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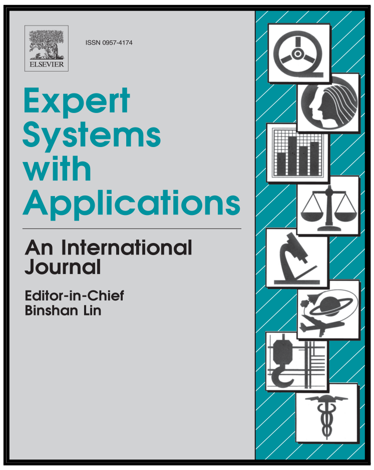

A robust fuzzy mathematical programming model for the closed-loop supply chain network design and a whale optimization solution algorithm

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highlights

- Robust fuzzy modeling can address the effect of uncertainty in parameters
- The priority-based solution encoding is useful in construction of meta-heuristics
- The proposed Whale Optimization Algorithm provides fast high-quality solutions
- The solution quality is consistent without parameter-dependent behavior

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A robust fuzzy mathematical programming model for the closed-loop supply chain network design and a whale optimization solution algorithm

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Abstract

The closed-loop supply chain (CLSC) management as one of the most significant management issues has been increasingly spotlighted by the government, companies and customers, over the past years. The primary reasons for this growing attention mainly down to the governments-driven and environmental-related regulations which has caused the overall supply cost to reduce while enhancing the customer satisfaction. Thereby, in the present study, efforts have been made to propose a facility location/allocation model for a multi-echelon multi-product multi-period CLSC network under shortage, uncertainty, and discount on the purchase of raw materials. To design the network, a mixed-integer nonlinear programming (MINLP) model capable of reducing total costs of network is proposed. Moreover, the model is developed using a robust fuzzy programming (RFP) to investigate the effects of uncertainty parameters including customer demand, fraction of returned products, transportation costs, the price of raw materials, and shortage costs. As the developed model was NP-hard, a novel whale optimization algorithm (WOA) aimed at minimizing the network total costs with application of a modified priority-based encoding procedure is proposed. To validate the model and effectiveness of the proposed algorithm, some quantitative experiments were designed and solved by an optimization solver package and the proposed algorithm. Comparison of the outcomes provided by the proposed algorithm and exact solution is indicative of high quality performance of the applied algorithm to find a near-optimal solution within the reasonable computational time.

Keywords: Closed-loop supply chain network design; Modified priority-based encoding; uncertainty; Whale optimization algorithm

1 Introduction

Economic and industrial changes are taking place quicker today than the past. Globalization of economic activities along with the rapid growth of technology and limited resources has involved the firms in a close competition with one another. Any organization that operates under these conditions has to maintain or increase its margin to survive in the market. The supply chain, which is also referred to as the logistics network, consists of suppliers, manufacturing centers, warehouses, distribution centers, and retail outlets, as well as raw materials, work-in-process inventory, and finished products that flow between the facilities (Simchi-Levi et al. 1999). In this set, the customers are considered as the very last members of a chain. Supply chain networks are classified into two general categories of (1) traditional supply chains as a forward or an open-loop chain and (2) integrated chains that are composed of components such as raw materials, manufacturing facilities, distribution centers, and customers; all of which are connected by the flow of materials and information in forward reverse chains, respectively (Stevens 1989). In contrast with a traditional supply chain where the material flow movements are directed from suppliers to

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customers, a reverse supply chain refers to the flow of materials from customers towards the supplier, and the consumed products move from the final consumer to the production centers. The integrity of forward and reverse supply chains result in a CLSC (Guide et al. 2003). One of the most comprehensive strategic decision in supply chain management is the network design problem that requires optimization of the whole supply chain for an efficient long-term operation. Network design determines the number, locations, and capacities of the production facilities and distribution channels in terms of the ingredients for consumption and production to be transferred from suppliers towards customers. Additionally, controlling uncertain parameters is another management task in the CLSC; uncertainties in supply (delays in sending raw materials or products), distribution and production processes, demand estimation, and quantity of the returned products are only a number of the problems in a practical CLSC network design. Hence, the complexity and dynamic nature of any supply chains impose high degrees of uncertainty and considerably affects network and supply chain decision-making process (Özkır and Başlıgıl 2012).

The effects of uncertainties on strategic decisions are by far more observable on tactical decisions (Pishvaee et al. 2011). Hence, although ignoring uncertainties at operational levels incurs costs, such imposed costs are often not remarkable as the system corrects itself in a short period of time. However, if uncertainties are ignored at strategic levels, the damage to the system is often more drastic and some times irreversible; as a result, designing a reliable supply chain network that can properly function under uncertainty is imperative to the competitive advantage of the chain. This paper consists of the following sections: In the next section, the literature related to the reverse and CLSC is reviewed. In Section 3, mathematical formulation of the proposed model and RFP are presented. Section 4 presents a modified priority-based encoding and the proposed WOA. Section 5 provides the quantitative outcome for a set of design problems with different sizes. Finally, the conclusions, managerial implications, and suggestions for future studies are presented in Section 6.

2 Literature review

Over recent years, regarding the rising importance in both academic and practical attraction of supply chain, especially reverse and CLSC ones, some researchers have focused on publishing a comprehensive review of the existing literature in this field, specifying the

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observed research gaps, and consequently proposing future research areas and paradigms. Research related to the (Fleischmann et al. 1997) can be considered as the first work reviewing the research conducted on reverse logistics networks. They classified the studies into three general categories of distribution planning, inventory, and production planning. Govindan et al. (2015) present a more comprehensive literature review regarding the closed-loop and reverse supply chains. They classify 382 papers published from 2007 to 2013 and propose a more detailed classification based on 10 factors, e.g. the year of release, approaches, objectives, functions, etc. They assert that almost 50% of the total surveys are linked to the CLSC network design, and almost 40% of them are connected to the reverse supply chain network design. Furthermore, their study revealed that 12% and 88% of the published papers are related to the single-objective and multi-objective models, respectively.

Nowadays, network design is considered as one of the most central tactical and strategic decisions to be attended to in supply chain management (SCM). In general, supply chain network design decisions include determining the number and locations of facilities (strategic decisions) and the quantity of flow between them (tactical decisions). In recent years, a few of articles have focused on integrated forward/reverse network design. The mentioned type of integration can prevent the sub-optimality and increase the level of network performance and coordination between forward and reverse processes. Furthermore, as mentioned above, uncertainty parameters strongly influence the strategic and tactical decisions in CLSC network design. In the following section, some of the articles discussing the reverse and closed-loop supply chain network design are presented.

Inderfurth (2005) studies a CLCS network based on a stochastic programming model. He defines a parameter to measure the uncertainty of quality as demand and return rates of the used products are stochastic. Altiparmak et al. (2006) propose a solution encoding to find the non-dominated set of solutions for a multi-objective supply chain network design problem. The objectives of their model are minimization of the total network costs and maximization of the satisfaction rate of the total customer demands within the access time. They use a genetic algorithm (GA) with priority-based encoding to solve their proposed model. Üster et al. (2007) present a multi-product CLSC network design, in which the location of the collection centers and reproduction centers are discussed by considering the forward and reverse flows. The aim of their model is to minimize the

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total cost including fixed, transportation, and processing costs. They use the Benders decomposition technique to approach the problem. Xu et al. (2008) propose a MINLP model for a multi-objective supply chain network design problem, in which a spanning tree-based GA with the prÜfer number representation is used to design the supply chain network to satisfy the customer demand with maximum customer service and minimum total network costs. Pishvaee et al. (2010b) develop a bi-objective mixed-integer linear programming (MILP) model for a logistics network problem to simultaneously minimize the total cost and maximize accountability. They use a mimetic algorithm to find a set of Pareto-optimal solutions, in which a new dynamic search strategy is used of by employing the priority-based encoding. In addition, they design a fuzzy bi-objective multi-period model for a CLSC network design problem, in which the demand, return rate of the used product, operation costs, transportation costs, and delivery time are considered to be uncertain. Özceylan et al. (2014) develop an integrated MINLP model to optimize the strategic decisions related to the flow of products in the forward and reverse supply chains along with making tactical decisions to balance the production line in the reverse supply chain. Zohal and Soleimani (2016) design a multi-echelon CLSC network for gold industry. They apply the ant colony optimization algorithm to find a near-optimal solution. The objectives of their proposed model are minimization of both the total network costs and carbon emission rates. Amin and Zhang (2013a) propose a stochastic multi-objective model to design the integrated forward/reverse logistics with regard to accountability and quality levels. In their model, the demand and return rates of the used products are considered uncertain with a minimization objective including transportation, purchasing, and disassembly costs. Talaei et al. (2016) also design a multi-objective MINLP model for a closed-loop green supply chain network to simultaneously minimize both the total network costs and carbon dioxide emission rates. They took advantage of an RFP approach to address the effects of uncertainty parameters on the network designs. Alfonso-Lizarazo et al. (2013) investigate a carbon sensitive supply chain network problem with green procurement. Amin and Zhang (2013b) apply the ϵ-constraint approach and used a numerical illustration of Copiers Industry to show the applicability of the proposed model. Among the most recent studies, Amin and Baki (2017) propose a multi-objective MIP by considering global factors like exchange rates and customs duties under an uncertain demand pattern and develop a fuzzy solution approach. Ghahremani Nahr et al. (2018) investigate a CLSC and propose a so called League Champion meta-heuristic algorithm in their solution approach. Alamdar et al. (2018) investigate the optimal decisions in CLSC under a fuzzy price and sales effort-dependent demand. They establish several game theory models to compare the behavior of a manufacturer, a retailer and a collector. Farrokh et al. (2018) use a fuzzy stochastic programming approach to a supply chain design while Jabbarzadeh et al. (2018) use a robust approach to design CLSC under operational and disruption risks. Soleimani et al. (2017) consider a green CLSC design accounting for environmental considerations, as well as lost working days and propose a genetic algorithm for solution method, and Rad and Nahavandi (2018) consider also a green multi objective CLSC whose objective functions are the economic cost, and environmental emissions,and of customer satisfaction. They develop an ant colony optimization solution algorithm for their model. Tosarkani and Amin (2018) conduct a Fuzzy analytic network process in a case study of battery supply chain design, while in another case study, Özceylan et al. (2017) develop a linear programming model for CLSC of the automotive industry in Turkey. A more detailed classification based on four factors including the certain and uncertain parameters, single and multi-period models, single and multi-product models, and single and multi-objective models is illustrated in Table 1.

Contribution highlights

The review of the existing literature reveals a need for a new supply chain network design model, capable of implementing real-world uncertain parameters. In order to make the model closer to the real-world dynamics, the present study develop a comprehensive model to consider uncertainty in periodic demand, raw material cost, transportation cost of material and goods, shortage cost, and finally the uncertain nature of the amount of return products (as a fraction of the total sales). Unlike many other studies, this model is capable of both opening and closing selected facilities, considering the associated cost of opening/closing, to redesign the supply chain network, if required. In addition, the proposed model seeks to minimize the total costs among uncertain parameters. It must be mentioned that the designed model is developed based on RFP. To approach the model, a novel WOA algorithm is proposed using a modified priority-based encoding to find an approximate optimal solution within a reasonable computational time.

