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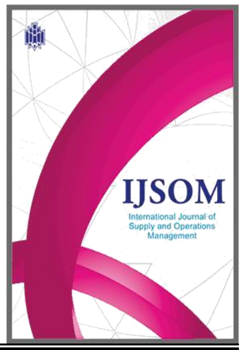

A Fuzzy Bi-objective Optimization Model to Design a Reverse Supply Chain Network: A Cuckoo Optimization Algorithm

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Abstract

The design and establishment of a logistics network is a strategic decision that lasts several years to work and the parameters of customer demand and return may be changed during this time. Therefore, an efficient logistics network should be designed in a way that can respond to uncertainties. The applications of such a network can be found in different industries like the battery industry. This study aims to determine the number of products sent among the centers at each time so that the total cost of reverse logistics and delay time is minimized. To address the uncertainty in the reverse logistics network (RLN), a fuzzy programming method is utilized. To tackle the complexity of the problem, the cuckoo optimization algorithm (COA) and genetic algorithm (GA) were developed. To compare these two optimization algorithms and find the superiority of them, a series of problem instances were generated. The obtained results demonstrated a satisfactory efficacy for both meta-heuristic algorithms. It was also revealed that the sum of values sent to the main manufacturer is equal to the values obtained from the exact solution method.
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Keywords: Reverse logistics; Time and cost optimization; Fuzzy theory; Cuckoo optimization algorithm; Genetic algorithm.

1. Introduction

Profound changes and developments in the business world and new conditions of production and trade in the current era have provided the ground for the emergence of new attitudes and paradigms that should be regarded by those involved in the field of production and trade. In this regard, a new approach and attitude towards the subject of logistics have emerged under the name of reverse logistics. Logistics covers the physical part of the supply chain and mainly contains all activities concerning the flow of materials and goods from the stage of supply of raw materials to the production of the final product, including transportation, warehousing, etc (Dey and Giri, 2020). Reverse logistics system is one of the most significant and vital aspects of any business and includes the supply, production, distribution of products/services and support for any type of them. In today's business era, where the product life cycle is getting shorter and shorter, product return policies are settled by fast response times and customer service, with more emphasis on return management, re-shaping and re-stocking of all goods. vOne of the new trends in logistics management is recycling or reusing products. In this method, products that reach the end of their useful life are repurchased from the end consumer, and after disassembly, the reusable parts of the product are returned to the life cycle in the form of discarded products. Reverse logistics management is a small but important area of the modern suppliers' chain and allows the companies' managers to return the returned goods and raw materials to suppliers and adopt policies, systems, and methods reducing the total cost of the supply chain system to maintain continuity and coordination of production and distribution activities and to prevent from the cessation of operations due to lack of inventory and usability of returned items and goods (McKinnon, Alan et al. 2010).

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Reverse logistics is especially popular due to its several competitive advantages. Environmental laws and economic interests, consumer awareness, and social responsibilities towards the environment are the pivotal drivers of this area (Keskin BB and Uster H. 2007; Bagheri-neghad Z., Kazemzadeh R. et al. 2013). In this regard, the design of a logistics network as a part of supply chain planning is of particular importance. Therefore, the proper design of this network can play a positive role in supply chain goals, especially cost reduction, responsiveness level, and efficiency (Chopra S. 2003). Applying the problems of reverse logistics network (RLN) design varies from linear models to complex non-linear models and from product delivery cost minimization to complex multi-objective optimization problems (Altiparmak, Gen et al. 2006). Since important issues in the real world involve more than one goal, regarding multiple goals at the same time is a good choice for most decision-makers. Moreover, the existence of uncertainty in the parameters of the problem is among the items that will be considered in this research.

Given the points mentioned about the importance of reverse logistics and its role in the supply chain, this paper attempts to design a logistics network that considers different objective functions in the reverse logistics problem. Accordingly, two objective functions of time and cost of operation are taken into account. An efficient logistics network must be designed in a way that meets uncertainties. Therefore, in this research, a fuzzy bi-objective programming approach is employed to account for the uncertain parameters.

The rest of the study is arranged as follows. A literature review of the logistics network is given in Section 2. The optimization problem of fuzzy time and cost in RLN and its parameters, objective function, and constraints are described in Section 3. The fuzzy bi-objective programming model is developed in Section 4. Our proposed COA and GA algorithms are discussed in Section 5. Section 6 reports the simulation results related to solving two meta-heuristic algorithms and their comparison. Section 7 ends with conclusions and some suggestions for future studies.

2. Literature review

The main target of any supply chain is to meet customer needs with the highest efficiency and the lowest cost. Structurally, the supply chain includes a network of retailers, wholesalers, distributors, manufacturers and suppliers; that each of them is the supplier of its downstream agent and the retailer meets the needs of the end customers. In this regard, the reverse logistics system includes the process of returned goods and how to properly deal with these items and all operations concerning the reuse of goods and materials to increase the productivity, profitability and efficiency of the logistics organization.

In recent years, most of the research works have concentrated on modeling the reverse logistics costs. Pishvaei et al. (2010) suggested a bi-objective mixed-integer nonlinear programming (MINLP) model for configuring an integrated direct and RLN. In order to treat the offered model, they developed a multi-objective memetic algorithm with a dynamic local search (LS) operator to determine a set of negligible solutions. In order to tackle complex optimization problems, various meta-heuristic methods have been proposed. One of the newest methods is COA which has been used in several studies (Akbari and Rashidi 2016; Amiri and Mahmoudi 2016; Wood 2016). Other useful meta-heuristic algorithms can be found in the studies performed by Saeedi Mehrabad et al. (2017), Goli et al. (2018, 2020a, 2020b).

