and then the mathematical modeling will be offered.

1) The reverse logistic network involves three echelons of return centers, processing centers, and manufacturers
2) In order to cover uncertainty, the input parameters are fuzzy numbers
3) Only one type of product is considered
4) The manufacturer demand end-life products collected in each period are specified from the beginning
5) A fixed cost is intended for reopening the processing centers
6) Maximum capacity for two return and processing centers
7) Cost of inventory is identical in all processing centers

Notations:

I : Number of return centers

J : Number of processing centers

M : Number of manufacturers

T : Time horizon

Problem parameters:

a_i : Capacity of return center (i)

b_j : Capacity of processing center (j)

$d_M(t)$: Manufacturer demand (M) in period (t)

$r_i(t)$: Product volume with end-life recovery at return center (i) in period (t)

c_{ij} : Cost of transport from return center (i) to processing center (j)

c_{jM} : Cost of transport from processing center (j) to manufacturer (M)

c_j^{op} : Fixed cost of opening a processing center (j)

c_j^H : Cost of inventory maintaining in a processing center (j) in each period

d_{ij} : Delivery time from return center (i) to processing center (j)

d_{jM} : Delivery time from processing center (j) to manufacturer (M)

p_j : Processing time of reusable product at processing center (j)

t_E : Customer expected delivery time

Decision variables:

$x_{ij}(t)$: Delivery quantity from return center (i) to processing center (j)

$x_{jM}(t)$: Delivery quantity from processing center (j) to manufacturer (M)

$y_j^H(t)$: Inventory delivered to processing center (j) in period (t)

z_j : It assumes 1 if the processing center (j) is used and 0 otherwise.

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

$$Min\ f_2 = \sum_{t=0}^{T}\left[\sum_{i=1}^{I}\sum_{j=1}^{J} d_{ij} x_{ij}(t) + \sum_{j=1}^{J}\left(d_{jM} + p_j\right) x_{jM}(t) - t_E d_M(t)\right] \tag{2}$$

$$\sum_{j=1}^{J} x_{ij}(t) \le r_i(t) \quad \forall i,t \tag{3}$$

$$\sum_{i=1}^{I} x_{ij}(t) + y_j^H(t-1) \le b_j z_j \quad \forall j,t \tag{4}$$

$$\sum_{j=1}^{J} x_{jM}(t) \le d_M(t) \quad \forall t \tag{5}$$

$$y_j^H(t-1) + \sum_{i=1}^{I} x_{ij}(t) - x_{jM}(t) = y_j^H(t) \quad \forall j,t \tag{6}$$

$$x_{ij}(t), x_{jM}(t), y_j^H(t) \ge 0 \quad \forall i,j,t \tag{7}$$

$$z_j \in \{0,1\} \quad \forall j \tag{8}$$

The first objective function of new model is the minimization of the reverse logistics costs including fixed cost of reopening the processing centers, shipping cost at return centers, processing centers, manufacturer, and inventory cost of the processing centers. The second objective function is the minimization of total delay of product delivery to customers which includes a delay in shipping products ordered by customers. In reverse logistics, meeting customer deadline is far more difficult than in direct logistics, due to the level of uncertainty depending on the recovery of end-of-life products. This can be resolved by minimizing the waiting time considering the delivery delay as the second objective function is applied. As it has been shown above, constraint (3) represents the volume of recovered end-of-life product. Constraints (4) and (5) represent the capacity of processing centers and manufacturer. In each period, the inventory is controlled at the processing center through constraint (6). The constraint (7) shows that decision variables $x_{ij}(t)$, $x_{iM}(t)$ and $y_j^H(t)$ are non-negative, while constraint (8) guarantees that z_j is a variable with value of either zero or one.