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Table 1: Review of some supply chain network models

Single period	Multiple period	Single product	Multiple product	Single objective	Multiple objective	Certain parameters	Unertain parameters	Author-date
*		*		*		*		Cruz-Rivera and Ertel (2009); Diabat et al. (2015); Fleischmann et al. (2001); Guide et al. (2003); Kannan et al. (2012); Khajavi et al. (2011); Lee and Dong (2008); Lee et al. (2006); Lieckens and Vandaele (2007); Louwers et al. (1999); Lu and Bostel (2007); Mahmoudzadeh et al. (2013); Neto et al. (2008) ; Pishvaee et al. (2010a); Schultmann et al. (2003); Wang and Hsu (2010)
*		*		*			*	Aras and Aksen (2008); Chouinard et al. (2008); Hatefi and Jolai (2014); Kara and Onut (2010) ; Lee et al. (2010); Lieckens and Vandaele (2007); Listeş (2007); Listeş and Dekker (2005); Pishvaee et al. (2009); Pishvaee et al. (2011); Qin and Ji (2010); Subramanian et al. (2013); Üster and Hwang (2016) ; Wang and Hsu (2010); Alamdar et al. (2018)
*		*			*	*		Bouzembrak et al. (2011); Elhedhli and Merrick (2012) ; Garg et al. (2015); Krikke et al. (2003); Özceylan et al. (2014); Pishvaee et al. (2010b)
*		*			*		*	Fallah et al. (2015); Paksoy et al. (2012); Saeedi et al. (2015); Saffari et al. (2015); Talaei et al. (2016)
*			*	*		*		Das and Chowdhury (2012); Dat et al. (2012); Demirel and Gökçen (2008); Jayaraman et al. (1999); Kannan et al. (2009) ; Lee et al. (2009); Mahmoudi et al. (2013); Pati et al. (2006); Pokharel and Mutha (2009); Salema et al. (2006)
*			*	*			*	Francas and Minner (2009); Govindan et al. (2015); Lee et al. (2009); Salema et al. (2006); Soleimani et al. (2014)
*			*		*	*		Abdallah et al. (2010); Üster et al. (2007); Wang et al. (2011)
*			*		*		*	Amin and Zhang (2012); Amin and Zhang (2013a); Amin and Zhang (2013b); Ramezani et al. (2013); Ghahremani Nahr et al. (2018)
	*	*		*		*		Alfonso-Lizarazo et al. (2013); Kannan et al. (2010)
	*	*		*			*	El-Sayed et al. (2010); Inderfurth (2005); Farrokh et al. (2018)
	*	*			*	*		Rad and Nahavandi (2018)
	*	*			*		*	Pishvaee et al. (2010b)
	*		*	*		*		Alumur et al. (2012) ; Beamon and Fernandes (2004); Kannan et al. (2010) ; Keyvanshokooh et al. (2013); Kim et al. (2006); Ko and Evans (2007); Özkır and Başlıgıl (2012); Ramudhin et al. (2008); Realff et al. (2004); Sasikumar et al. (2010) ; Özceylan et al. (2017)
	*		*	*			*	Cardoso et al. (2013); Shi et al. (2011); Zeballos et al. (2012); Zeballos et al. (2014); Tosarkani and Amin (2018); Jabbarzadeh et al. (2018)
	*		*		*	*		Pasandideh and Asadi (2016); Pasandideh et al. (2015a)
	*		*		*		*	Pasandideh et al. (2015b) ; Subulan et al. (2015); Soleimani et al. (2017) **This Paper**

3 Problem definition and mathematical formulation

In this problem, a multi-product, multi-period, multi-echelon CLSC network is designed under discounts, shortage, and uncertainty. This research was initially motivated by the case of a local automotive manufacturer in Iran. Due to international sanctions against the country and subsequent difficulties in sourcing material and supply, CLSC has become as an increasingly important source of supplying critical parts, elements and material in the country and within this industry. However, generalizing the initial model, this paper presents a more holistic approach to CLSC optimization, as we believe this model is capable of addressing different manufacturing sectors with similar frameworks (within the reach of slight customization). This boarder approach is particularly of interest, as a review on other literature shows a great attempt has already been made on different sectors and industries with minimum effort to generalize the results. Among those literature with focus on a specific industry are, electronics and digital equipment (Rad and Nahavandi 2018; Amin and Baki 2017); battery (Tosarkani and Amin 2018); tire (Amin et al. 2017; Sahebjamnia et al. 2018); e-commerce in an Indian firm (Prakash et al. 2018); yarn, fabric, and apparel (Kim et al. 2018); glass (Hajiaghaei-Keshteli and Fard 2018); and washing machine (Jeihoonian et al. 2017).

The description of our supply chain network is given as follows. The forward flow network includes raw-material suppliers, production centers, warehouses, distribution centers, and customer zones. The reverse network includes collection centers, repair centers, recycling and disposal centers, as well as all facilities with limited capacities. As our general map is illustrated in Figure 1, in the forward flow network, the raw-material suppliers ship the raw materials needed to produce the new products in the production centers. The raw materials are sent to the warehouses after being processed in the production centers. Then, distribution centers deliver them to final customers. In the reverse flow, a proportion of the products returned from the customers is collected by the collection centers, where fixable and upgradeable products are sent to repair centers after inspection. The rest is sent to a recycling centers. The repaired products at the repair centers, like new ones, go back to the forward flow and are sent back to the distribution centers and the potential warehouses. In addition, recyclable products after disassembly at recycling centers are sent to the production center for reuse (if they could be reused); otherwise, they are sent to disposal centers.

To specify the study scope, the following assumptions are made to formulate the problem:

- The discount offered by the raw material supplier is of a quantity discount type.
- All the facilities have limited and identified capacities.
- The location of all centers has to be determined.

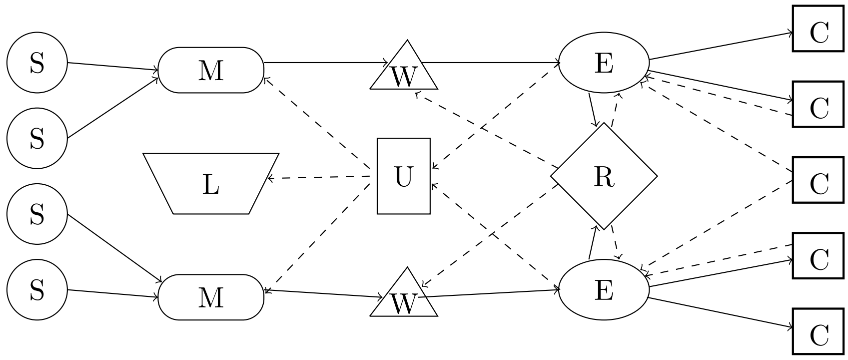

Figure 1: The map of a multi-echelon CLSC network

- Unmet demand of customers (shortage) is back-ordered.
- Customer demand of each product must be satisfied until the last time period.
- Distribution and collection centers are considered as hybrid centers.
- The customer demand, fraction of returned product, transportation cost between facilities, purchase cost, and shortage cost are considered as uncertainty parameters.

With consideration of the above-mentioned assumptions, the most important issues addressed in this paper are as follow:

- To locate the raw material supplier, production centers, warehouses, hybrid distribution/ collection centers, repair centers, recycling centers, and disposal centers
- To determine the optimal flow between the located centers
- To find an appropriate level of discount.

The following subsections define the notations used the formulation of our proposed model.

3.1 Sets

Symbol	**Definition**	**index**
S	Set of raw-material suppliers	$\forall s \in S$
M	Set of production centers	$\forall m \in M$
W	Set of potential warehouses	$\forall w \in W$
E	Set of distribution/collection centers	$\forall e \in E$
C	Set of customer zone	$\forall c \in C$
R	Set of repair centers	$\forall r \in R$

U	Set of recycling centers	$\forall u \in U$
L	Set of disposal centers	$\forall l \in L$
T	Set of periods	$\forall t \in T$
P	Set of products	$\forall p \in P$
I	Set of raw-materials	$\forall i \in I$
H	Set of discount levels	$\forall h \in H$
N	Set of Transportation mode	$\forall n \in N$.

The following sets are also defined to offer definitions of the model parameters and the decision variables:

$G^1 = S \cup M \cup W \cup E \cup C$

$A' = \{(i,j)|(i \in M, j \in W) \cup (i \in W, j \in E) \cup (i \in E, j \in C)\}$

$A'' = \{(i,j)|(i \in S, j \in M)\}$

$G^2 = C \cup E \cup R \cup U \cup L$

$A''' = \{(i,j)|(i \in C, j \in E) \cup (i \in E, j \in R) \cup (i \in E, j \in U) \cup (i \in R, j \in E) \cup (i \in R, j \in W)\}$

$A'''' = \{(i,j)|(i \in U, j \in L) \cup (i \in U, j \in M)\}$

$G = (G^1 \cup G^2) \backslash C$

$A_1 = A'' \cup A''''$ and $A_2 = A' \cup A'''$.

3.2 Parameters

f_{jt}	The fixed cost of facility $j \in G$ in period t
op_{jt}	The opening cost of facility $j \in G$ in period t
cl_{jt}	The closing cost of facility $j \in G$ in period t
$tc^1_{ijj'n}$	Unit transportation cost of raw-material i between facilities $(j,j') \in A_1$ with transportation mode n
$tc^2_{pjj'n}$	Unit transportation cost of product p between facilities $(j,j') \in A_2$ with transportation mode n
h_{imt}	Unit inventory holding cost of raw-material i by production center m in period t
h'_{pwt}	Unit inventory holding cost of product m by potential warehouse w in period t

pr_{isht} Unit purchase cost of raw-material i by raw-material supplier s with discount level h in period t

va_{isht} Lower limit on the business volume of raw material i by raw-material supplier s that corresponds to the discount interval h in period t ($va_{i,s,1,t} = 0, \forall s, i, t$)

c^1_{pmt} Unit production of product p by production center m in period t

c^2_{pet} Unit distribution cost of product p by distribution/collection center e in period t

c^3_{pet} Unit collection cost of returned product p by distribution/collection center e in period t

c^4_{prt} Unit repair cost of product p by repair center r in period t

c^5_{put} Unit recycling cost of product p by recycling center u in period t

c^6_{ilt} Unit disposal cost of raw-material i by disposal center l in period t

π_{pct} Unit shortage cost of product p in supplying demand of customer zone c in period t

δ_{ip} The number raw-material i needed to produce a unit of product p

dem_{pct} Demand of product p of customer zone c in period t

α_{pct} Fraction of returned product p from customer zone c in period t

β_{pt} Fraction of repairable product p in period t

γ_{pt} Fraction of repaired product p in period t that sends to distribution/collection center

θ_{it} Fraction of usable raw-material i in period t

cap^1_{si} Capacity of supplier s for raw-material i

cap^2_{mi} Capacity of production center m of raw-material i

cap^3_{mp} Capacity of production center m of product p

cap^4_{wp} Capacity of potential warehouse w of product p

cap^5_{ep} Capacity of distribution center e of product p

cap^6_{wp} Capacity of distribution center e of product p

cap^7_{rp} Capacity of repair center r of product p

cap^8_{up} Capacity of recycling center u of product p

cap^9_{li} Capacity of disposal center l of raw-material i

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3.3 Decision variables

$X^1_{ijj'nt}$ Quantity of raw-material i shipped between facilities $(j, j') \in A_1$ with transportation mode n in period t

$X^2_{ijj'nt}$ Quantity of product p shipped between facilities $(j, j') \in A_2$ with transportation mode n in period t

Q_{ist} Total quantities ordered for raw material i from supplier s in period t over the planning horizon

VQ_{imt} Quantity of raw-material i stored at production center m in period t

IQ_{pwt} Quantity of product p stored at potential warehouse w in period t

UD_{pct} Quantity of non-satisfied demand of product p of customer c in period t

Y_{jt} 1 if facility $j \in G$is opened in period t; 0 otherwise.