Ulko and Bookbinderm (2012) studied the effects of different cost scenarios on the design of logistics networks. They obtained multiple optimal solutions for the cost and time of delivery to maximize the suppliers' profit. Dat et al. (2012) proposed a multi-level RLN design model consisting of collection sites, treatment sites (equipment recycling and repair), disassembly sites and final sites (disposal facilities and primary and secondary markets). They implemented their proposed methodology on the recycling of end-of-life electrical and electronic products. Bilgen and Çelebi (2013) presented an integrated production scheduling model and distribution planning in a dairy supply chain (considering the reverse logistics system) with the aim of maximizing the profitability of the entire network. For this purpose, an MILP model was suggested to formulate the problem. Moreover, they designed a simulation approach to solve the problem. In other studies, Niknejad and Petrovic (2014) presented a model of integrated RLN with different product recycling routes. To this end, a fuzzy MILP model was suggested to deal with the uncertain nature of the parameters. Govindan et al. (2015) conducted a comprehensive review of closed-loop supply chain and reverse logistics to review 382 articles from 2007 to 2013. Karimi et al. (2015) studied the problem of multi-period multi-product closed-loop supply chain design for dairy products in conditions of uncertainty. In this study, the forward supply chain included three levels of suppliers, manufacturing plants and distribution centers, and the reverse supply chain included collection, recycling and production centers. The aim of the research was to minimize the total cost of the chain. Since their problem was investigated in uncertain conditions, they applied the chance-constrained programming technique to model the problem. Dondo and Méndez (2016) developed an operational planning model for forward and reverse logistics activities in a multi-level logistics network. In their research, the issue of distribution and recovery was thoroughly investigated. A decomposition-based heuristic approach was developed in order to solve the proposed problem by achieving near-optimal solutions. Ardalan et al. (2016) presented a supply chain network with multi-state demand. In their study, an MILP model was offered to formulate the problem. The objectives of this study were to maximize the profits of the entire supply chain network. They employed a Lagrangian relaxation technique to solve the problem and validate the model. Gao et al. (2016) examined pricing decisions in a closed-loop supply chain network (CLSCN) design problem by considering the game theory approach. In this regard, strategies such as reverse logistics service, advertising related to recycling policies and workers' training program were considered and analyzed. Zahiri and Pishvaee (2017) designed a blood supply chain network under an uncertain environment. For this purpose, a bi-objective MILP optimization model was suggested in which the total cost is minimized and the demand coverage is maximized. Due to the uncertainty of the data, two robust probabilistic programming models were developed based on the credibility criterion. The results of the case study demonstrated the appropriate performance of the proposed models. Keshavarz Ghorabaee et al. (2017) offered a multi-objective multi-product multi-product reverse supply chain model under uncertainty. The objectives of this study were to minimize the total cost and maximize the greenness points of the purchased raw materials. To solve the proposed model, they applied several multi-objective decision-making (MODM) techniques.

Das & Roy (2019) studied the effect of carbon emission in a multi-objective transportation-location problem. They developed the neutrosophic compromise programming to get the Pareto solutions. Pervin et al. (2020) developed an integrated vendor-buyer model with quadratic demand under inspection to minimize the total cost. Ghosh & Roy (2021) developed a fuzzy multi-objective product blending transportation problem considering truck load constraints. Moreover, Ghosh et al. (2021) developed a fuzzy multi-objective for the fixed-charge transportation problem. Das et al. (2021) developed a multi-objective transportation-allocation problem considering carbon emission in inventory management. The fuzzy programming is applied to get the Pareto solutions. Paul et al. (2021) formulate and solve an economic order quantity model with default risk. They studied the demand effect and risk on optimal credit period for a deteriorating inventory model. Midya et al. (2021) developed a fuzzy multi-stage multi-objective fixed-charge solid transportation problem in a green supply chain. A min-max goal programming was used to obtain Pareto solutions.

In addition, other similar studies are presented as follows: modeling of reverse logistics activities at the end of life of the vehicles (Demirel, Demirel et al. 2016), reverse logistics design for the wastes of the electronic equipment (Kilic, Cebeci et al. 2015), outsourcing of reverse logistics activities (Agrawal, Singh et al. 2016), forward and backward logistics design for CLSCN (Pedram, Bin Yusoff et al. 2017) and integrated its structure for new products (Gaur, Amini et al. 2017). A scenario-based multi-objective MILP model was offered by Gao and Cao (2020) to design a sustainable RLSCN under uncertainty. They took into account the facility reconstruction within the proposed network and tried to minimize the total expected emission cost, maximize the total profit and maximize the total expected number of job opportunities. Kargar et al. (2020a) conducted a study to design an RLN for medical waste management during the COVID-19 outbreak. The objectives were to minimize the total cost and total risk of `operations at the same time. They employed the revised Multi-Choice Goal Programming (MCGP) technique to tackle the problem. In another study, Kargar et al. (2020b) proposed a fuzzy Goal Programming (GP) method to deal with a tri-objective MILP model for reverse supply chains of medical waste. The aims were to minimize the total cost, total stored waste and maximize the scores related to treatment technologies.

Regarding the mentioned contents, this study provides a bi-objective optimization model of time and cost. The uncertainties considered in this study are implemented using fuzzy theory. For this purpose, a credibility-based approach is utilized for the fuzzification process. Moreover, a COA is developed to solve a large-scale problem that has not been done in this field, so far. According to the research literature review, this study provides a mathematical model to optimize two objectives of time and cost using fuzzy parameters in an RLN at three levels of return centers, processing and manufacturer in one product. The study considers the retrieved end-of-life product and the amount of the manufacturer demand and the amount of end-of-life products collected in each period is definite from the beginning. Moreover, the COA algorithm is used to solve a large-scale problem that has not been done in this field, so far.

3. Problem definition

Reverse logistics is among the topics addressed in the field of RLN and CLSCN management of various industries. It seems that no serious attention has been paid to it in different industries of the country, so far. Over the recent years, many factories and industries in developed countries have started to study this field and have accounted for reverse logistics as one of the important processes in their supply chain. In a supply chain environment, when reverse logistics design is raised, time and cost in the amount of products retrieved by the customer are key factors. Also, inventory control and distribution planning as basic support activities influence the total cost of the supply chain and customer service level (Farahani and Elahipanah 2008). In this study, an RLN with two objectives of cost and time is designed in form of fuzzy. In this network, there are a customer area, several recovery centers, several processing centers and a manufacturer that delivers the retrieved products to the customers through reverse logistics. Figure 1 represents the proposed reverse logistic network.