3.1. Fuzzy

Fuzzy set theory was first proposed by Lotfi Zadeh in 1965 in a paper titled "Fuzzy Sets" (Zadeh, 1965). The fuzzy logics view world not as zero and one, but as a gray range of facts. Since it requires no accurate information, the fuzzy approach can provide an efficient model compared to other methods, such as the probability approach that requires sufficient knowledge of uncertain distribution parameters. In fact, the probability approaches need to specify distribution of parameters and then determine their values, which is extremely difficult in comparison to fuzzy approach (Ballin, 2011). In situations where parameters are uncertain, fuzzy scheduling algorithm can create a real flexible system (Ko&Evans, 2007; Keskin & Uster, 2007). Moreover, the computational complexity of fuzzymodeling is far lower than other approaches (Zimmermann, 1992).The fuzzy set $\tilde{A}$ from Reference X is a set of ordered pairs formulated as Equation (9).

$$\tilde{A} = \left\{\left(x, \mu_{\tilde{A}}(x)\right) \mid x \in X\right\} \tag{9}$$

Where $\mu_{\tilde{A}}(x)$ is obtained through Equation (10).

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

According to Equation (10), it can be stated that the membership function of each member from set X is extended to interval[0,1]. The most common fuzzy numbers used in previous studies are triangular and trapezoidal fuzzy numbers

(Balin, 2011). In this study, trapezoidal fuzzy numbers $\xi = (a,b,c,d)$ are used to fuzzify new model which has been displayed in Figure 2. The membership function can be seen in Equation (11).

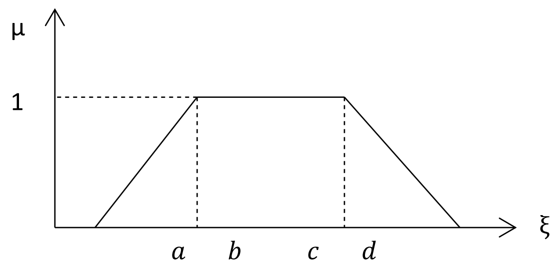

Figure 2. Trapezoidal fuzzy number

$$\mu(x) = \begin{cases} \dfrac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d-x}{d-c} & c \le x \le d \\ 0 & OW. \end{cases} \tag{11}$$

The theory of possibility was introduced by Zadeh (1978). According to Zadeh (1978), possibility distributions provide a graded semantics to natural statements. Possibility can be seen as a non-numerical version of probability theory with a simple approach to reasoning with uncertain probabilities (Dubois and Prade, 2000).

With the development of fuzzy logic, mathematical theory has been developed in order to understand and identify possible events under uncertain or vague conditions in the decision-making process. The ambiguity of mathematical theories, possibility theory to the best and most consistent theory is making as uncertainties in environment. In summary, the content of this theory can be expressed in the analysis of events and circumstances, where we are not only looking for possible events and in uncertain condition, we are seeking all possible contingencies with the possibility that these developments are introduced possibility of conflicting events. This is our attitude and the contradictory events are not mutually exclusive and like the theory of probability, they will not face each other. In probability theory is an attempt to index the probability of an event dedicated to the probability of its negation of our interpretation. While in probability theory, only one probable or chance to describe the probability of an event is the theory of possible uses of the concept, possibility, and necessity of an event. The necessity for any set U is defined as follows:

The event necessity (the necessity event = 1- the event possible contradictory).

Moreover, the necessity value of the trapezoidal fuzzy variable, according to the definition is displayed in Equation (12).

$$Nec\{\xi \le r\} = 1 - \sup_{\xi \ge r} \mu_x(x) = \begin{cases} 0 & x \le c \\ 1 - \dfrac{d-x}{d-c} = \dfrac{x-c}{d-c} & c \le x \le d \\ 1 & x \ge d \end{cases} \tag{12}$$

According to the above fact and definition of Cr, the validation function for trapezoidal fuzzy number can be seen in Equation (13) and Figure 3:

$$Cr\{\xi \le r\} = \frac{1}{2}\{pos\{\xi \le r\} + Nec\{\xi \le r\}\} = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{2(b-a)} & a \le x \le b \\ \dfrac{1}{2} & b \le x \le c \\ \dfrac{1}{2}(1+\dfrac{x-c}{d-c}) & c \le x \le d \\ 1 & x \ge d \end{cases} \tag{13}$$

