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RESEARCH ARTICLE **Open Access**

A Mathematical Model to Optimize Cost, Time in the three echelon Supply Chain in Post COVID 19 pandemic

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Abstract
The purpose of this paper is to optimize cost & time in the three echelon supply chain network (SCN). This paper developed a linear programing (LP) model to consider economic data. The overall objective of the present study is to use high-quality raw materials, at the same time in post COVID 19 pandemic and the highest profitability is achieved. The episode of COVID-19 has quickened the building of flexible supply chains (FSC), and supply chain digitalization (SCD) is steadily being recognized as an empowering implies to this conclusion. In any case, researchers for the most part concur that more experimental considers will have to be conducted on how digitalization can encourage supply chain flexibility at different stages and improve supply chain execution in a profoundly dubious environment. Optimization of supply chain performance indicators in minimization of cost and time and maximization of sustainability indexes of the system. The differences of solving methods found that between genetic algorithms (GAs) and LP approaches can be explained by handling the constraints and their various logics. To deal with ambiguity in the reverse logistics network, a fuzzy approach has been applied. To solve the problem in large dimensions, 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 two algorithms were compared and superiority of each of them was discussed. The study's findings can assist decision-makers in developing strategic policies to overcome the recovery challenges in the post-COVID-19 era.
Keywords: *Reverse Logistics, Optimization, Fuzzy, Metaheuristic Algorithms*

Introduction

The past two years have been a particularly challenging time of transition for supply chain managers due to the COVID-19 pandemic and related macro business trends. Given that many of the challenges to the global supply chain are expected to continue for the foreseeable future, identifying resources that will allow firms to gain competitive advantage is critical (Paul et al., 2021). As we know, in the post-Covid era, due to the delay in sending orders, this issue has become the biggest problem for the conversion chains in the world therefore we have to do the best in this matter to minimize loss. In today's highly volatile and unpredictable environment, the success of an enterprise depends on its ability to coordinate in a complex communication networks among members of the supply chain (Mena et al., 2013). 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 extent of the challenges varies depending on the severity of the event(s). For instance, firms may experience greater

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challenges in recovering from major outbreaks, such as epidemics or pandemics (Gurbuz & Ozkan, 2020, Queiroz et al., 2020). This is because such outbreaks have severe and long-term impacts on businesses and their operations and generally require more robust recovery strategies (Koonin, 2020). The reverse logistics management is an important part of today's supply chains that allows 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 (Mohammadi &Rasi,2022). RL is particularly popular due to the many competitive advantages such as environmental and economic benefits (Rasi, 2018 & Ahmadpoor et al., 2023). 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 RL network (Ozceylan et al., 2014). Consumer awareness towards the environment and social responsibility are key drivers of this area (Keskin and Üster, 2007 & Bagheri et al., 2013).

RL network development models include a wide range of linear and nonlinear models, from minimizing cost of delivery 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 efficient decision making process. Also, ambiguity is another real-world consideration that should be taken into account. This paper attempts to develop a logistic network considering different objective functions in a reverse logistics 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. Supply chain executives measure the effectiveness that flow using the On-Time Delivery (OTD) metric. We found that 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 and cost of operation are considered to maximize revenue of organizations. Due to ambiguity of parameters and variables in real world, we assumed that time and cost is not certain therefore we use fuzzy. In contrast, an efficient logistics network should be developed in a manner that can respond to fuzziness of environment. Insights from this study will also be beneficial to other industries or emerging economies. When major crises and disruptions in supply chains are investigated, the deep upstream portions are often ignored. This study delves into these areas to help understand how some of the most vulnerable regions of global supply chains can respond and recover quickly from disruptions. The innovation of this paper is to provide fuzzy multi objective model to optimize cost and time concurrently in post Covid 19 era. Specifically, decisions on the recovery planning are subject to multi-dimensional uncertainty stemming from singular and correlated disruptions in demand, supply, and production capacities. This is a new and understudied research area. In this study, we examine, SC recovery for high-demand items. We first developed a fuzzy mathematical model to optimise recovery for a three-echelon SC exposed to the multi-dimensional impacts of Covid-19 pandemic. This allows to generalize a novel problem setting with simultaneous demand, supply, and capacity uncertainty in a multi-echelon SC recovery context.