The goal of this study is to specify the amount of products to be sent between centers in each time period so that the total cost and time of the reverse logistics network are minimized. The first objective function is to minimize the cost of the whole reverse logistics network, which includes the fixed cost to open processing centers, the cost of inter-center transportation, and the holding cost of inventory. The second objective function is time minimization, which is considered as the amount of delay in sending customer orders. In reverse logistics, meeting customer delivery time is much more difficult than in forward logistics. The reason for this is the uncertain rate of recovery of end-of-life products. To resolve this concern, we can minimize the waiting time by taking into account the amount of shipping delay as a function of the second objective.

As mentioned, a fuzzy approach has been used to meet the uncertainty in the RLN. Thus, all input parameters of the problem, expressed in the following, are considered in form of fuzzy numbers.

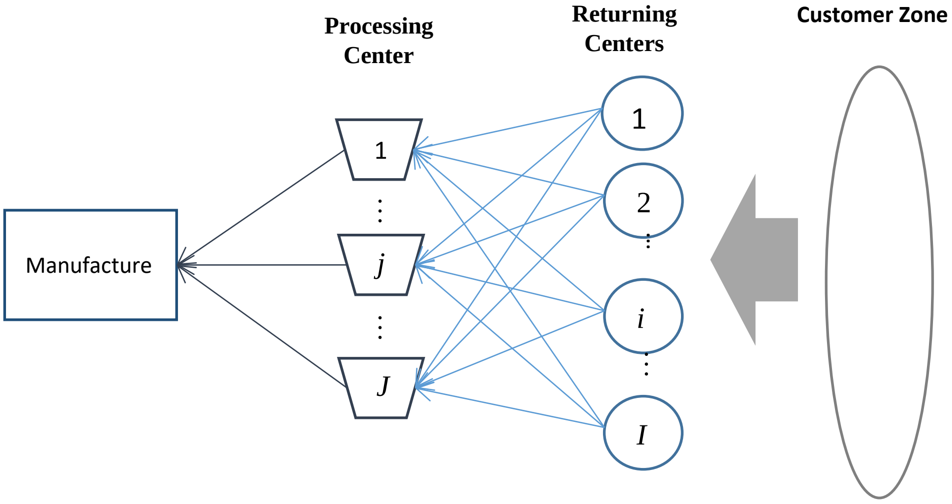

Figure 1. Proposed reverse logistic network.

3.1. Research assumptions

The assumptions of the fuzzy bi-objective mathematical programming model of time and cost in the reverse logistics system are stated below.

i. RLN is designed to include three levels of return centers, processing and manufacturer.
ii. In order to consider the uncertainty, the input parameters of the problem are in the form of fuzzy numbers.
iii. Only one type of product is considered.
iv. The amount of manufacturer demand and the amount of end-of-life products collected in each period is determined from the beginning.
v. There is a fixed cost for reopening the processing centers.
vi. The maximum capacity for both return and processing centers is definite.
vii. The inventory maintenance cost of all processing centers is the same.

3.2. Model sets

M : Manufacturer

I : Set of return centers

T : Set of time horizon

J : Set of processing centers

3.3. Model parameters and decision variables

b_j : Processing center capacity *j*

c_{jM} : Shipping cost from processing center *j* to manufacturer *M*

c_j^H : Inventory maintenance cost in processing center *j* per period

c_{ij} : Shipping cost from return center *i* to processing center *j*

c_j^{op} : Fixed cost of reopening the processing center *j*

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

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

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

p_j : Reusable product processing time in the processing center *j*

t_E : Expected shipping time of the customer

$r_i(t)$: Amount of products with the final life retrieved in the return center *i* in period *t*

$x_{ij}(t)$: Amount of products sent from the return center *i* to the processing center *j* in period *t*

$x_{jM}(t)$: Amount of products sent from processing center *j* to manufacturer *M* in period *t*

$y_j^H(t)$: Amount of inventory products sent to the processing center *j* in period *t*

z_j : If processing center *j* is used, it is 1, otherwise it is 0.

3.4. Mathematical model of the problem

The first objective function seeks to minimize the total cost of RLN comprising the fixed cost of reopening the processing centers, the cost of inter-center transportation, and the cost of inventory maintenance. The second objective function is time minimization, which is considered as the amount of delay in delivering customer orders. Due to the uncertain retrieval rate of end-of-life products, timely delivery of customer orders in reverse logistics is much more difficult than direct logistics. To solve this problem, the waiting time can be minimized by considering the amount of delivery delay as the second objective function.

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

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

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

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

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

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

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

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

Constraint (3) expresses that the amount of product sent from the return center *i* to the processing center *j* in period *t* is at most equal to the amount of retrieved end-of-life product in the return center *i* in period *t*. Constraints (4) and (5) indicate the capacity of the processing center and manufacturer, respectively. Inventory control in the processing center in each period is reviewed with constraint (6). Constraint (7) indicates that the decision variables $x_{ij}(t), x_{jM}(t)$ and $y_j^H(t)$ are not negative and constraint (8) ensures that the variable z_j is 0 or 1.

4. Fuzzy bi-objective modeling

This study employs fuzzy logic for modeling and problem-solving. The fuzzy set theory is used more than other techniques due to the advantages stated in a variety of research studies (Goli et al. 2020a; Tirkolaee et al., 2021). Owing to the lack of need for sufficient and accurate information, the fuzzy programming technique renders a more effective model than other approaches, such as the probabilistic method requiring sufficient knowledge for the distribution of uncertain parameters. In fact, in probabilistic approaches, specifying the distribution of problem parameters and determining its value is necessary that is very problematic in comparison with the fuzzy approach (Balin 2011). In situations where the parameters are uncertain, the development of a fuzzy programming method results in a truly flexible system (Behnamian and Ghomi 2014). Moreover, the computational complexity of fuzzy modeling is much less than other methods (Slowinski and Hapke 2000). The fuzzy set $\tilde{A}$ from the reference X is a set of ordered pairs and is written as Eq. (9) (Zadeh 1965).