A_{isht} 1 if the quantity purchased of raw material i from supplier s in period t falls in the discount interval h; 0 otherwise

3.4 Deterministic modeling

The deterministic mathematical model of the problem can be presented as follows.

$$
\begin{aligned}
\min Z = \sum_{t \in T} \Bigg\{ & \sum_{j \in G} (f_{jt} Y_{jt} + op_{jt} Y_{jt}(1 - Y_{j,t-1}) + cl_{jt} Y_{jt}(1 - Y_{j,t+1})) \\
& + \sum_{n \in N} \left(\sum_{i \in I} \sum_{(j,j') \in A_1} tc^1_{ijj'n} X^1_{ijj'nt} + \sum_{p \in P} \sum_{(j,j') \in A_2} tc^2_{pjj'n} X^2_{pjj'nt} \right) \\
& + \sum_{i \in I} \sum_{j \in M} h_{ijt} VQ_{ijt} + \sum_{p \in P} \sum_{j \in W} h'_{ijt} IQ_{pjt} + \sum_{p \in P} \sum_{j \in C} \pi_{pjt} UD_{pjt} \\
& + \sum_{i \in I} \sum_{j \in S} \sum_{j' \in M} \sum_{h \in H} \sum_{n \in N} pr_{ijht} A_{ijht} X^1_{ijj'nt} \\
& + \sum_{p \in P} \sum_{n \in N} \Bigg(\sum_{j \in M} \sum_{j' \in W} c^1_{pjt} + \sum_{j \in E} \sum_{j' \in C} c^2_{pjt} + \sum_{j \in C} \sum_{j' \in E} c^3_{pj't} + \sum_{j \in E} \sum_{j' \in R} c^4_{pj't} \\
& + \sum_{j \in E} \sum_{j' \in U} c^5_{pj't} \Bigg) X^2_{pjj'nt} + \sum_{i \in I} \sum_{j \in U} \sum_{j' \in L} \sum_{n \in N} c^6_{j'it} X^1_{ijj'nt} \Bigg\}
\end{aligned} \tag{1}
$$

s.t.

$$A_{ijht} va_{ijht} \leq Q_{ijt}, \qquad \forall j \in S, h \in H, i \in I, t \in T \tag{2}$$

$$\sum_{h \in H} A_{ijht} = Y_{jt}, \qquad \forall j \in S, i \in I, t \in T \tag{3}$$

$$Q_{ijt} = \sum_{j' \in M}^{n \in N} X^1_{ijj'nt}, \qquad \forall j \in S, i \in I, t \in T \tag{4}$$

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$$\sum_{j\in S}\sum_{n\in N} X^1_{ijj'nt} + \sum_{j\in U}\sum_{n\in N} X^1_{ijj'nt} + VQ_{ij',t-1} - \sum_{p\in P}\sum_{j\in W}\sum_{n\in N} X^2_{pj'jnt}\delta_{ip} = VQ_{ij't},$$

$$\forall j' \in M, i \in I, t \in T \qquad (5)$$

$$\sum_{j\in M}\sum_{n\in N} X^2_{pjj'nt} + \sum_{j\in R}\sum_{n\in N} X^2_{pjj'nt} + IQ_{pj',t-1} - \sum_{j\in E}\sum_{n\in N} X^2_{pj'jnt} = IQ_{pj't},$$

$$\forall j' \in W, p \in P, t \in T \qquad (6)$$

$$\sum_{j\in W}\sum_{n\in N} X^2_{pjjnt} + \sum_{j\in R}\sum_{n\in N} X^2_{pjj'nt} = \sum_{j\in C}\sum_{n\in N} X^2_{pj'jnt}, \qquad \forall j' \in E, p \in P, t \in T \qquad (7)$$

$$\sum_{j\in E}\sum_{n\in N} X^2_{pjjnt} - UD_{pj',t-1} + UD_{pj't} = dem_{pj't}, \qquad \forall j' \in C, p \in P, t \in T \qquad (8)$$

$$\alpha_{pj't}\sum_{j\in E}\sum_{n\in N} X^2_{pjj'n,t-1} = \sum_{j\in E}\sum_{n\in N} X^2_{pj'jnt}, \qquad \forall j' \in C, p \in P, t \in T \qquad (9)$$

$$\beta_{pt}\sum_{j\in C}\sum_{n\in N} X^2_{pjj'nt} = \sum_{j\in U}\sum_{n\in N} X^2_{pj'jnt}, \qquad \forall j' \in E, p \in P, t \in T \qquad (10)$$

$$(1-\beta_{pt})\sum_{j\in C}\sum_{n\in N} X^2_{pjj'nt} = \sum_{j\in U}\sum_{n\in N} X^2_{pj'jnt}, \qquad \forall j' \in E, p \in P, t \in T \qquad (11)$$

$$\gamma_{pt}\sum_{j\in E}\sum_{n\in N} X^2_{pjj'nt} = \sum_{j\in E}\sum_{n\in N} X^2_{pj'jnt}, \qquad \forall j' \in R, p \in P, t \in T \qquad (12)$$

$$(1-\gamma_{pt})\sum_{j\in E}\sum_{n\in N} X^2_{pjj'nt} = \sum_{j\in W}\sum_{n\in N} X^2_{pj'jnt}, \qquad \forall j' \in R, p \in P, t \in T \qquad (13)$$

$$\theta_{it}\sum_{p\in P}\sum_{j\in E}\sum_{n\in N} X^2_{pjj'nt}\delta_{ip} = \sum_{i\in I}\sum_{j\in M}\sum_{n\in N} X^1_{1j'jnt}, \qquad \forall j' \in U, i \in I, t \in T \qquad (14)$$

$$(1-\theta_{it})\sum_{p\in P}\sum_{j\in E}\sum_{n\in N} X^2_{pjj'nt}\delta_{ip} = \sum_{p\in P}\sum_{j\in L}\sum_{n\in N} X^1_{Ij'jnt}, \qquad \forall j' \in U, i \in I, t \in T \qquad (15)$$

$$\sum_{j'\in M}\sum_{n\in N} X^1_{ijj'nt} \le cap^1_{ji}Y_{jt}, \qquad \forall j \in S, i \in I, t \in T \qquad (16)$$

$$VQ_{ijt} \le cap^2_{ji}Y_{jt}, \qquad \forall j \in M, p \in P, t \in T \qquad (17)$$

$$\sum_{j'\in W}\sum_{n\in N} X^2_{pjj'nt} \le cap^3_{jp}Y_{jt}, \qquad \forall j \in W, p \in P, t \in T \qquad (18)$$

$$IQ_{pjt} \le cap^4_{jp}Y_{jt}, \qquad \forall j \in W, p \in P, t \in T \qquad (19)$$

$$\sum_{j\in W}\sum_{n\in N} X^2_{pjj'nt} + \sum_{j\in R}\sum_{n\in N} X^2_{pjj'nt} \le cap^5_{j'p}Y_{j't}, \qquad \forall j' \in E, p \in P, t \in T \qquad (20)$$

$$\sum_{j\in C}\sum_{n\in N} X^2_{pjj'nt} \le cap^6_{j'p}Y_{j't}, \qquad \forall j' \in E, p \in P, t \in T \qquad (21)$$

$$\sum_{j\in E}\sum_{n\in N} X^2_{pjj'nt} \le cap^7_{j'p}Y_{j't}, \qquad \forall j' \in U, p \in P, t \in T \qquad (22)$$

$$\sum_{j\in E}\sum_{n\in N} X^2_{pjj'nt} \le cap^8_{j'p}Y_{j't}, \qquad \forall j' \in R, p \in P, t \in T \qquad (23)$$

$$\sum_{j\in U}\sum_{n\in N} X^1_{ijj'nt} \le cap^9_{j'i}Y_{j't}, \qquad \forall j' \in L, p \in P, t \in T \qquad (24)$$

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$$VQ_{im,0} = 0, \qquad \forall i \in M, t = 1 \tag{25}$$

$$IQ_{pw,0} = 0, \qquad \forall j \in W, t = T \tag{26}$$

$$UD_{pc,0} = 0, \qquad \forall j \in P, t = T \tag{27}$$

$$X^1_{ijj'nt}, VQ_{imt}, Q_{ist} \geq 0, \qquad \forall (j, j') \in A_1, i \in I, n \in N, t \in T, s \in S, m \in M \tag{28}$$

$$X^2_{pjj'nt}, IQ_{pmt}, UD_{PCt} \geq 0, \qquad \forall (j, j') \in A_2, p \in P, n \in N, t \in T, w \in W, c \in C \tag{29}$$

$$Y_{jt} \in \{0, 1\}, \qquad \forall j \in G, t \in T. \tag{30}$$

The objective function (1) intends to minimize the total supply chain network costs including the annual fixed costs, costs of opening and closing the facilities (first row), transportation costs of raw materials and manufactured products (second row), holding costs of raw materials and finished products, as well as the shortage penalty cost (third row), raw material cost associated with the discount (fourth row) operational costs associated with the facilities as the cost of producing, distributing, collecting, repairing and recycling, respectively (in the fifth row), and finally disposal of products. The constraint in inequality (2) represents the total amount of raw materials purchased from the suppliers at their expressed discount levels. Constraint (3) ensures that the selected supplier purchases the raw materials at only one discount interval. Constraint (4) sends the total raw materials purchased from the suppliers to the production centers. Constraint (5) presents the volume of raw materials sent by the supplier and recycling centers to the plant, where a portion is stored in the warehouse of the factory after production. Constraint (6) controls the input and output volumes of the warehouse. Equation (7) is a balance constraint on the distribution center and ensures that the input flow from the repair center and warehouse to the repair center is equal to the output flow from the distribution center to the customers. Constraint (8) guarantees that customer demand must be met till the last moment. Constraint (9) presents a percentage of products which are returned a period after being bought by customers. Constraints (10)–(11) indicate that the proportion of repairable goods which are sent from collection centers to the repair center and the proportion of irreparable ones to the recycling centers after inspection in the collection centers. Constraints (12) indicates that a portion of repaired items are returned back to the distribution centers while (13) shows that the rest of the repaired items is sent to warehouses. Similarly, constraints (14) shows the portion of recycled raw material which are re-sent to the manufacturing centers after inspection and disassembling

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the products while (15) shows the rest of them that are sent to the the disposal centers. Constraints (16)-(17) are related to the capacity of the network facilities, i.e. the capacity of the supplier in raw material procurement, the amount of storage of each raw material in the warehouse, and the production capacity of each product for created factories, respectively. Constraint (19) ensures that if a warehouse is established, its capacity cannot exceed the predetermined capacity. Constraints (20)–(21) state that if dual collection and recycling centers are created, the amount of distribution and collection does not exceed the capacity of the facility while constraint (22) shows the maximum ability for recycling the products at the recycling center. Constraint (23) indicates the maximum capacity of the repair centers in terms if number of products and similarly, Constraint (24) restricts disposal amount of unusable raw materials. Constraints (25)–(27) set the initial value of raw material, finished product and back orders. Finally, constraints (28)–(30) define the type of decision variables and their range.