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.

Literature Review

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). Min et al. (2005) developed a mixed integer nonlinear programming model aimed at minimizing costs in 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. One of the newest methods is cuckoo optimization algorithm which has been used in several studies (Akbari and Rashidi, 2016, Amiri and Mahmoudi, 2016, Wood, 2016). Melachrinoudis et al. (2005) used a multi-objective physical methodology to redesign the structure of network in order to reduce cost. To design closed-loop logistics network of third-party logistics service providers, 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 logistics network has been evaluated. Ülkü and 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). Marzban et al., (2022) considered the social dimension of supply chain sustainability (SCS), and the most attention has been paid to the environmental and economic aspects. According to Razkov et al (2022), the impacts of the Covid-19 widespread and their proactive intervention by versatile operational choices in numerous arrange plan structures in expectation of and amid the widespread. In generalized terms, in specific, they examine the effect of stock pre-positioning in expectation of a widespread and the adjustment of production-ordering approach amid the pandemic. The examination is performed for both two- and three-echelon supply chains and diverse scenarios for widespread flow.

Problem Statement

Today, one of the important issues in the field of SC in different industries is RSC. 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 SC. In this paper, two time and cost factors are considered as key factors for products recovery process. Additionally, inventory control and distribution planning are essential supporting processes that affect the total cost of the SC and customer service level (Farahani and Elahipanah, 2008). In this study, a RLN with objectives of minimizing time and cost was designed with the fuzzy approach. In this network, there are a customer area several recovery centers, several processing centers and a manufacturer that delivers the recovered products to customers through RL process. If the recovered products are delivered to customers at the expected time, service will be satisfactory. In the design of RLN, there should be a balance between total cost and delayed delivery. 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 RLN, a fuzzy approach has been used.

Research assumptions

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

- The RLs 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 have fixed cost.

Problem Indicators

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

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

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

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

Mathematical model

The first objective function is to minimize the total cost of RLN 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 RL, 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.

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

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

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

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

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

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

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

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

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) respectively represent the capacity of processing center and manufacturer. Constraint (6) control amount of inventory at each processing center. Constraint (7) show that decision variables of $x_{ij}(t)$ and $y_j^H(t)$ are non-negative and constraint (8) ensures that the variable z_j is binary variable.

Fuzzy bi-objective Modeling

In this study, the fuzzy theory is used for modeling the problem. Most of 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 parameters of the problem are uncertain, the presentation of the fuzzy scheduling algorithm creates a flexible system (Behnamian and Ghomi, 2014). In addition, the computational complexity of fuzzy modeling is far less than other approaches (Sowinski and 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. 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. Since the trapezoidal fuzzy number, as a vital concept of fuzzy set, can express linguistic assessments by transforming them into numerical variables objectively. Then, some operations on a trapezoidal fuzzy soft set are defined, such as complement operation, “AND” operation, and “OR” operation. Finally, a Multiple Criterion Decision-Making (MCDM) problem under a fuzzy environment is analyzed by trapezoidal fuzzy soft sets with the demonstration of a numerical example. This paper also uses traditional fuzzy soft sets to deal with the MCDM problem. The membership function of a trapezoidal fuzzy number is piecewise linear and trapezoidal, which can express vagueness information caused by linguistic assessments through transforming them into numerical variables objectively. As well as the consideration of characters of soft sets, the purpose of this paper is to combine the concept of trapezoidal fuzzy number and soft set. Our previous researches about soft sets focus on the application of soft sets in some areas, including data analysis in incomplete information system, combined forecasting about international trade and regional development evaluation.

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

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 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 $\xi = (a,b,c,d)$; its representation is according to Fig. 1 and its membership function is in the form of equation (11).