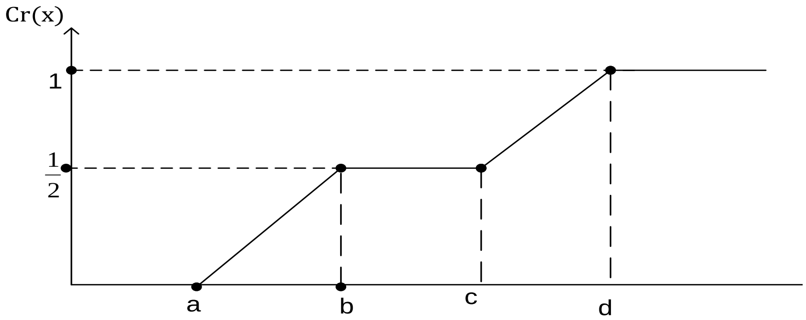

Figure 3. Possibility function for trapezoidal fuzzy number

According to definitions above, the optimistic value represented by $\xi_{\sup}(\alpha)$ can be calculated through Equations (14) and (15):

$$\xi_{\sup}(\alpha) = \sup\{x \mid Cr\{\xi \ge x\} \ge \alpha\} \tag{14}$$

$$Cr\{\xi \ge x\} \ge \alpha \Rightarrow \{1 - Cr\{\xi \le x\}\} \ge \alpha \Rightarrow Cr\{\xi \le x\} \le 1-\alpha \tag{15}$$

For $\alpha > \frac{1}{2}$, we have:

$$\alpha > \frac{1}{2} \Rightarrow 1-\alpha < \frac{1}{2} \tag{16}$$

$$Cr\{\xi \le x\} \le 1-\alpha \Rightarrow \frac{x-a}{2(b-a)} \le 1-\alpha \Rightarrow x-a \le 2(b-a)(1-\alpha) \tag{17}$$

$$x \le (2-2\alpha)b - (2-2\alpha-1)a \Rightarrow x \le (2\alpha-1)a + (2-2\alpha)b \tag{18}$$

Hence, the value of $\xi_{\sup}(\alpha)$ for $\alpha > \frac{1}{2}$ can be obtained through Equation (19):

$$\xi_{\sup}(\alpha) = \sup\{x \mid Cr\{\xi \ge x\} \ge \alpha\} = (2\alpha-1)a + (2-2\alpha)b \tag{19}$$

Similarly, the pessimistic value represented by $\xi_{\inf}(\alpha)$ can be calculated for $\alpha > \frac{1}{2}$ as follows:

$$\xi_{\inf}(\alpha) = \inf\{x \mid Cr\{\xi \le x\} \ge \alpha\} = (2-2\alpha)c + (2\alpha-1)d \tag{20}$$

According to definitions above, the parameters in the objective function are defuzzified through the average of four fuzzy numbers according to Equation (21). The defuzzification of parameters within the problem involves constraints, depending on the type of constraint, Equations (22) and (23) are applicable (Liu and Liu. 2002; Pishvaee and Torabi, 2010).

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

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

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

3.2 Fuzzification of the mathematical model

According to the concepts presented so far, the uncertainty in the reverse logistics problem, fuzzy set theory and validation approach, this section presents two-objective fuzzy mathematical model. As mentioned in the problem assumptions, a real model is developed by considering input parameters in uncertain trapezoidal fuzzy numbers. Hence, two-objective fuzzy mathematical model will be developed as follows:

According to defuzzification procedure presented in previous section, Equations (21) to (23) were employed depending on the type of parameter, while the fuzzy mathematical model for time and cost in the reverse logistics system is reformulated as follows:

$$Min\ f_1 = \sum_{t=0}^{T}\left[\sum_{j=1}^{J}\tilde{c}_j^{op} z_j + \sum_{i=1}^{I}\sum_{j=1}^{J}\tilde{c}_{ij}x_{ij}(t) + \sum_{j=1}^{J}\tilde{c}_{jM}x_{jM}(t) + \sum_{j=1}^{J}\tilde{c}_j^H y_j^H(t)\right] \tag{24}$$

$$Min\ f_2 = \sum_{t=0}^{T}\left[\sum_{i=1}^{I}\sum_{j=1}^{J}\tilde{d}_{ij}x_{ij}(t) + \sum_{j=1}^{J}\left(\tilde{d}_{jM} + \tilde{p}_j\right)x_{jM}(t) - t_E\tilde{d}_M(t)\right] \tag{25}$$

$$\sum_{j=1}^{J} x_{ij}(t) \le \tilde{r}_i(t) \quad \forall i,t \tag{26}$$

$$\sum_{i=1}^{I} x_{ij}(t) + y_j^H(t-1) \le \tilde{b}_j z_j \quad \forall j,t \tag{27}$$

$$\sum_{j=1}^{J} x_{jM}(t) \le \tilde{d}_M(t) \quad \forall t \tag{28}$$

$$y_j^H(t-1) + \sum_{i=1}^{I} x_{ij}(t) - x_{jM}(t) = y_j^H(t) \quad \forall j,t \tag{29}$$

$$x_{ij}(t), x_{jM}(t), y_j^H(t) \ge 0 \quad \forall i,j,t \tag{30}$$

$$z_j \in \{0,1\} \quad \forall j \tag{31}$$

As a result of defuzzification presented in the previous section, depending on the type of the parameter, the relations (32) to (39) used fuzzy mathematical model of objective time and cost in reverse logistics system are rewritten as follows:

$$\begin{aligned} Min\ f_1 = \sum_{t=0}^{T}\Bigg[&\sum_{j=1}^{J}\left(\frac{c_{j1}^{op}+c_{j2}^{op}+c_{j3}^{op}+c_{j4}^{op}}{4}\right)z_j + \sum_{i=1}^{I}\sum_{j=1}^{J}\left(\frac{c_{ij1}+c_{ij2}+c_{ij3}+c_{ij4}}{4}\right)x_{ij}(t) \\ &+ \sum_{j=1}^{J}\left(\frac{c_{jM1}+c_{jM2}+c_{jM3}+c_{jM4}}{4}\right)x_{jM}(t) + \sum_{j=1}^{J}\left(\frac{c_{j1}^{H}+c_{j2}^{H}+c_{j3}^{H}+c_{j4}^{H}}{4}\right)y_j^H(t)\Bigg] \end{aligned} \tag{32}$$

$$Min\ f_2 = \sum_{t=0}^{T}\Bigg[\sum_{i=1}^{I}\sum_{j=1}^{J}\left(\frac{d_{ij1}+d_{ij2}+d_{ij3}+d_{ij4}}{4}\right)x_{ij}(t)$$
$$+\sum_{j=1}^{J}\left(\left(\frac{d_{jM1}+d_{jM2}+d_{jM3}+d_{jM4}}{4}\right)+\left(\frac{p_{j1}+p_{j2}+p_{j3}+p_{j4}}{4}\right)\right)x_{jM}(t)$$
$$-t_E\left(\frac{d_{M1}(t)+d_{M2}(t)+d_{M3}(t)+d_{M4}(t)}{4}\right) \qquad (33)$$

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

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

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

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

$$x_{ij}(t),\ x_{jM}(t),\ y_j^H(t)\ge 0 \quad \forall i,j,t \qquad (38)$$

$$z_j\in\{0,1\} \quad \forall j \qquad (39)$$

4. Case Study

Azar Resin Chemical Industrial Company (ARCIC) was established in 1995 in Qazvin province, Iran. The first phase of the company's productions started in 1996 which comprises amino resins. This company is one of the most active and leading companies among the resin manufacturing factories in Iran. The case study model is elaborated at ARCIC, involving 4 return centers, 3 processing centers, 1 manufacturer, and 2 periods. At the first step, we collected data on the processing center including capacity (b_j), fixed cost of reopening (C_j^{op}), processing time of products (P_j), inventory maintenance cost (C_j^H), shipping cost and delivery from processing center to manufacturer (C_{jM} and d_{jM}) , the manufacturer (M) demand in each period ($d_M(t)$) , shipping cost and delivery time from return center (i) to processing center (j) (C_{ij} and d_{ij}), and finally, the volume of end-of-life products recovered at return centers in each period ($r_i(t)$).