3.5 Uncertainty modeling

3.5.1 Trapezoidal fuzzy programming model

To tackle uncertainty parameters in the objective function and constraints, some fuzzy models such as chance constraint fuzzy programming (FP) have been developed. It is a well-recognized method that relies on profound mathematical concepts such as the expected value of a fuzzy number in the objective function and possibility and the necessity measure in the constraints. Inuiguchi and Ramık (2000) propose various fuzzy number forms such as triangular and trapezoidal fuzzy number to support uncertain model. Here we use the trapezoidal fuzzy distribution to show the basic FP model and the necessity measure to control the conservatism level of satisfying the constraints. Consider the following mathematical model as the base:

$$\text{(FP1)} \qquad \min Z = ax + fy \tag{31a}$$

s.t.

$$b_i x \geq c_i, \qquad \forall i = 1, ..., l \tag{31b}$$

$$d_i x = e_i y, \qquad \forall i = 1, ..., m \tag{31c}$$

$$x, y \geq 0. \tag{31d}$$

Suppose vector a (variable costs), c (customer demand), and coefficient matrix d (fraction of the returned product) are the uncertain parameters of the problem. So, to construct its FP counterpart model and tackle the uncertainty parameters, the expected value and necessity measure are made use of in the objective function and constraints, respectively. The necessity measure is used to convert fuzzy chance constraints into their equivalent crisp ones. Eq. (32) expresses the membership function of a trapezoidal fuzzy number, $\tilde{a}$, by four sensitive points (i.e. $\tilde{a}_{(p)}, \tilde{a}_{(rp)}, \tilde{a}_{(ro)}, \tilde{a}_{(o)}$) shown on Figure 2.

$$\mu_{\tilde{a}}(x) \begin{cases} 0, & x < p \\ \frac{x-a^p}{a^{rp}-a^p}, & p \leq x \leq rp \\ \frac{a^0-x}{a^0-a^{ro}}, & ro \leq x \leq o \\ 0, & x \geq o. \end{cases} \tag{32}$$

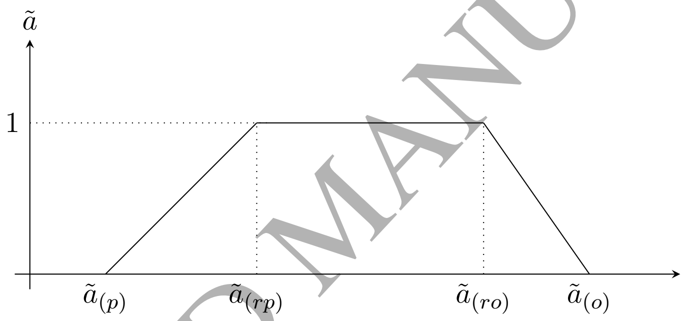

Figure 2: Fuzzy parameter $\tilde{a}$

Therefore, the following model which all fuzzy parameters defined as trapezoidal ones is considered as the FP counterpart expression for (31a–31d):

$$\text{(FP2)} \qquad \min Z = \tilde{a}^t x + f y \tag{33a}$$

s.t.

$$NEC(b_i x \geq c_i) \geq \vartheta_n, \qquad \forall i = 1, ..., l \tag{33b}$$

$$NEC(\tilde{d}_i x = e_i y) \geq \vartheta_n, \qquad \forall i = 1, ..., m \tag{33c}$$

$$x, y \geq 0. \tag{33d}$$

Knowing that uncertainty parameters of the constraints must be formed with a satisfaction level of at least ϑ_n, the equivalent crisp parametric model of (33a–33d) can be written as follows:

$$\text{(CFP)} \qquad \min EV[Z] = \left(\frac{a^p + a^{rp} + a^{ro} + a^o}{4}\right) x \tag{34a}$$

s.t.

$$b_i x \geq (1-\vartheta_n) c_i^{ro} + (\vartheta_n) c_i^o, \qquad \forall i = 1, ..., l \tag{34a}$$

$$[(\vartheta_n) d_i^{rp} + (1-\vartheta_n) d_i^p] x \leq e_i y, \qquad \forall i = 1, ..., m \tag{34b}$$

$$[(\vartheta_n) d_i^{o} + (1-\vartheta_n) d_i^{ro}] x \geq e_i y, \qquad \forall i = 1, ..., m \tag{34c}$$

$$x, y \geq 0, \qquad 0 \leq \vartheta_n \leq 1. \tag{34d}$$

According to the above-presented descriptions, the equivalent auxiliary crisp model of the CLSC network design model, given in (1–30), can be formulated as follows:

$$\begin{aligned}
\min EV[Z] = &\sum_{t\in T}\Bigg\{\sum_{j\in G}\left(f_{jt}Y_{jt} + op_{jt}Y_{jt}(1-Y_{j,t-1}) + cl_{jt}Y_{jt}(1-Y_{j,t+1})\right)\\
&+ \sum_{(j,j')\in A_1}\sum_{i\in I}\sum_{n\in N}\frac{1}{4}\left(tc^{1p}_{ijj'n} + tc^{1rp}_{ijj'n} + tc^{1ro}_{ijj'n} + tc^{1o}_{ijj'n}\right)X^1_{ijj'nt}\\
&+ \sum_{(j,j')\in A_2}\sum_{p\in P}\sum_{n\in N}\frac{1}{4}\left(tc^{2p}_{ijj'n} + tc^{2rp}_{ijj'n} + tc^{2ro}_{ijj'n} + tc^{2o}_{ijj'n}\right)X^2_{pjj'nt}\\
&+ \sum_{j\in W}\sum_{p\in P} h'_{ijt} IQ_{pjt} + \sum_{j\in M}\sum_{i\in I}\sum_{t\in T} h_{ijt} VQ_{jit}\\
&+ \sum_{j\in C}\sum_{p\in P}\frac{1}{4}\left(\pi^p_{pjt} + \pi^{rp}_{pjt} + \pi^{ro}_{pjt} + \pi^o_{pjt}\right) UD_{pct}\\
&+ \sum_{j\in S}\sum_{j'\in M}\sum_{i\in I}\sum_{n\in N}\sum_{h\in H}\frac{1}{4}\left(pr^p_{ijht} + pr^{rp}_{ijht} + pr^{ro}_{ijht} + pr^o_{ijht}\right) A_{ijht} X^1_{ijj'tn}\\
&+ \sum_{p\in P}\sum_{n\in N}\Bigg(\sum_{j\in M}\sum_{j'\in W} c^1_{pjt} + \sum_{j\in E}\sum_{j'\in C} c^2_{pjt} + \sum_{j\in E}\sum_{j'\in C} c^3_{pjt} + \sum_{j\in E}\sum_{j'\in R} c^4_{pjt}\\
&+ \sum_{j\in E}\sum_{j'\in U} c^5_{pjt}\Bigg) X_{pjj'nt} + \sum_{j\in U}\sum_{j'\in L}\sum_{i\in I}\sum_{n\in N} c^6_{ij't} X_{ijj'nt}\Bigg\}
\end{aligned}$$

s.t.

$$\sum_{j\in E}\sum_{n\in N} X_{pjj'nt} - UD_{pj',t-1} + UD_{pj't} \geq (1-\vartheta_1) dem^{ro}_{pj't} + (\vartheta_1) dem^o_{pj't},$$

$$\forall j' \in C, p \in P, t \in T \tag{35}$$

$$\left[(\vartheta_2)\alpha^{rp}_{pj't} + (1-\vartheta_2)\alpha^p_{pj't}\right]\sum_{j\in E}\sum_{n\in N} X^2_{pjj'n,t-1} \leq \sum_{j\in E}\sum_{n\in N} X^2_{pj'jnt},$$

$$\forall j' \in C, p \in P, t \in T \tag{36}$$

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$$\left[(\vartheta_2)\alpha^{o}_{pj't} + (1-\vartheta_2)\alpha^{ro}_{pj't}\right] \sum_{j\in E}\sum_{n\in N} X^2_{pjj'n,t-1} \leq \sum_{j\in E}\sum_{n\in N} X^2_{pj'jnt},$$

$$\forall j' \in C, p \in P, t \in T \quad (37)$$

$$0.5 \leq \vartheta_1, \vartheta_2 < 1 \quad (38)$$

(10)–(30).