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

where $\mu_{\tilde{A}}(x)$ is obtained from Eq. (10).

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

Considering the above-mentioned equation, it can be said that the membership function maps each member of the X set into the interval [0, 1]. The most common fuzzy numbers used in the research and application are trapezoidal and triangular fuzzy numbers. In this study, trapezoidal numbers are used for the fuzzification of the model. Trapezoidal fuzzy numbers are in form of quaternary $\xi = (a, b, c, d)$; it is illustrated in Figure 2 and its membership function is as Eq. (11):

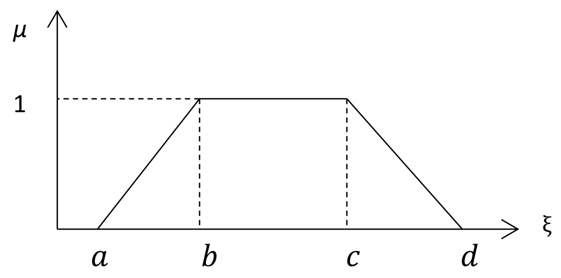

Figure 2. Trapezoidal fuzzy number.

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

According to the criteria of possibility and obligation, the validity criterion is presented in form of Eq. (12) (MEHLAWAT and GUPTA 2014; Zhang, Huang et al. 2015).

$$Cr(A) = \frac{1}{2}\{Pos(A) + Nec(A)\} \tag{12}$$

According to the above-mentioned items and definition of *Cr*, the validity function of the trapezoidal fuzzy number will be as Eq. (13):

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

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

$$\xi_{\sup}(\alpha) = \sup\{x \mid Cr\{\xi \geq x\} \geq \alpha\} = (2\alpha - 1)a + (2 - 2\alpha)b \tag{14}$$

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

$$\xi_{\inf}(\alpha) = \inf\{x \mid Cr\{\xi \leq x\} \geq \alpha\} = (2 - 2\alpha)c + (2\alpha - 1)d \tag{15}$$

According to Eq. (16), the average of four fuzzy numbers is used for de-fuzzification of parameters considered in the form of fuzzy objective function. Depending on the type of constraint, Eqs. (17) and (18) are employed for de-fuzzification of parameters being in the problem constraints (Liu and Liu 2002; Pishvaee, Torabi et al. 2012; Lu, Du et al. 2016).

$$\xi = \frac{(a + b + c + d)}{4} \tag{16}$$

$$Cr\{\xi \leq x\} \geq \alpha \Leftrightarrow x \geq (2 - 2\alpha)c + (2\alpha - 1)d \tag{17}$$

$$Cr\{\xi \geq x\} \geq \alpha \Leftrightarrow x \leq (2\alpha - 1)a + (2 - 2\alpha)b \tag{18}$$

This section develops a fuzzy bi-objective mathematical model based on the stated concepts, the existing uncertainties in reverse logistics problem, fuzzy set theory and validity approach. To develop a more realistic model, as presented in the problem assumptions, all input parameters of the problem are considered as uncertain and of the trapezoidal fuzzy number type. Thus, the proposed fuzzy bi-objective mathematical model will be as follows:

$$Min\ f_1 = \sum_{t=0}^{T}[\sum_{j=1}^{J}\tilde{c}_j^{op} z_j + \sum_{i=1}^{I}\sum_{j=1}^{J}\tilde{c}_{ij} x_{ij}(t) + \sum_{j=1}^{J}\tilde{c}_{jM} x_{jM}(t) + \sum_{j=1}^{J}\tilde{c}_j^{H} y_j^{H}(t)] \tag{19}$$

$$Min\ f_2 = \sum_{t=0}^{T}[\sum_{i=1}^{I}\sum_{j=1}^{J}\tilde{d}_{ij} x_{ij}(t) - t_E \tilde{d}_M(t) + \sum_{j=1}^{J}\left(\tilde{d}_{jM} + \tilde{p}_j\right) x_{jM}(t)] \tag{20}$$

$$\sum_{j=1}^{J} x_{ij}(t) \leq \tilde{r}_i(t) \quad \forall i, t \tag{21}$$

$$\sum_{i=1}^{I} x_{ij}(t) + y_j^{H}(t-1) \leq \tilde{b}_j z_j \quad \forall j, t \tag{22}$$

$$\sum_{j=1}^{J} x_{jM}(t) \leq \tilde{d}_M(t) \quad \forall t \tag{23}$$

$$y_j^{H}(t-1) + \sum_{i=1}^{I} x_{ij}(t) - x_{jM}(t) = y_j^{H}(t) \quad \forall j, t \tag{24}$$

$$x_{ij}(t), x_{jM}(t), y_j^{H}(t) \geq 0 \quad \forall i, j, t \tag{25}$$

$$z_j \in \{0,1\} \quad \forall j \tag{26}$$

Considering the de-fuzzification method presented in the previous section, depending on how to use a parameter, Eqs. (16) to (18) are employed and a fuzzy bi-objective mathematical model of time and cost in reverse logistics system is rewritten as follows:

$$Min\ f_1 = \sum_{t=0}^{T} [\sum_{j=1}^{J}\left(\frac{c_{j1}^{op}+c_{j2}^{op}+c_{j3}^{op}+c_{j4}^{op}}{4}\right) z_j + \sum_{i=1}^{I}\sum_{j=1}^{J}\left(\frac{c_{ij1}+c_{ij2}+c_{ij3}+c_{ij4}}{4}\right) x_{ij}(t)$$
$$+\sum_{j=1}^{J}\left(\frac{c_{jM1}+c_{jM2}+c_{jM3}+c_{jM4}}{4}\right) x_{jM}(t) + \sum_{j=1}^{J}\left(\frac{c_{j1}^{H}+c_{j2}^{H}+c_{j3}^{H}+c_{j4}^{H}}{4}\right) y_j^H(t)] \tag{27}$$