This problem is solved by GAMS on a machine with the following specifications: RAM 4GB, CPU core i7-6700K within less than a second. The value of the objective function (sum of the two cost and time objective function) is 6480.125 IRR. However, it should be noted thatthe objective function of time is converted into cost while all three processing centers are used. Other outputs of the case study have been listed in Tables 1, 2, and 3. The inventory delivery to each processing centers in each period has been displayed in Table (1).

Table 1. Inventory Delivered to Processing Centers

Processing center	Period	
	1	2
1	-	46
2	67	91
3	32	55

According to Table 1, inventory in the first period is not delivered to processing center 1, while 46 units of inventory in the second period are delivered to processing center 1. By the same token, the inventories delivered in each period to the other two processing centers have been illustrated. Table 2 displays the end-of-life products delivered from return center (i) to processing center (j) in two periods.

Table 2. The Volume of Products Delivered between Return and Processing Centers

Return center	Processing center	Period	
		1	2
1	1	-	-
	2	-	-
	3	32	35
2	1	-	-
	2	26	-
	3	-	21
3	1	-	37
	2	-	-
	3	31	-
4	1	-	9
	2	41	24
	3	-	3

As can be seen, return center 1 in two periods 1 and 2 delivered no products to processing centers 1 and 2. It delivered 32 and 35 units of product to processing center 3 in the first and second periods, respectively. By the same token, the volume of products delivered in each period has been illustrated. Finally, Table 3 displays the volume of products delivered from processing center to manufacturer.

Table 3. Volume of products delivered to manufacturer

Processing center	Period	
	1	2
1	-	-
2	-	-
3	31	36

Table 3 shows that manufacturer received no products from processing centers 1 and 2 in two periods, while processing center 3 in the first and second periods received 31 and 36 units, respectively.

4.1. Cuckoo algorithm for time-cost fuzzy mathematical model in reverse logistics system

Cuckoo search is an optimization algorithm developed by Xin-sheYang and Suash Deb in 2009. It was inspired by the obligate brood parasitism of some Cuckoo species by laying their eggs in the nests of other host birds (of other species). Some host birds can engage direct conflict with the intruding Cuckoos (Behnamian and Ghomi, 2014; Rajabioun, 2011). For example, if a host bird discovers eggs are not their own, it will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere. Some Cuckoo species, such as new world brood-parasitic Tapera have evolved in such a way that female parasitic Cuckoos are often very specialized in mimicry in colors and pattern of eggs of a few chosen host species. Cuckoo search idealized such breeding behavior, and thus can be applied to various optimization problems.

According to Cuckoo algorithm described earlier, input parameters are initiated as follows. Each Cuckoo travels only λ% of the entire path to the ideal target entailing a deviation of φ radians. In thisstudy, λ is random number between 1 and 0, while φ is a number generated between $\pi/6$ and $-\pi/6$. The number of iterations in Cuckoo algorithm is considered to be 50.

4.2. Computational results and implications for academic and practitioner

In order to optimize time and cost, new fuzzy mathematical model is solved through Cuckoo optimization algorithm. The input parameters are generated based on case study i.e. ARCIC. This problem is solved through Cuckoo optimization algorithm within 20 seconds and the value of objective function is 6496.958 IRR. The value of the objective function of cost is 10074.29 IRR, while value of objective function of delay cost is 2919.625 IRR.In this problem, all three processing centers for new model have been solved by metaheuristic algorithm.The inventory delivered to processing center in each period has been shown in Table 4.