3.5.2 The proposed robust fuzzy programming

Now, we present the robust formulation of the obtained fuzzy mathematical model. Assuming again that only vectors a, c, and the coefficient matrix d are the uncertain parameters, according to the (CFP) model, the (RFP) model is formulated as follows:

$$\text{(RFP)} \qquad \min E[Z] = EV[Z] + \omega(Z_{max} - Z_{min}) + \rho[c_i^o - (1-\vartheta_n)c_i^{ro} - (\vartheta)c_i^o]$$
$$+ \tau[d_i^{ro} + (\vartheta_n)d_i^{rp} + (1-\vartheta_n)d_i^p - (\vartheta_n)d_i^o - (1-\vartheta_n)d_i^{ro} - d_i^p] \quad (39a)$$

s.t.

$$b_i x \geq (1-\vartheta_n)c_i^{ro} + (\vartheta_n)c_i^o, \qquad \forall i = 1, ..., l \quad (39b)$$

$$[(\vartheta_n)d_i^{rp} + (1-\vartheta_n)d_i^p]x \leq e_i y, \qquad \forall i = 1, ..., l \quad (39c)$$

$$[(\vartheta_n)d_i^o + (1-\vartheta_n)d_i^{ro}]x \geq e_i y, \qquad \forall i = 1, ..., m \quad (39d)$$

$$x, y \geq 0, \qquad 0 \leq \vartheta_n \leq 1. \quad (39e)$$

Similar to (CFP) model, the first term in the objective function is the expected value of Z, which results in minimization of the expected total network costs. The second term, i.e., $\omega(Z_{max} - Z_{min})$, indicates the difference between the two extreme possible values of Z where ω represents the weight of this term against the three other terms in objective function. Moreover, Z_{max} and Z_{min} can be defined as follows:

$$Z_{max} = a^o x + fy \quad (40a)$$

$$Z_{min} = a^p x + fy \quad (40b)$$

Therefore, the existence of the second term results in controlling the optimality robustness of the solution vector under the expected optimal value of Z. The third and fourth terms determine the confidence level of each chance constraint. ρ and τ are the unit penalty of possible violation of each constraint, and $[c_i^o - (1-\vartheta_n)c_i^{ro} - (\vartheta_n)c_i^o]$ and $[d_i^{ro} + (\vartheta_n)d_i^{rp} + (1-\vartheta_n)d_i^p - (\vartheta_n)d_i^o - (1-\vartheta_n)d_i^{ro} - d_i^p]$ indicate the difference between the worst case value of uncertainties parameters in chance constraints. Therefore, the proposed robust fuzzy programming model for CLSC network design is as follows:

$$\begin{aligned}\min Z' =& EV[Z] + \omega(Z_{max} - Z_{min})\\ &+\sum_{c\in C}\sum_{p\in P}\sum_{t\in T}\Big\{\Big[dem_{cpt}^o - (1-\vartheta_1)dem_{cpt}^{ro} - (\vartheta_1)dem_{cpt}^o\Big]\\ &+\tau\Big[\alpha_{pct}^{ro} + (\vartheta_1)\alpha_{pct}^{rp} + (1-\vartheta_1)\alpha_{pct}^{p} - (\vartheta_n)\alpha_{pct}^{o} + (1-\vartheta_1)\alpha_{pct}^{ro} - \alpha_{pct}^{p}\Big]\Big\} \qquad (41)\end{aligned}$$

s.t.

$$Z_{max} = \sum_{t\in T}\Big\{\sum_{j\in G}(f_{jt}Y_{jt} + op_{jt}Y_{jt}(1-Y_{j,t-1}) + cl_{jt}Y_{jt}(1-Y_{j,t+1})) \qquad (42)$$

$$\begin{aligned}&+\sum_{n\in N}\Big(\sum_{i\in I}\sum_{(j,j')\in A_1} tc_{ijj'n}^{1o}X_{ijj'nt}^1 + \sum_{p\in P}\sum_{(j,j')\in A_2} tc_{pjj'n}^{2o}X_{pjj'nt}^2\Big)\\ &+\sum_{i\in I}\sum_{j\in M} h_{ijt}VQ_{ijt} + \sum_{p\in P}\sum_{j\in W} h'_{ijt}IQ_{pjt} + \sum_{p\in P}\sum_{j\in C}\pi_{pjt}^o UD_{pjt}\\ &+\sum_{i\in I}\sum_{j\in S}\sum_{j'\in M}\sum_{h\in H}\sum_{n\in N} pr_{ijht}^o A_{ijht}X_{ijj'nt}^1\\ &+\sum_{p\in P}\sum_{n\in N}\Big(\sum_{j\in M}\sum_{j'\in W} c_{pjt}^1 + \sum_{j\in E}\sum_{j'\in C} c_{pjt}^2 + \sum_{j\in C}\sum_{j'\in E} c_{pj't}^3 + \sum_{j\in E}\sum_{j'\in R} c_{pj't}^4\\ &+\sum_{j\in E}\sum_{j'\in U} c_{pj't}^5\Big)X_{pjj'nt}^2 + \sum_{i\in I}\sum_{j\in U}\sum_{j'\in L}\sum_{n\in N} c_{j'it}^6 X_{ijj'nt}^1\Big\} \qquad (43)\end{aligned}$$

$$Z_{min} = \sum_{t\in T}\Big\{\sum_{j\in G}(f_{jt}Y_{jt} + op_{jt}Y_{jt}(1-Y_{j,t-1}) + cl_{jt}Y_{jt}(1-Y_{j,t+1})) \qquad (44)$$

$$\begin{aligned}&+\sum_{n\in N}\Big(\sum_{i\in I}\sum_{(j,j')\in A_1} tc_{ijj'n}^{1p}X_{ijj'nt}^1 + \sum_{p\in P}\sum_{(j,j')\in A_2} tc_{pjj'n}^{2p}X_{pjj'nt}^2\Big)\\ &+\sum_{i\in I}\sum_{j\in M} h_{ijt}VQ_{ijt} + \sum_{p\in P}\sum_{j\in W} h'_{ijt}IQ_{pjt} + \sum_{p\in P}\sum_{j\in C}\pi_{pjt}^p UD_{pjt}\\ &+\sum_{i\in I}\sum_{j\in S}\sum_{j'\in M}\sum_{h\in H}\sum_{n\in N} pr_{ijht}^p A_{ijht}X_{ijj'nt}^1\\ &+\sum_{p\in P}\sum_{n\in N}\Big(\sum_{j\in M}\sum_{j'\in W} c_{pjt}^1 + \sum_{j\in E}\sum_{j'\in C} c_{pjt}^2 + \sum_{j\in C}\sum_{j'\in E} c_{pj't}^3 + \sum_{j\in E}\sum_{j'\in R} c_{pj't}^4\\ &+\sum_{j\in E}\sum_{j'\in U} c_{pj't}^5\Big)X_{pjj'nt}^2 + \sum_{i\in I}\sum_{j\in U}\sum_{j'\in L}\sum_{n\in N} c_{j'it}^6 X_{ijj'nt}^1\Big\} \qquad (45)\end{aligned}$$

(10)–(30), (35)–(38).

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The proposed RFP model is a MINLP model. The NP-hardness of supply chain network design problem has been proved in a good number of studies (e.g., Jayaraman et al. 2003). They consist of two different parts, i.e. facility location problem and quantity flow optimization among facilities and therefore, they are reducible to facility location problems which have been proved to be NP-complete by Davis and Ray (1969). So the discussed CLSC network design problem is considered as NP-hard in the present study. Approaching this problem in large sizes by exact solutions is very time-consuming and sometimes impractical. Therefore, several meta-heuristic algorithms with different representations have been developed to obtain near-optimal solutions; though all the proposed algorithms are not efficient. In the present study, a WOA algorithm based on modified priority-based encoding was applied, which will be described in the following section.

4 Solution approach

While exact methods used to be a good way for solving problems, ranging from linear problems to non-linear problems, the recent decades have seen an increase in the number of heuristic and meta-heuristic approaches to solve very complex problems. Using exact approaches to solve problems which have a large scale seems not to be the best way therefore, researchers have inclined to use heuristic and meta-heuristic approaches to solve complex problems. In other words, the exact solution methods are ineffective to find the optimum solution for large scale problems so, it has set the stage for solving problems by heuristic and meta-heuristic approaches. Here we present a new population-based meta-heuristic optimization algorithm inspired from animal behavior, called WOA using modified a new priority-based encoding in order to cover the feasible search space. On the other hand we present the corresponding decoding approach for solving the designed CLSC network.

4.1 Solution representation (priority based encoding)

The debate about solution presentation is both timely and crucial. The path towards encoding and decoding may be steep and strewn with challenges, which affect the algorithms to find the optimum solution in the feasible solution space. Tree-based solution is one way of representing supply chain network design problems. Gen and Cheng (2000)

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introduced three ways of encoding tree, contains edge-based encoding, vertex-based encoding, and edge-vertex encoding, however, there are several other ways of encoding tree. In this paper, we have used vertex-based encoding which is modified in order to solve the CLSC network problem. Furthermore, a priority-based encoding developed is based on the work of Gen and Cheng (2000). The most noticeable about this encoding is that it can solve the quantity flow optimization, facility location problem and proper amount shortage in each period simultaneously. We consider two-level supply chain network as shown in Figure 3 with ($|K|$) sources and ($|J|$) depots. The length of this solution is equal to $|K|+|J|$ and the location of each cell represents the priorities in each period. We regard two different procedures for decoding the solution, ranging from forward to reverse supply chain. The variation between these two procedures are related to the potential sources that must be located. The shortage of demand in the forward supply chain, may lead to less number of source location than that of the time at which all demand must be satisfied. On the other hand, all the returned products, must be collected in forward supply chain, which means that the number of sources should be such that capacity of located sources be able collect all returned products. In the following we explained the decoding procedures of solutions for forward and reverse supply chain.

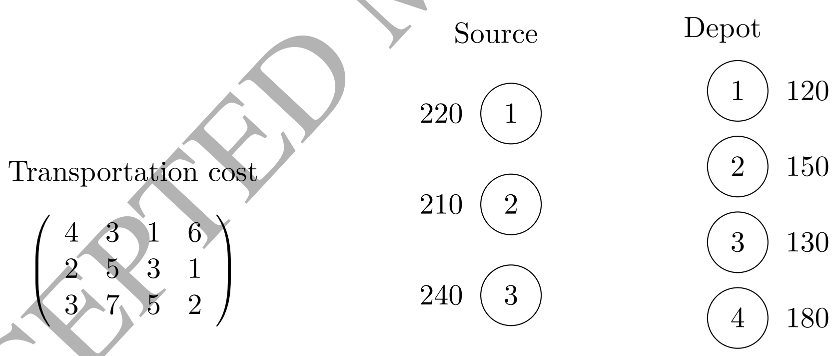

Figure 3: Sample of two-level supply chain network

4.1.1 The decoding of the solutions for forward supply chain

In the first stage of the process, we select the cell number with the highest priority among sources as a number of sources that must be opened. Then, we select the highest priorities among sources and reduce the other priorities to zero. The next stage is updating the solution, in which before connecting to a node (source or depot) with the minimum transportation cost, select the node (depot or source) with the highest priority. Subsequently, determining the amount of shipment between the selected nodes by calculating minimum of the total demand and the shortage of previous periods, and capacity. Next, the priority of depot or source is reduced to zero. If total demand of depots is greater than total capacity of the selected sources, the amount of shortage for each depot is calculated. This process is repeated until all priorities are equal to zero. Table 2 presents the trace table for the forward supply chain network, and Figure 4 shows how this modified priority-based encoding is obtained.