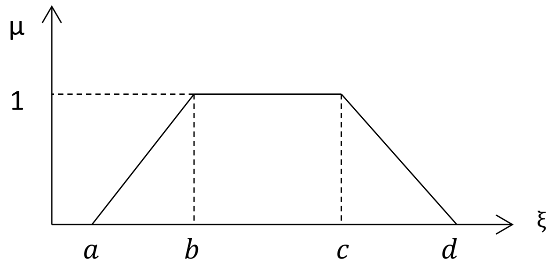

Figure 1. Trapezoidal Fuzzy Number

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

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

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

Possibility criterion is shown through Equation (13):

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

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).

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

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 and Liu (2006). The definition of the credibility criterion is in accordance with the criteria of possibility and necessity in form of equation (15) (Mehlawat and Gupta, 2014, Zhang et al., 2015).

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

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

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

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

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

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

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

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

$$\xi_{\sup}(\alpha)=\sup\left\{x\mid Cr\left\{\xi\ge x\right\}\ge\alpha\right\}=(2\alpha-1)a$$

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

$$\xi_{\inf}(\alpha)=\inf\left\{x\mid Cr\left\{\xi\le x\right\}\ge\alpha\right\}=(2$$

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 and Liu, 2002, Pishvaee et al., 2012, Lu et al., 2016) .

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

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

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

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:

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

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

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

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

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

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

$$x_{ij}(t),\ x_{jM}(t),\ y_j^H(t)\ge0\quad\forall i,j,t \tag{30}$$

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

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:

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

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

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

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

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

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

Proposed Meta-heuristic Algorithms

Since most of the logistics network design problems are NP-hard (Altiparmak et al., 2006, Lee and 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.

Cuckoo search optimization algorithm

In this study, a Cuckoo optimization 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 eggs faster than eggs of host bird and grow faster (Payne and Sorensen, 2005). Figure (2) illustrates the flowchart of 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 and Rashidi, 2016). The maximum egg laying radius is determined based on the total number of eggs, the current number of eggs of cuckoo and the upper and lower limit of the variables of problem according to equation (37).

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

In the above equation (37), α is the parameter to maximize ELR value which is adjustable? Additionally var_{hi} and var_{low} 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 cuckoo search more environments (Rajabioun, 2011). In order to design cuckoo optimization algorithm in this research, λ is a random number generated between 1 and 0 and φ is also a number between $-\pi/6$ and $\pi/6$. 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.

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.