Table 4. Inventory Delivered to Processing Centers

Processing center	Period	
	1	2
1	8.5	57.5
2	80.5	90.5
3	40	80

According to Table 4, the inventory delivered to processing centers in the first period is far less than that delivered in the second one. Table (5) displays volume of end-of-life products delivered from return center (i) to processing center (j) in two periods.

Table 5. The Volume of Products Delivered between Return and Processing Centers

Return center	Processing center	Period	
		1	2
1	1	-	-
	2	16	17.5
	3	16	17.5
2	1	-	-
	2	26	10.5
	3	-	10.5
3	1	10.3	37
	2	10.3	-
	3	10.3	-
4	1	13.6	12
	2	13.6	12
	3	13.6	12

Evidently, the return center delivered no products to processing center 1 in two periods. In the first and the second periods, however, 16 and 17.5 units of products are delivered to processing centers 2 and 3, respectively. By the same token, the volume of products delivered in each period has been illustrated. It should be noted that total volume of products delivered from return center to processing centers in each period is equal to value in exact solution. According to ARCIC data, the calculations of variable in Cuckoo algorithm are correct. Finally, Table 6 displays volume of products delivered from processing center to manufacturer.

Table 6. Volume of Products Delivered to Manufacturer

Processing centers	Period	
	1	2
1	15.5	-
2	15.5	-
3	36	-

Table 6 shows that manufacturer received no products from processing centers 1 and 2 in two periods, while processing center 3 received 36 units in the second period. In this table, the total value of products delivered to manufacturer is equal to that obtained from the exact solution. Figure 4 shows how objective function varies according to number of iterations.

According to Figure 4, the value of objective function decreases as the number of iterations grows. This suggests desirable efficiency of newly proposed algorithm. On the other hand, the values of objective function in the first little iteration reduces sequentially. However, this value remains constant from certain iteration, indicating the ideal efficiency of proposed Cuckoo algorithm, since it meets convergence within a few iterations.

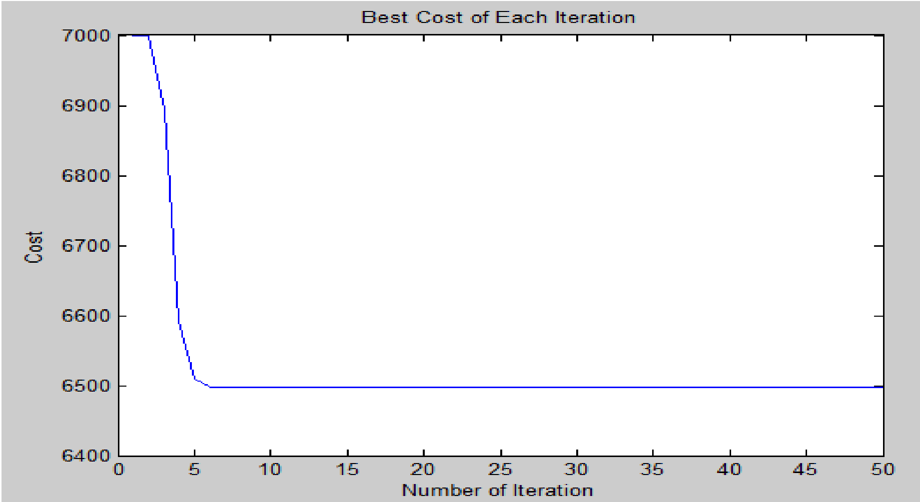

Figure 4. Variations of objective function

A summary of the results for case study are presented in Tables 4- 6. The results show that the value of goods sent between centers in each time period according to the total cost of reverse logistics and time is minimized. According to Table 6, we optimized volume of products delivered to manufacturer in processing centers. We found that we can assign maximum units to processing center 3. These results help to understand how many units assigned to each processing centers minimize costs and deliver products on time to customers. According to Figure 3, we minimized variation of objective functions.

Using multi objective model under uncertainty by fuzzy parameters in this study provides easier way to find the complexity of the decision making problem through classifying the complex criteria, thereby helping to facilitate important decision making. The managerial implications that extracted from this study are:

- According to first and the second objectives, the RSCM costs are minimized by considering volume of products delivered to each manufacturer and balance time and cost of RSCM.