Table 2: Trace table of decoding procedure for forward supply chain network

Iteration	$v(k+j)$	cap_k	$dem_{jt} + \sum_{t \in T} s_{t-1}$	k	j	X_{kjt}
0	[0 7 2—5 3 6 4]	(0,210,240)	(120,150,130,180)	2	4	180
1	[0 7 2—5 3 6 0]	(0,30,240)	(120,150,130,0)	2	1	30
2	[0 0 2—5 3 6 0]	(0,0,240)	(90,150,130,0)	3	3	130
3	[0 0 2—5 3 0 0]	(0,0,110)	(90,150,0,0)	3	1	90
4	[0 0 2—0 3 0 0]	(0,0,20)	(0,150,0,0)	3	2	20
5	[0 0 0—0 3 0 0]	(0,0,0)	(0,130,0,0)	-	3	-
6	[0 0 0—0 0 0 0]	(0,0,0)	(0,130,0,0)			

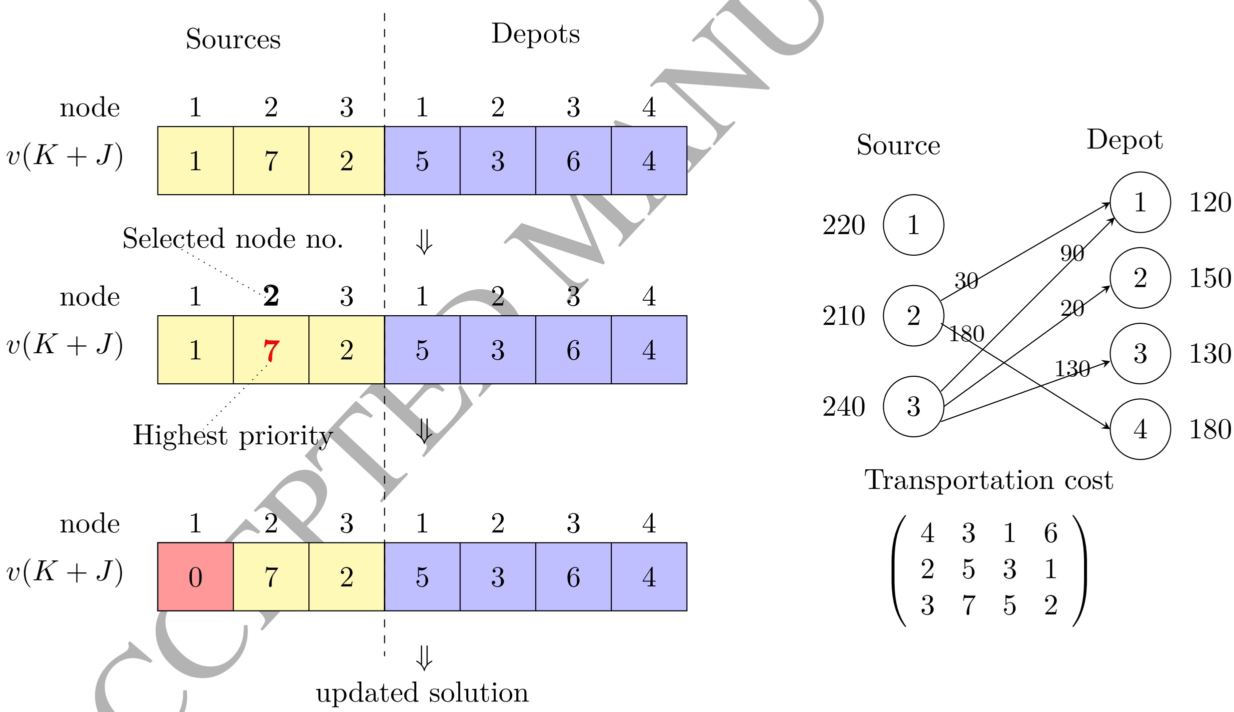

Figure 4: Sample of two-level supply chain network

This decoding process is conducted in the specific framework; its decoding algorithm as well as calculation table in the first period is illustrated in Algorithm 1.

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Algorithm 1 Decoding algorithm of forward supply chain network

Require: Sets of K, J, T; The demand, capacity and transportation costs; encoded solution $v(K+J)$

Ensure: X_{kjt}: Quantity of shipment between source k and depot j S_{jt}: Shortage of depot j in period t Y_{kt}: Opening of a center at location k in period t

for $t = 1$ to T **do**
  Select a node on $l = \arg\max\{v(k), \forall k \in K\}$, so that $\sum_{k \in K} Y_{kt} = l$
  while $|d| < l$ **do**
    Select a node on $d = \arg\max\{v(k), k \in K\}$
    if $|d| = l$ **then** $v(k-l) = 0, \forall k \in K, l \in L$
    $tr_{(k-l),i} = \infty, \forall j \in |J|, k \in K, l \in L$
    $cap_{(k-l)=0, \quad \forall k \in K, l \in L}$
  end while
  while $v(|k| + j) \neq 0, \forall j \in J$ **do**
    $X_{kjt} = 0, S_{jt} = 0, \forall j \in J, k \in K, t \in T$
    Select a node based on $l = \arg\max\{v(t), t \in |K| + |J|\}, \forall j \in J, k \in K$
    if $l \in K$ a source is selected $k^* = l$ **then**
      $j^* = \arg\min\{tr_{kj} | v(j) \neq 0\} \forall j \in J$ select a depot with minimum cost
    else if $l \in j$ a depot selected $j^* = l$ **then**
      $k^* = \arg\min\{tr_{kj} | v(j) \neq 0\} \forall k \in K$ select a source with minimum cost
    end if
Update demands and capacities:
    $X_{k^*j^*t} = \min(cap_{k^*}, dem_{j^*t} + S_{j^*t})$
    $cap_{k^*} = cap_{k^*} - X_{k^*j^*t}$
    $dem_{j^*t} = dem_{j^*t} + S_(j^*t - 1) - X_(k^*j^*t)$**Step 8.**
    if $cap_{k^*} = 0$ **then** $v(k^*) = 0$
    if $dem_{j^*t} = 0$ **then** $v(j^*) = 0$
  end while
  if $\sum_j X_{kjt} > 0$ **then** $Y_{kt} = 1$
  if $dem_{jt} > 0$ **then** $S_{jt} = S_{j,t-1} + dem_{jt}$
end for

4.1.2 The decoding of the solutions for reverse supply chain

Once again, consider the two-level supply chain network that shown in Figure 3. To decode the solution, in the first section, the cell with the highest priority among source nodes is selected, then if capacity of the selected source is less than total returned products the next highest priority is also selected. This procedure will continue while the total capacity of sources is less than total returned products of depots. In the next stage, the priorities of the nodes which are not selected are decrease to zero. Then, select the node (depot or source) with the highest priority and connect it with the node which has the minimum transportation cost. After that, the amount of shipment between the selected nodes is determined by taking the minimum of returned products and capacity. Then the priority (depot or source) is reduced to zero and this process is repeated until all priorities equal to zero. Table 3 presents the trace table for the reverse supply chain network, and

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Figure 5 demonstrates how its modified priority-based encoding is obtained. The decoding algorithm of solution for a reverse supply chain network is also given in Algorithm 2.

Algorithm 2 Decoding algorithm of reverse supply chain network

Require: Sets of K, J, T; The returned product, capacity and transportation costs; encoded solution $v(K+J)$

Ensure: X_{kjt}: Quantity of shipment between source k and depot j Y_{kt}: Opening of a center at location k

Step1.
for $t = 1$ to T **do**
  while $capT = \sum_{j=1}^{J} R_{jt}$ **do**
    Select a node on $l = \arg\max\{v(k), k \in K\}$
    $capT = \sum_{l=1}^{K} cap_l$
    if $capT < \sum_{j=1}^{J} R_{jt}$ **then**
      $v(k-l) = 0, \forall k \in K, l \in L$
      $tr_{j,(k-l)} = \infty \quad \forall j \in J, k \in K, l \in L$
    end if
  end while
  while $v(|k|+j) \neq 0, \forall j \in J$ **do**
    $X_{kjt} = 0, S_{jt} = 0, \forall j \in J, k \in K$
    Select a node based on $l = \arg\max\{v(t), t \in |K|+|J|\}, \forall j \in J, k \in K$
    if $l \in K$ a source is selected $k^* = l$ **then**
      $j^* = \arg\min\{tr_{kj}|v(j) \neq 0\} \forall j \in J$ select a depot with minimum cost
    else if $l \in j$ a depot selected $j^* = l$ **then**
      $k^* = \arg\min\{tr_{kj}|v(j) \neq 0\} \forall k \in K$ select a source with minimum cost
    end if
Update demands and capacities:
      $X_{k^*j^*t} = \min(cap_{k^*}, R_{j^*t})$
      $cap_{k^*} = cap_{k^*} - X_{k^*j^*t}$
      $R_{j^*t} = R_{j^*t} - X_(k^*j^*t)$
    if $cap_{k^*} = 0$ **then** $v(k^*) = 0$
    if $R_{j^*t} = 0$ **then** $v(j^*) = 0$
    if $\sum_j X_{kjt} > 0$ **then** $Y_{kt} = 1$
  end while
end for

In this paper, as mentioned before, the problem is a multi-level, multi-product, multi-period CLSC network design, and the proposed solution should consider these items. Therefore, as illustrated in Figure 6, the priority based encoding is represented by a matrix, where T is a number of time periods, P is a number of products, S is a number of raw material supplier, M is a number of production centers, W is a number of potential warehouses, E is a number of hybrid distribution/collection centers, R, U, L are the numbers of repair centers, recycling centers, and disposal centers, respectively.