$$Min\ f_2 = \sum_{t=0}^{T}\left[\sum_{i=1}^{I}\sum_{j=1}^{J}\left(\frac{d_{ij1}+d_{ij2}+d_{ij3}+d_{ij4}}{4}\right) x_{ij}(t) + \sum_{j=1}^{J}(\left(\frac{d_{jM1}+d_{jM2}+d_{jM3}+d_{jM4}}{4}\right)\right.$$
$$+\left(\frac{p_{j1}+p_{j2}+p_{j3}+p_{j4}}{4}\right)) x_{jM}(t) - t_E\left(\frac{d_{M1}(t)+d_{M2}(t)+d_{M3}(t)+d_{M4}(t)}{4}\right)] \tag{28}$$

$$\sum_{j=1}^{J} x_{ij}(t) \le \left[(2\alpha-1) r_{i1}(t) + (2-2\alpha) r_{i2}(t)\right] \quad \forall i,t \tag{29}$$

$$\sum_{i=1}^{I} x_{ij}(t) + y_j^H(t-1) \le z_j \left[(2\beta-1) b_{j1} + (2-2\beta) b_{j2}\right] \quad \forall j,t \tag{30}$$

$$\sum_{j=1}^{J} x_{jM}(t) \le \left[(2\gamma-1) d_{M1}(t) + (2-2\gamma) d_{M2}(t)\right] \quad \forall t \tag{31}$$

Eqs. (24)-(26).

There are several methods to solve the bi-objective mathematical model. In this study, a total weighted objective functions approach is used to solve the proposed model. Therefore, two single-objective metaheuristic algorithms are developed. In the following, two meta-heuristic algorithms are designed to treat the offered model and their results are studied and compared with each other for a variety of produced problem instances.

5. Proposed meta-heuristic algorithms

Since most logistics network design problems are NP-hard (Altiparmak, Gen et al. 2006; Lee and Dong 2009b; Pishvaee M. S. and Torabi S. A. 2010), precise methods have not been able to solve such large-scale problems; Therefore, heuristic and meta-heuristic methods are designed to tackle them. In this section, each of the algorithms and how they work are briefly presented.

5.1. Cuckoo optimization algorithm

Here, a COA is developed to optimize time and cost in the fuzzy multi-objective model. Figure 3 illustrates the flowchart of COA (Rajabioun 2011). Naturally, each cuckoo lays between 5 to 20 eggs. Hence, these numbers are used as the upper and lower bounds of egg assignment to each cuckoo in various iterations. The other habit of each cuckoo is that it lays its eggs in a certain range called maximum Egg Laying Radius (ELR) (Akbari and Rashidi 2016). According to Eq. (32), ELR is determined based on the total number of eggs, the number of current cuckoo eggs, and the upper and lower bounds of the problem variables.

$$ELR = \alpha \times \frac{Number\ of\ \ current\ cuckoo's\ eggs}{Total\ \ number\ of\ \ eggs} \times \left(\mathrm{var}_{high} - \mathrm{var}_{low}\right) \tag{32}$$

Where α represents a parameter based on which the maximum ELR value is set. Also, var_{hi} and var_{low} are the upper and the lower limits of the variable, respectively. After egg laying, P% of all eggs (usually 10%) having less profit function is annihilated. The rest of the eggs are fed and grown in the host nests. After forming the cuckoo groups, the group having the highest average profit (optimality) is chosen as the target group and other groups migrate toward it. Each cuckoo travels only λ% of the entire path to the current ideal goal and it also has a radian deviation φ. In order to design an efficient COA in this research, λ, a random number between 0 and 1 and φ, a number between $\pi/6$ and -$\pi/6$ are generated, respectively. The upper and lower bounds of the variable are assumed to be 0 and 1 in ELR calculation, respectively. The flowchart of COA is illustrated in Figure 3.

5.2. Genetic algorithm

Genetic actions mimic the process of inherited gene transfer to generate new offspring in each generation. An important part of the genetic algorithm (GA) is the creation of new chromosomes called offspring through some old chromosomes called parents. This important process is carried out by genetic actions. In general, these actions are performed by two operators named crossover and mutation. Obviously, to better identify chromosomes, there must be an indicator to evaluate the chromosomes. In the case of function optimization problems, this indicator usually takes a value the same as the objective function value of the problem, that is, each chromosome is converted into the corresponding solution and placed in the objective function. If each chromosome has a better objective function, the solution will be more appropriate. However, for some more complex problems, it is necessary to represent the fitness function. To reproduce a new population, a method should be utilized to select the best solution as far as possible. Two widely applicable methods are the random selection by roulette wheel and the competitive selection method. Figure 4 indicates the process of problem-solving by GA by a flowchart.