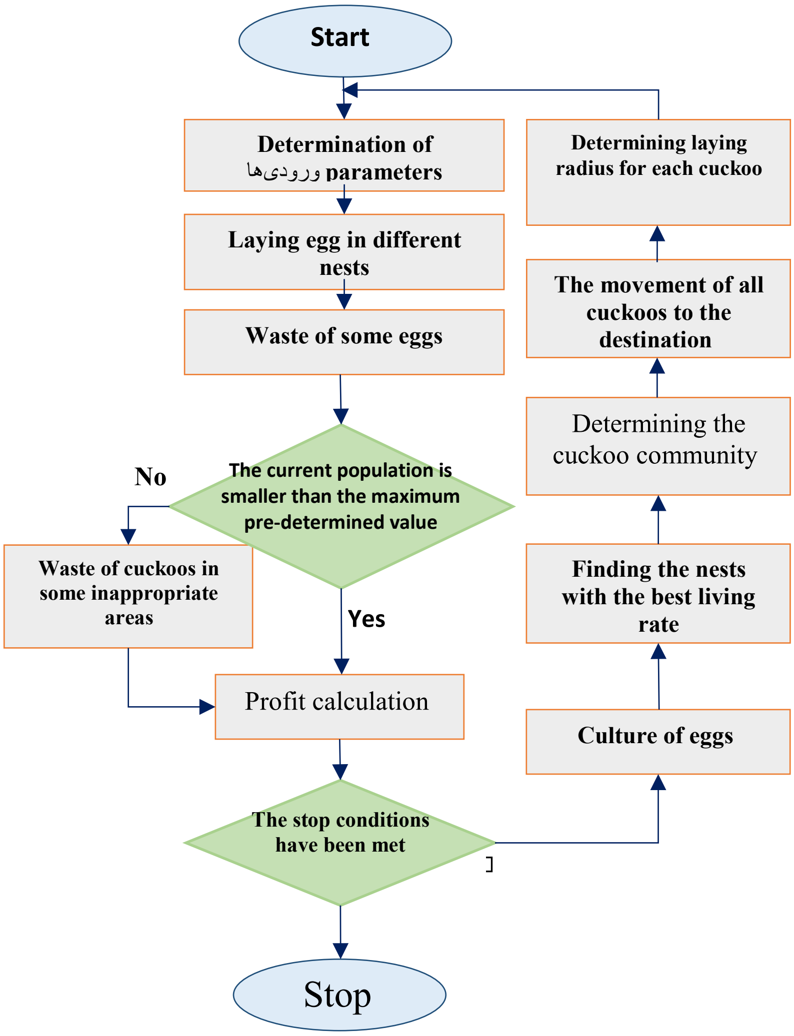

Figure 2. *Cuckoo Flowchart Algorithm*

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 “global optimal" point. Known methods in this area include 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 has a high efficiency.In general, these actions are performed by two intersection and mutation operators. The intersection 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 intersection rate. Intersection rate is the ratio of the number of newborn babies produced in each generation to size of the main population. This rate determines the expected number of chromosomes that are altered by the mentioned operator. The larger intersection rate allows a wider segment of the search space to be searched. If the intersection 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 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, optimal mutation rate should be chosen. Obviously, an index is required for detection of 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 corresponding solution and placed in the objective function. The problem-solving process by a genetic algorithm is illustrated in Figure (3) in the form of a flowchart.