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Table 3: Trace table of decoding procedure for reverse supply chain network

Iteration	$v(k)$	cap_k	$CapT$	$\sum_{j=1}^{J}$	j	$v(k^*)$
0	[1 7 2]	(220,210,240)	210	580	2	[0 7 0]
1	[1 0 2]	(220,0,240)	470	580	3	[0 7 2]
2	[1 0 0]	(200,0,0)	670	580	1	[1 7 2]
Iteration	$v(k^*+j)$	cap_k	R_{jt}	k^*	j	X_{jk^*t}
0	[1 7 2—5 3 6 4]	(220,210,240)	(120,150,130,180)	2	4	180
1	[1 7 2—5 3 6 0]	(220,30,240)	(120,150,130,0)	2	1	30
2	[1 0 2—5 3 0 0]	(220,0,240)	(90,150,130,0)	1	3	130
3	[1 0 2—5 3 0 0]	(90,0,240)	(90,150,0,0)	2	3	90
4	[1 0 2—0 3 0 0]	(90,0,150)	(0,150,0,0)	1	2	90
5	[0 0 2—0 3 0 0]	(0,0,150)	(0,60,0,0)	3	2	60
6	[0 0 0—0 0 0 0]	(0,0,90)	(0,0,0,0)			

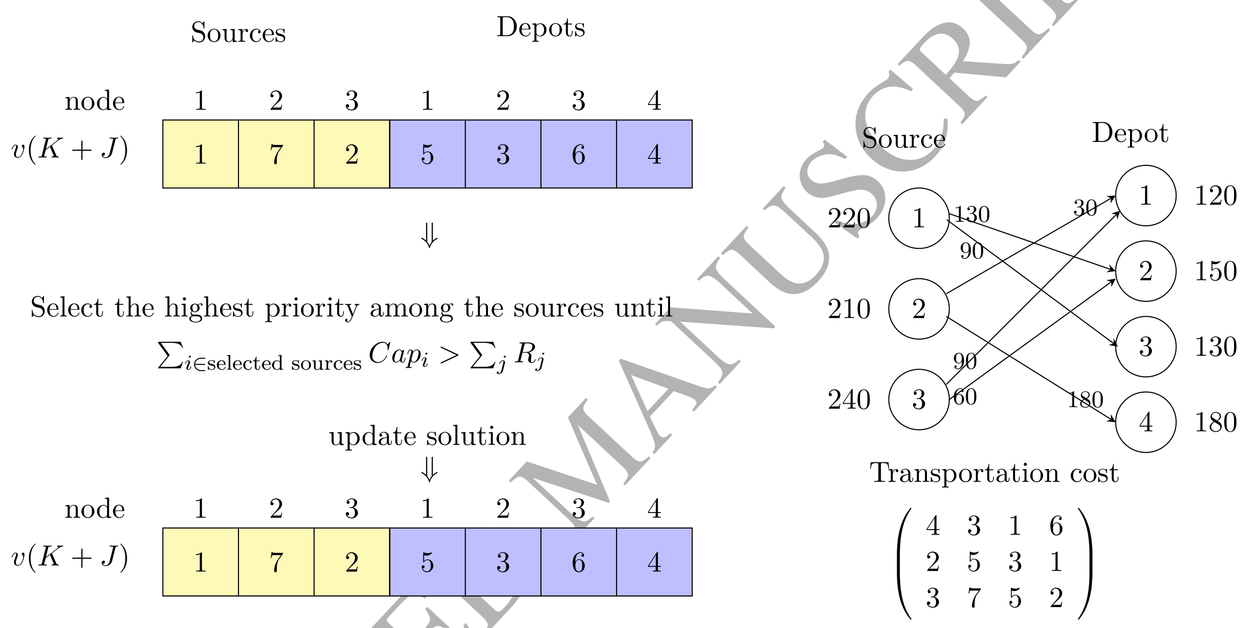

Figure 5: The decoding of the solution for two-level reverse supply chain network

4.2 The whale optimization algorithm (WOA)

We have applied a WOA, as was first presented by Mirjalili and Lewis (2016). This algorithms is based the hunting behavior of humpback whales using a spiral to bubble-net attacking mechanism and the best search agent to chase the prey. The most intriguing thing about the humpback whales is their interesting hunting method. This foraging behavior is called bubble-net feeding method (Watkins and Schevill 1979). It is worth noting that bubble-net feeding is a unique behavior that can only be characterized with humpback whales. In this respect, the spiral bubble-net feeding maneuver is mathematically modeled in order to perform optimization. This novel meta-heuristic algorithm has been applied in several recent optimization studies which deal with large scale problems.

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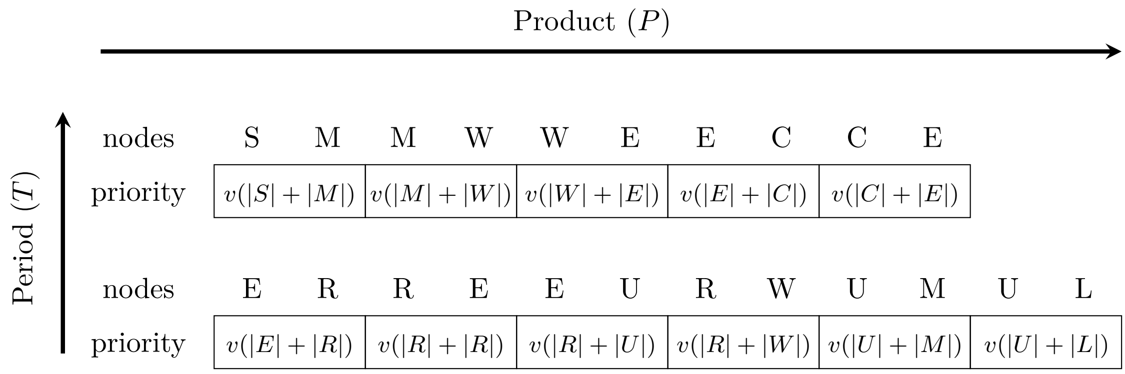

Figure 6: The solution encoding for multi-echelon multi-period multi-product CLSC network

Aljarah et al. (2018) employ it to solve a wide range of machine learning optimization problems; Oliva et al. (2017) use it for parameter estimation of photovoltaic cells; while Sahu et al. (2018) apply WOA for the power system stability enhancement problem. Various other applications in image segmentation, feature selection, wireless route optimization, fault estimation in power systems, wind speed forecasting and etc. exist in very recently published studies in the literature.

In the following, the mathematical model of *encircling prey*, *spiral bubble-net* feeding maneuver, and *search for prey* provided and then, the WOA algorithm is presented. The reader may also refer to Mirjalili and Lewis (2016) for more details.

4.2.1 Encircling prey

Humpback whales identify the location of prey and spin around them. However, the position of the optimal solution (i.e, prey) in the optimization search space is not certain, so the algorithm assumes that the current best candidate solution is the target prey and repeatedly, updates and defines the best search agent as represented in the following equations:

$$\vec{Y} = \left| \vec{D} \odot \vec{X}^*_{t+1} - \vec{X}_t \right| \tag{46}$$

$$\vec{X}_{t+1} = \vec{X}^*_t - \vec{C} \odot \vec{Y} \tag{47}$$

where $|\,.\,|$ indicates the element-wise absolute values of a vector, and $\odot$ denotes the element-wise (Hadamard) product of two vectors. $\vec{C}$ and $\vec{D}$ are coefficient vectors while $\vec{X}^*$ is the position vector of the best solution obtained in the corresponding iterations t

and $t+1$. The vectors $\vec{C}$ and $\vec{D}$ are calculated as follows:

$$\vec{C} = 2\vec{a} \odot \vec{r} - \vec{a} \tag{48}$$

$$\vec{D} = 2\vec{r} \tag{49}$$

where $\vec{a}$ is linearly reduced from 2 to 0 over during the iterations and $\vec{r}$ is a random vector in $[0, 1]$.

4.2.2 Bubble-net attacking method

The mathematical model for the bubble-net behavior of humpback whales is designed in two ways:

Shrinking encircling behavior: it is modeled by reducing the value of $\vec{a}$ in the Eq. (48) which decreases the fluctuation range of $\vec{C}$, as well. Therefore, $\vec{C}$ is confined to the interval $[-a, a]$. By assigning random values to $\vec{C}$ in $[-1, 1]$, the new position of a search agent is obtained anywhere within the original position of the agent and the position of the current best agent.

Spiral updating position: This approach calculates the distance between the whale and prey, and provides a spiral shaped equation between them as given below.

$$\vec{X}_{t+1} = e^{bl} \cos(2\pi l).\vec{Y'} + \vec{X}_t^* \tag{50}$$

where $\vec{Y'} = \left| \vec{X}_t^* - \vec{X}_t \right|$ denotes the distance of the whale from prey (i.e, the best solution obtained so far); the constant b defines the shape of the logarithmic spiral and l is a random number from the interval $[-1, 1]$. Since humpback whales swim around the prey within a shrinking circle and along a spiral-shaped path, it is assumed that the shrinking encircling mechanism and the spiral model $Pe\%$ and 1-$Pe\%$ in the position updating of whales,, respectively. Hence, the mathematical model is as follows:

$$\vec{X}_{t+1} = \begin{cases} \vec{X}_t^* - \vec{C} \odot \vec{Y} & \text{if } p < Pr \\ e^{bl}.\cos(2\pi l).\vec{Y'} + \vec{X}_t^* & \text{if } p \geq Pe \end{cases} \tag{51}$$

where p is a random number drawn from $[0, 1]$.

4.2.3 Search for prey

Humpback whales search randomly according to the position of each other. Thereby, here $\vec{C}$ with the random values greater than 1 or less than -1 are used to push the search agent to move away from the reference. The new position is obtained by Eq. (53)Contrary to the attacking phase, the position of a search agent is updated according to a randomly chosen search agent rather than the current best search agent. This procedure and $|\vec{C}| > 1$ facilitate the WOA algorithm to run a global search.

$$\vec{Y} = \left| \vec{D}.\vec{X}_{rand} - \vec{X} \right| \tag{52}$$

$$\vec{X}_{t+1} = \left| \vec{X}_{rand} - \vec{C}.\vec{Y} \right| \tag{53}$$

where $\vec{X}_{rand}$ is a random position vector chosen from the current population. The WOA initiates with a series of random solutions in which, search agents update their positions with respect to either a randomly chosen search agent or the current best solution. Throughout the iterations for updating the position of the search agents, if $|\vec{C}| > 1$ a random search agent is chosen, while if $|\vec{C}| < 1$ the best solution is selected. Given the value of p, WOA is able to alternate between either a spiral or circular movement. The pseudo code of the WOA is given in Algorithm 3.

Algorithm 3 The pseudo code of the WOA algorithm

```
Initialize the whales population X_i (i = 1, 2, ..., n)
T := maximum number of iterations
Pe := The possibility of the behavior of whales
Calculate the current fitness of each search agent
X_1^* = the best search agent
for t = 1 to T do
    for each search agent do
        Update a, C, D, l, p
        if p < Pe then
            if |C| < 1 then
                Update the location of the current agent by Eq.(46)
            elseif |C| ≥ 1
                elect a random search agent (X_rand)
                Update the location of the current fitness by Eq.(53)
            end if
        elseif p ≥ Pe then
            Update the location of the current search by Eq.(50)
            calculate the new fitness of each search agent
        end if
        if new fitness< current fitness then X_t^* = X_t
    end for
end for
```

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The search space in the solution of the designed CLSC network is discrete, which means that components of each individual from the population cannot have an arbitrary amount, and allowable values are limited only to natural numbers from 1 to N. Hence, the continuous search space has to be changed in WOA algorithm to discrete search space. An example of change in the solution search space is shown in Figure 7.

Node	1	2	3	4	5	6
Random number in continuous space	0.94	1.19	0.17	5.98	4.16	4.27

Decreasingly sorted with respect to the random numbers

Priority in discrete space	4	6	5	2	1	3
Random number in continuous space	5.98	4.27	4.16	1.19	0.94	0.70

Figure 7: An example of change in the solution search space

5 Numerical results

5.1 Sample problems

In this section several numerical experiments are generated to validate the developed RFP model and also to assess the performance of the proposed WOA algorithm in terms of the objective-function value and required CPU time. As there were no benchmarks available in the literature for this specific problem, 5 sample instances were generated each with 10 replications containing random data. The size of the exemplified problems and their corresponding parameter values are presented in Tables 4 and 5, respectively. Hence, the deterministic parameters and each point of the trapezoidal fuzzy number of uncertainty parameters were randomly generated based on a uniform distribution in pre-specified intervals.