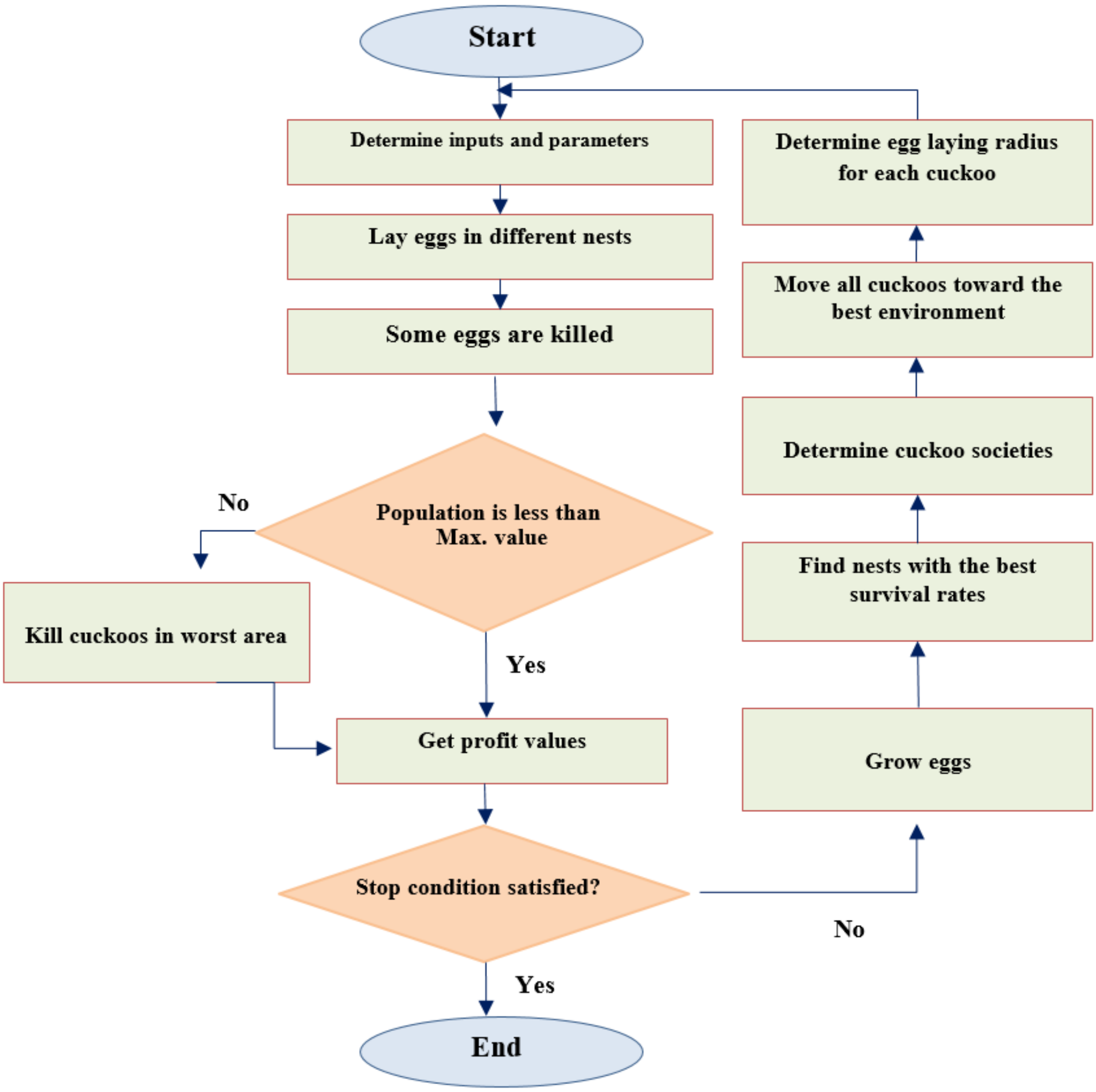

Figure 3. Proposed COA flowchart

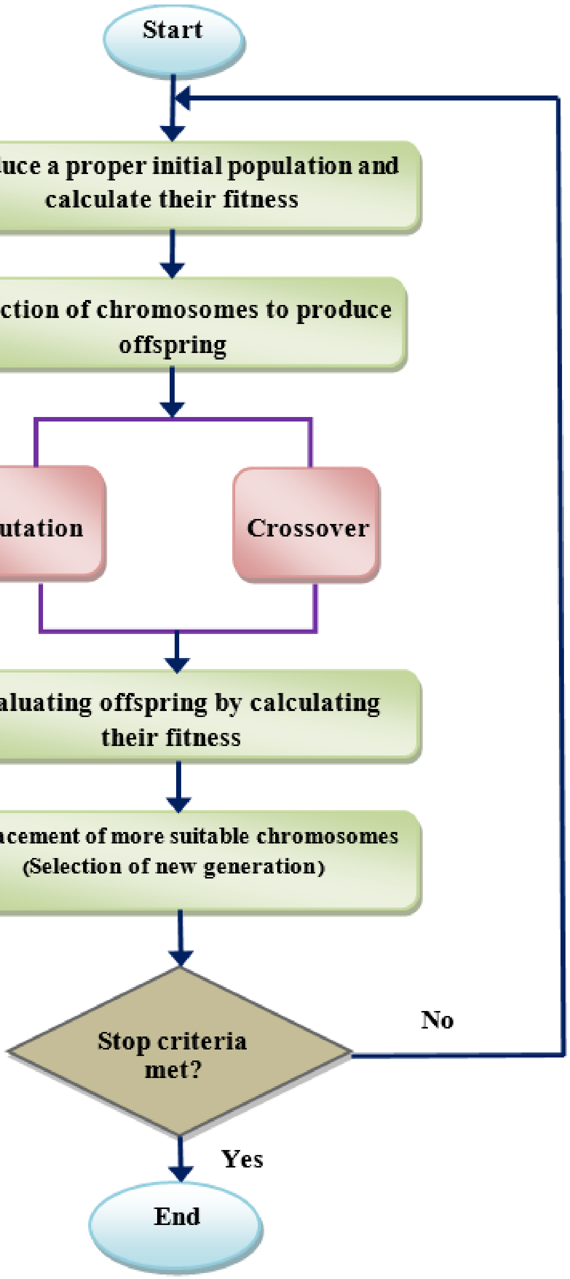

Figure 4. Proposed GA flowchart.

5.3. Algorithms parameters tuning

In order to tune algorithm parameters, the trial-and-error method is applied. Tables 1 and 2 show the set of initial values of parameters related to COA and GA, respectively.

Table 1. COA parameters value

Parameter	Notation	Value		
Initial number of Cuckoos	initialCuckoo	5	10	15
Max number of Cuckoos	Nmaxcuckoo	50	80	100
Minimum number of eggs	Neggmin	1	2	5
Maximum number of eggs	Neggmax	2	5	10
Number of iteration	maxit	50	100	150

Table 2. GA parameters value

Parameter	Notation	Value		
Initial population	npop	50	100	150
Number of iteration	Max_iteration	100	150	200
Crossover rate	Cross_rate	0.6	0.7	0.8
Mutation rate	Mut_rate	0.3	0.2	0.1

The best value of each parameter is shown in Tables 3 and 4, respectively.