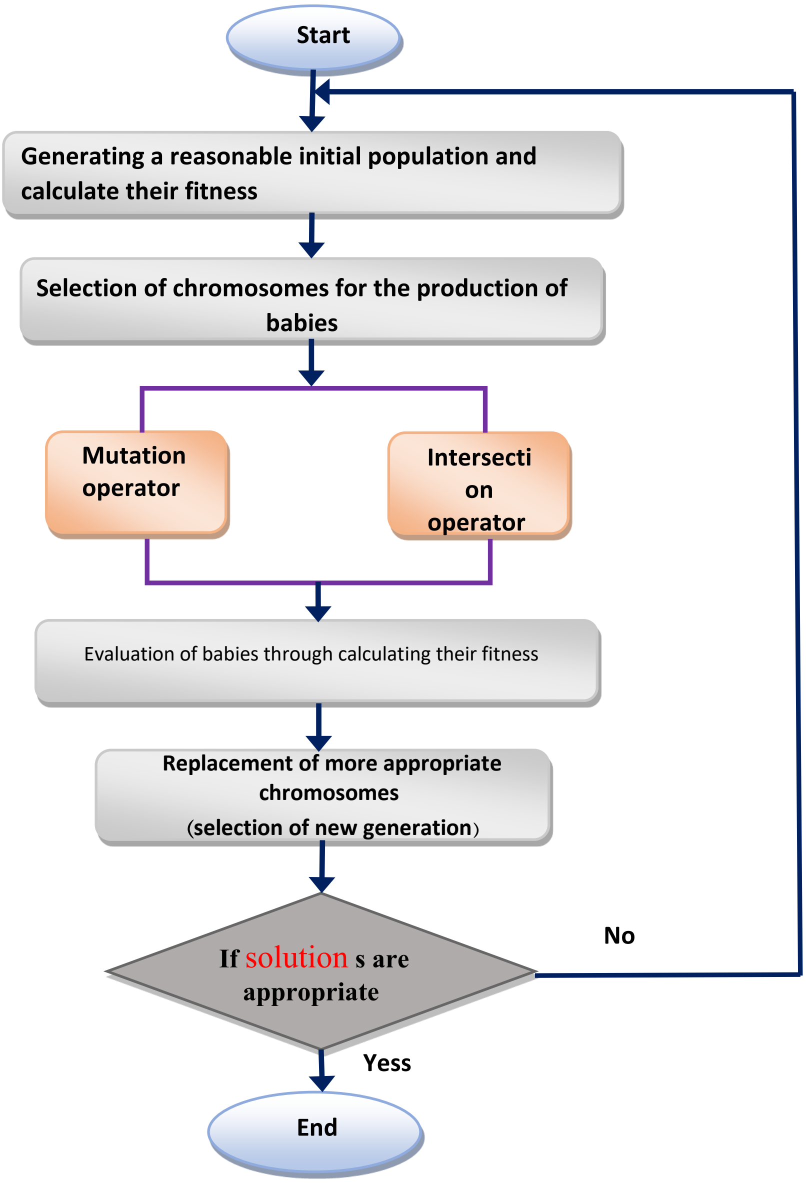

Figure 3. *Flowchart of Genetic Algorithm*

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 generating input data, given that these data are fuzzy, 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 was implemented in 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 problems

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 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	$N_{Cluster}$

RPD (Relative Performance Deviation) criterion

The relative performance 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 are executed 10 times in order to reduce 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 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. Tables (3) comprises two algorithms by RPD and time indexes and suggest that although cuckoo algorithm performs better in all proposed cases, in terms of time of algorithm implementation, it spends 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 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 GA	RPD COA	Time GA	Time 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

Managerial Implication

It is recommended that managers, according to the research findings try to reduce costs and delay orders in industrial factories. 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 to monitor quantity of returned products in supply chain in uncertainty condition to insure of increasing profit in all of levels.

Conclusion and Future Research

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 remanufactured in different time periods so that the total cost of reverse logistics and delay time to be minimized. The impacts of COVID-19 on SCs are annihilating and have spread over diverse arrange stages. The high – demand and basic item SCs have transcendently been altogether influenced the widespread due to its multi-dimensional impacts, such as request surge and decrease in supply and generation capacities, where in the degree of varieties is questionable.

Without appropriate arranging and procedures, companies 0 may lose significant request and, thus, benefit within the short – term possibly confronting total shutdown within the medium to long term. We took up this issue and studied the recovery of an SC for a high-demand item (e.g., hand sanitizers or face masks). We began by defining a stochastic mathematical model to optimise a recovery plan in a three-stage SC facing the multi-dimensional impacts of the COVID-19 pandemic. In this setting, we developed a constrained programming mathematical model that optimises the total SC profit in the recovery window by considering the multi-dimensional yet uncertain impacts of a pandemic. Our definition generalizes a one of a kind issue setting with synchronous request, supply, and capacity instabilities in a multi-stage SC recuperation setting. Within the numerical show, we considered different methodologies that can at the same time upgrade the generation capacity and crude fabric supply. The demonstrate too considered the taken a toll of misplaced deals on the off chance that firms are incapable to meet the request or see that relinquishing deals would be more beneficial than expanding capacity to meet the short-term and sudden request. This highlight of the demonstrate empowers professionals to choose expanding capacities to meet request and relinquishing deals. Through this study, it is concluded that the total profit is found to be at a maximum when the selling price of the producer, buyer, and supplier is increased by 20 percent. To achieve the maximum profit, the total number of shipments from the buyer to the supplier must be reduced. To reduce the transportation cost, the cost of the producer of keeping the inventory safe will also have to be reduced. The important conclusions observed in this model are as follows: If a reduction in the inflation rate is assumed, then there is an increase in the total profit; conversely, if there is an increase in the inflation rate, then the total profit continuously decreases. The biggest advantage of this research is for those countries who are ready to complete vaccine manufacturing quickly and to reach the last member of the supply chain to improve their country's economy. The discoveries uncovered that companies seem altogether progress their add up to benefit by executing the techniques recommended for different scenarios and the show created in this think about. 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 were 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 delay 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.

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