- In this study, the proposed mathematical model used trapezoidal fuzzy method. Trapezoidal fuzzy numbers help to find better solutions because fuzzy logic can be built on top of the experience of experts.

- Optimization of the mathematical model through Cuckoo algorithm because it has local search capability along with general search, search with a population variable (due to the destruction of the population in poor areas) ,overall move towards better with the loss of inappropriate solutions, and the ability to quickly solve optimization problems with high dimensions.

5. Conclusion

According to the characteristics of ARCIC and objective functions, a new two-objective cost-time fuzzy mathematical model was developed to solve the problem. Moreover, the uncertainty was covered in the reverse logistics network through fuzzy approach. Hence, all input parameters were defined as trapezoidal fuzzy numbers. Since most logistics network design problems are NP-hard, exact methods cannot solve such problems at larger scale. For that purpose, the heuristic and metaheuristic techniques were developed at larger scale. Among the various methods for solving the mathematical model, the Cuckoo Search (CS) algorithm was selected. Recent studies indicate that PSO algorithms can outperform genetic algorithms (GA) and other conventional algorithms for many optimization problems. This can partly be attributed to the broadcasting ability of the current best estimates which potentially give better and quicker convergence towards the optimality. A general framework for evaluating statistical performance of evolutionary algorithms has been discussed in detail. In comparison to GA, PSO, and CS, we can see that the CS is much more efficient for finding the global optima with higher success rates. Each function evaluation is virtually instantaneous on modern personal computer. For example, the computing time for 10,000 evaluations on a 3GHz desktop is about 5 seconds. Simulations and comparison show that CS is superior to these existing algorithms for multimodal objective functions. This is partly due to the fact that there are fewer parameters to be fine-tuned in CS than in PSO and genetic algorithms. In fact, apart from the population size n, there is essentially one parameter p_a. Furthermore, our simulations also indicate that the convergence rate is insensitive to the parameter p_a. This also means that we do not have to fine tune these parameters for a specific problem. Subsequently, CS is more generic and robust for many optimization problems, comparing with other metaheuristic algorithms (Xing and Deb, 2009). In this study, the time-cost was optimized in the multi-objective fuzzy model through Cuckoo search algorithm.

Then, the computational results obtained from solving various problems were reported. Finally, the newly proposed algorithm was validated through a case study, where the results were compared against the exact solution. The results demonstrated the desirable performance and the accuracy of the newly proposed metaheuristic algorithm, which managed to solve the problem and obtain values similar to those of the exact solution.

There are some limitations in the current study that can be addressed in future researches. First, the case was limited to a small number of processing centers in two periods in a relatively concentrated RSCM and there was an opportunity to explore more deeply the numbers processing centers. Second, in this study, researchers due to lack of access to local data contained in the company of this objective were avoided while other researchers have been suggested to minimize space for their goals. Third, this study only considered one product due to the nature of the company, while other researchers are recommended to study multi products.

In this study, effort was made to employ an exact solution (mathematical programming model) and implement it in GAMS in order to achieve an optimized, exact solution. In addition to the proposed method, there are other exact solution methods, such as branch and bound or dynamic programming. The problem could not be solved through exact methods at larger scale due to extreme complexity. Hence, this study adopted a metaheuristic optimization algorithm known as Cuckoo, even though other new metaheuristic techniques could be used, such as immune algorithms, water droplet evaporation algorithms, etc. Since the cost of supply and delay were inherently identical, this study involved the weighted approach to combine the two objectives. In addition, this method can be used for solving multi-objective problems. Several methods can be employed to solve the large-scale problems, including Non-dominated Sorting Genetic Algorithm (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO), Multi-Objective Genetic Algorithm (MOGA) and Ant-Colony Optimization (ACO). In the next stage, the results can be compared to those obtained in the current study. The uncertainty in this study was covered by fuzzy approach. In this regard, other techniques, such as possible scenario-based solutions can be employed.

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