Table 3. Best value for COA parameters

Parameter	Notation	Best Value
Initial number of Cuckoos	initialCuckoo	10
Max number of Cuckoos	Nmaxcuckoo	100
Minimum number of eggs	Neggmin	1
Maximum number of eggs	Neggmax	10
Number of iteration	maxit	150

Table 4. Best value for GA parameters

Parameter	Notation	Best Value
Initial population	npop	100
Number of iteration	Max_iteration	200
Crossover rate	Cross_rate	0.8
Mutation rate	Mut_rate	0.3

5.4. Solution representation

Each solution was considered as a chromosome and each chromosome consisted of a certain number of genes. The number of genes was found based on the problem structure. A chromosome generated in this study contains two stages. In the first stage, the number of genes is calculated by the number of retuning and processing centers while the second one is including the number of processing centers and a manufacturer as shown in Figure 5.

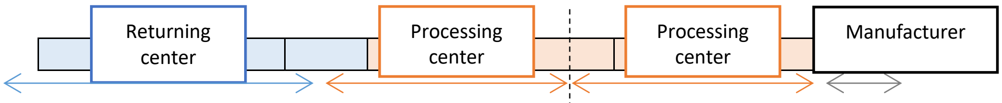

Figure 5. Chromosome illustration

5.5. Crossover and mutation operators

In this study, a one-cut point crossover is applied to create offspring chromosomes from two randomly selected parents. Two new offspring are obtained using the following Equations.

$$p_1 = b\ pfn + (1-b)\,psn \tag{33}$$

$$p_2 = (1-b)\,pfn + b\ psn \tag{34}$$

where *b* is a random array with size of parents, and *pfn* and *psn* are the dimensions of the first and second parent, respectively.

In order to implement mutation operators, one center is randomly selected, and then one of its chromosomes is changed randomly with another. It should be mentioned that after applying these two operators, the feasibility of generated solution will be checked.

5.6. The proposed COA validation

To test the efficiency of the suggested algorithm, a small-scale sample problem is generated and solved by both the exact and COA approach. 4 returning centers, 3 processing centers, and a manufacturer are considered. Parameters value is reported in Table 5.

Table 5. Problem parameters value

Parameter	Value
Demand ($d_M(t)$)	U ~ [30 50]
Capacity (b_j)	U ~ [80 105]
Opening cost of processing center (c_j^{op})	U ~ [10 22]
Processing time (p_j)	U ~ [9 19]
Inventory cost (c_j^H)	U ~ [12 25]
Shipping cost (c_{ij}) c_{jM} و	U ~ [10 25]
Delivery time (d_{ij}) d_{jM} و	U ~ [7 19]
Amount of product with the final life retrieved ($r_i(t)$)	U ~ [25 55]

The sample problem is solved exactly by CPLEX solver in GAMS software. The objective function is calculated by the weighted sum of two objectives equal to 6480. Then, this problem is also solved by COA in MATLAB software that is reached to 6496. In both methods, all 3 processing centers are applied. Table 6 represents the objective function value and computational time of the two approaches.

Table 6. Comparison of two proposed methods.

Method	GAMS	COA
Objective function value	6480	6497
Computational time (s)	1	20

The amount of product shipping to the processing centers and manufacturer is reported in Tables 7 and 8, respectively.

Table 7. The amount of product transported to the processing center

Method	GAMS		COA	
Processing center	Period			
	1	2	1	2
1	-	46	85	57.5
2	67	91	50.5	90.5
3	32	55	40	80

Table 8. The amount of product transported to the manufacture

Method	GAMS		COA	
Processing center	Period			
	1	2	1	2
1	-	-	15.5	-
2	-	-	15.5	-
3	31	36	-	36

Results show that the amounts of products shipped from returning center to the processing center and transported from the processing center to the manufacturer are the same in both methods.

6. Evaluation of the developed algorithms

Here, the performance of the two algorithms is assessed and compared. To evaluate the quality and dispersion of meta-heuristic algorithms, the criteria of relative percentage deviation (RPD) and computational time are employed. To make these comparisons, 18 problem instances with different values obtained from the number of return centers, number of processing centers and time horizon, production and the best results arising from solving the problems by algorithms are given in Table 9. According to the table, the values of input data are fuzzy; First, 4 numbers are randomly generated using a uniform distribution. Then they are arranged in ascending order and are used as input data. The proposed algorithms are implemented in MATLAB R2016a software.

Table 9. Values of input data for problem instances.

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

Each of the controlling parameters considered for the algorithms has a significant effect on the solution quality and computational time. For example, increasing the population in GA may increase the computational load of the algorithm and its inefficiency. However, this increase in the number of countries enhances the possibility of finding an optimal global solution. Considering the several performed experiments and the results arising from them, the effective range for each controlling parameter of algorithms is obtained. To set the algorithm parameters, each algorithm was run several times, and finally, the best combination of algorithm parameters was obtained shown in Table 10.

Table 10. Parameters of GA and COA**.**

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

6.1. RPD criterion

RPD criterion shows the deviation rate of algorithms to the best possible value of the objective function. Therefore, if this value is lower, the algorithm shows better performance. It is calculated as follows:

$$RPD = \frac{sol - Bestsol}{Bestsol} * 100 \tag{35}$$

Where *sol* is the solution obtained from the execution of the algorithm and *Bestsol* is the best solution obtained from the algorithms. The comparative results are given in Table 11. Moreover, the run time comparison is illustrated in Figure 6.

Table 11 reports the implementation results of algorithms for hypothetical problems. According to Table 11, it can be inferred that although the COA performs better in all proposed problems, it takes more computational time to reach the solution in all cases (see Figure 6). Furthermore, when the dimension of the problem increases, the computational time to reach the near-optimal solution is increased exponentially. Furthermore, a sensitivity analysis is done on the confidence level (α) to evaluate the uncertainty effect on the objective function. As shown in Figure 7, the higher confidence levels, the less fluctuation in cost and time, and subsequently, the total cost will decline.

Table 11. Computational results for the proposed problem instances.

No.	J	I	T	RPD		Time	
				GA	COA	GA	COA
1	4	3	5	0.63	0	26.61	34.20
2	5	4	5	0.32	0	37.32	48.67
3	7	5	6	0.40	0	68.80	89.48
4	8	5	6	0.05	0	78.33	102.77
5	10	7	8	0.18	0	161.69	205.81
6	12	8	8	0.07	0	213.30	273.38
7	13	8	9	0.22	0	262.11	331.63
8	14	10	10	0.05	0	385.44	473.89
9	15	12	10	0.15	0	477.54	597.45
10	16	12	12	0.03	0	608.54	726.32
11	18	12	12	0.12	0	686.11	844.70
12	20	12	12	0.05	0	757.06	953.91
13	21	13	12	0.17	0	830.63	1035.21
14	22	15	15	0.14	0	1352.67	1624.86
15	24	17	15	0.09	0	1562.65	1925.78
16	26	19	17	0.12	0	2059.28	2639.20
17	28	21	20	0.03	0	2864.03	3978.73
18	30	23	22	0.02	0	4335.88	4631.85

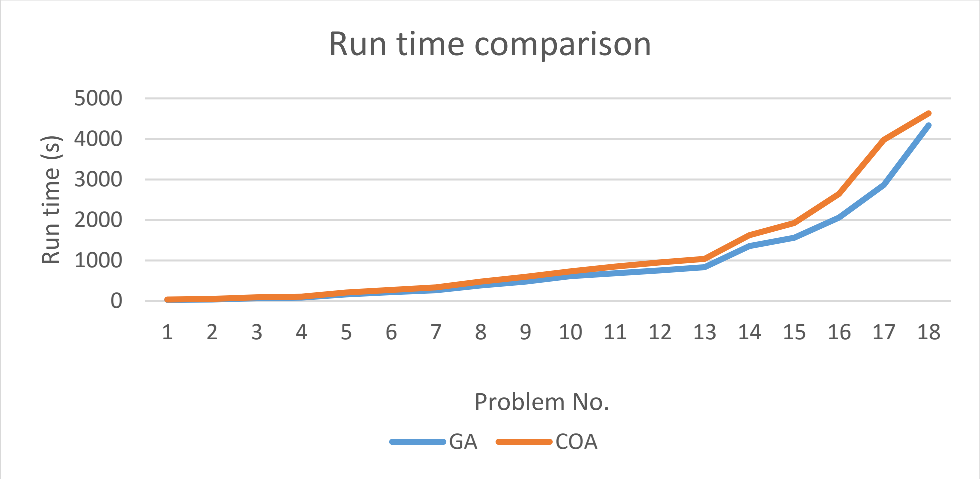

Figure 6. Computational time comparison of the algorithms.

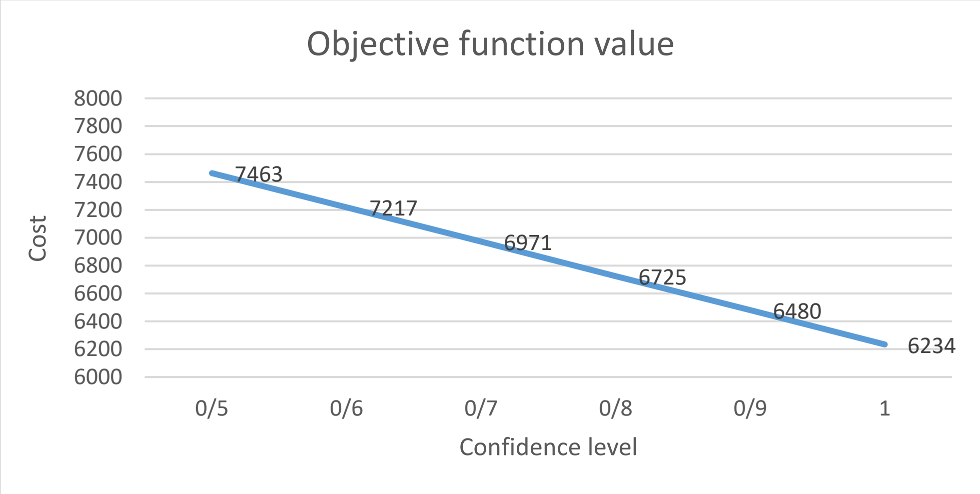

Figure 7. Confidence level effect on the total cost.

7. Discussion, Conclusion and Outlook

This work proposed a fuzzy bi-objective optimization model in a reverse logistics system that can be regarded in real-life industries like the battery supply chain. The aim was to find the amount of products sent among centers in each time period so that the total cost of reverse logistics and total delay time are minimized. A fuzzy bi-objective programming approach was employed to meet the uncertainty in the RLN. Finally, a mathematical programming model and two meta-heuristic algorithms were developed to tackle the problem. To solve the large-scale problem, the proposed COA and GA were implemented in MATLAB software. Then, a number of sample problems in different dimensions according to the number of return centers, the number of processing centers and time horizon were generated and their results were analyzed and compared to each other. The computational results revealed that COA performed better than GA in finding a better solution but it takes a longer time.

In the area of reverse supply chain design, there are other effective components, such as pollutants that can be studied to protect the environment. Other levels of the supply chain, such as recovery and repair, disposal and reuse will also be added to the problem. In addition, other new meta-heuristic methods can be used, such as the invasive weed optimization (IWO) algorithm (Sangaiah et al., 2020) and particle swarm optimization (PSO) algorithm (Tirkolaee et al., 2019). Since the supply cost and delay cost are of the same nature, this study used a weighted approach to combine two objectives. Moreover, other uncertainty techniques including robust optimization (Tirkolaee et al., 2020; Lotfi et al., 2020), stochastic control (Temoçin and Weber 2014) and application of neural networks as well as learning-based tools (Wang et al., 2018, 2020a, 2020b) can be applied and compared to the proposed fuzzy programming approach. In conclusion, this study met the existing uncertainty in the problem using the fuzzy approach. In this regard, other approaches, such as probabilistic and scenario-based approaches can be used.

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