Table 4: The size of the sample problems

Instance no.	Levels $(S \times M \times W \times E \times C \times R \times U \times L \times T \times P \times I \times N \times H)$
1	$(6 \times 6 \times 6 \times 6 \times 10 \times 4 \times 4 \times 4 \times 6 \times 2 \times 2 \times 3 \times 3)$
2	$(8 \times 8 \times 8 \times 8 \times 15 \times 5 \times 5 \times 5 \times 8 \times 3 \times 3 \times 4 \times 3)$
3	$(10 \times 10 \times 10 \times 10 \times 20 \times 6 \times 6 \times 6 \times 10 \times 4 \times 4 \times 5 \times 3)$
4	$(12 \times 12 \times 12 \times 12 \times 25 \times 8 \times 8 \times 8 \times 12 \times 5 \times 5 \times 6 \times 3)$
5	$(15 \times 15 \times 15 \times 15 \times 30 \times 10 \times 10 \times 10 \times 18 \times 6 \times 6 \times 7 \times 3)$

As the acquired results from WOA is sensitive to their initial parameters, the Taguchi tuning method was used for tuning the parameters to find the best solution. Using the

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Table 5: Pre-specified intervals to generate parameters based on a uniform distributions

Certain parameters Parameter	Value	Parameter	Value
f_{st}	$\sim U(40000, 45000)$	c^1_{mpt}	$\sim U(0.5, 1.5)$
f_{mt}	$\sim U(50000, 60000)$	c^2_{ept}	$\sim U(0.5, 1.5)$
f_{wt}	$\sim U(50000, 60000)$	c^3_{ept}	$\sim U(0.5, 1.5)$
f_{et}	$\sim U(50000, 60000)$	c^4_{rpt}	$\sim U(0.5, 1.5)$
f_{rt}	$\sim U(50000, 60000)$	c^5_{upt}	$\sim U(0.5, 1.5)$
f_{ut}	$\sim U(50000, 60000)$	c^6_{lit}	$\sim U(0.5, 1)$
f_{lt}	$\sim U(50000, 60000)$	h_{mit}	$\sim U(0.2, 0.5)$
cl_{st}	$\sim U(4000000, 6000000)$	h'_{wpt}	$\sim U(0.8, 1.2)$
cl_{mt}	$\sim U(3500000, 6000000)$	$\gamma_p t$	$\sim U(0.4, 0.5)$
cl_{wt}	$\sim U(4000000, 7000000)$	δ_{ip}	$\sim U(1, 3)$
cl_{et}	$\sim U(6000000, 9000000)$	β_{pt}	$\sim U(0.4, 0.5)$
cl_{rt}	$\sim U(1500000, 4000000)$	θ_{it}	$\sim U(0.2, 0.3)$
cl_{ut}	$\sim U(3500000, 4000000)$	cap^1_{mi}	$\sim U(4000, 6000)$
cl_{lt}	$\sim U(3000000, 6000000)$	cap^2_{wp}	$\sim U(2000, 2500)$
op_{st}	$\sim U(2500000, 5000000)$	cap^3_{ep}	$\sim U(200, 300)$
op_{mt}	$\sim U(2500000, 4500000)$	cap^4_{si}	$\sim U(12000, 15000)$
op_{wt}	$\sim U(3000000, 6000000)$	cap^5_{mp}	$\sim U(1600, 2200)$
op_{et}	$\sim U(5000000, 8000000)$	cap^6_{ep}	$\sim U(1300, 1500)$
op_{rt}	$\sim U(1000000, 3000000)$	cap^7_{rp}	$\sim U(200, 250)$
op_{ut}	$\sim U(1000000, 3000000)$	cap^8_{li}	$\sim U(1000, 1600)$
op_{lt}	$\sim U(2000000, 4000000)$	cap^9_{up}	$\sim U(200, 250)$
va_{isht}	$\sim U(4000, 10000)$		

	Uncertain parameters $a \cong (\tilde{a}^p, \tilde{a}^{rp}, \tilde{a}^{ro}, \tilde{a}^o)$			
Parameter	$\tilde{a}^p$	$\tilde{a}^{rp}$	$\tilde{a}^{ro}$	$\tilde{a}^o$
dem_{pct}	$\sim U(50, 100)$	$\sim U(100, 150)$	$\sim U(150, 200)$	$\sim U(200, 300)$
α_{pct}	$\sim U(0.1, 0.2)$	$\sim U(100, 150)$	$\sim U(0.3, 0.4)$	$\sim U(0.4, 0.5)$
pr_{isht}	$\sim U(1, 1.1)$	$\sim U(0.2, 0.3)$	$\sim U(1.25, 1.4)$	$\sim U(1.4, 1.5)$
$tc^1_{ijj'n}$	$\sim U(2, 2.5)$	$\sim U(1.1, 1.25)$	$\sim U(3, 3.5)$	$\sim U(3.5, 4)$
$tc^2_{ijj'n}$	$\sim U(5, 8)$	$\sim U(2.5, 3)$	$\sim U(12, 15)$	$\sim U(15, 20)$
π_{pct}	$\sim U(100, 120)$	$\sim U(8, 12)$	$\sim U(150, 170)$	$\sim U(170, 200)$

Taguchi method, first, the appropriate factors (initial parameters) were determined and the level of each factor was selected. Then, design of experiments for this control factor was specified to find the best combination of factors for WOA. In Table 6, the number of whales (W), maximum number of iterations ($Maxit$), and the probability of choosing between either the shrinking encircling mechanism or the spiral model (Pe) in WOA are given as the initial parameters. In this regard, the experiment was repeated 10 times for each run and their average results were considered as the fitness value. The best combination of WOA parameters values were obtained as 200 for (W), 200 for (Maxit), and 0.6 for (Pe).

After tuning the WOA parameters, the minimum values of the constraints satisfaction ϑ_1 and ϑ_2 were set as 0.8 to analyze the WOA results. Furthermore, weight coefficient (ω=0.6) and penalty coefficients (ρ=τ=400) were considered. For more accurate calcula-

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Table 6: Proposed parameter levels for parameter tuning the WOA algorithm

Factors	Level 1	Level 2	Level 3	Level 4
W	100	200	300	500
$Maxit$	100	150	200	250
Pe	0.1	0.2	0.4	0.6

tions, each sample was repeated 3 times for each run using WOA algorithm. Therefore, the average results of the objective function of 3 runs were selected as the conclusion base for the WOA algorithm. In Table 7, the results of the objective function for each problem using exact solution and the WOA algorithm are summarized. In the last column, the solution percentage of gap between the results of exact solution and the WOA is presented. In Figure 8 computational times of the exact solution and WOA approach are depicted.

Table 7: The average results for each sample problem

Instance no.	Exact sln.	WOA	Gap %	Instance no.	Exact sln.	WOA	Gap %
	14301344	14485117	1.285		78386933	79738576	1.724
	14358138	14489158	0.913		77713144	79280658	2.017
1	14024170	14148818	0.889	4	79939904	81553417	2.018
	14588111	14726523	0.949		79792082	81884694	2.623
	14062490	14189029	0.900		70203507	71681793	2.106
	14216932	14342359	0.882		70027579	72167927	3.056
	23851373	24272419	1.765		100029552	103202277	3.172
	24658085	24988196	1.339		109777804	112038650	2.059
2	24333818	24636302	1.243	5	100476705	103799111	3.307
	24679723	24959943	1.135		100326207	103271172	2.935
	27539829	28106536	2.058		99958730	103294321	3.337
	27600702	27983786	1.388		109693223	111995260	2.099
	47757356	48787591	2.157				
	47401887	48272553	1.837				
3	47931709	48972971	2.172				
	48262991	49061752	1.655				
	48037320	48956153	1.913				
	47790428	48811230	2.136				

As shown, the execution time of the optimization software package is exponentially increasing in the size of the problem instance. Its computational time has become more than that of the WOA from instance #1 onward, while the solution gaps for the algorithm do not exceed 3.33%. This reveals inefficacy of the solvers for large-scale problems whereas the optimal solution might not even achieved. According to the results shown in Table 7, the solution gaps vary from 0.88% to 3.33% for all test problems. Furthermore, the maximum gap for the largest test problem is less than 3.33% which is quite acceptable.

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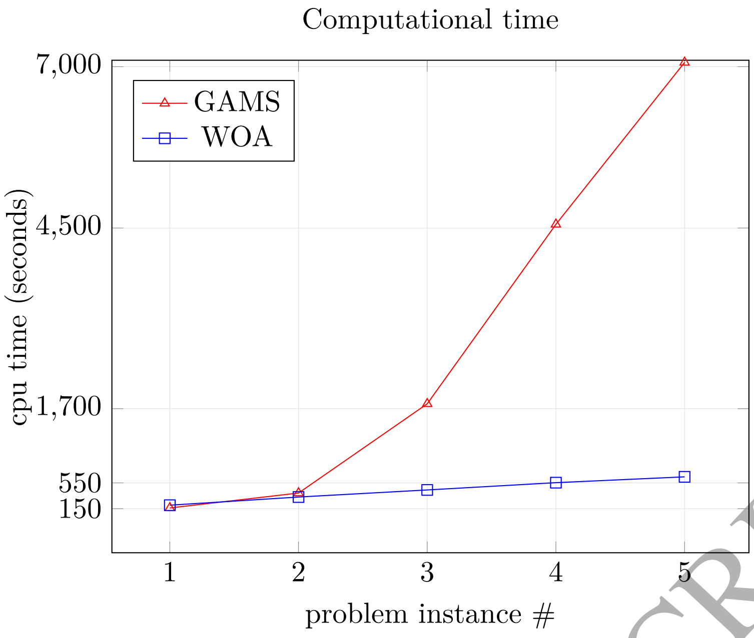

Figure 8: The average computational time of methods for each sample problem

5.2 Sensitivity analysis

In this section, two different experiments are considered to conduct a sensitivity analysis of the minimum values of the constraints satisfaction and penalty coefficients on the RFP model. In the first experiment, it is assumed that the penalty coefficients were constant. In the second experiment, it is assumed that the minimum values of the constraints satisfaction are constant. Tables 8 and 9 present different average results of the minimum values of the constraints satisfaction ($\vartheta_n, n = 1, 2$) and penalty coefficients (ρ, τ), which are provided by the exact solution and WOA algorithm in the RFP model, respectively. As shown in Table 8 and 9 with an increase in ($v_n, n = 1, 2$), the value of the objective function increases in an ascending order, while with an increase in (ρ, τ) the objective values do not shift which indicates that the initial penalty factors are large enough and optimality is obtained without penalty paying for constraint violation.

6 Conclusion, managerial insights, and directions for future studies

This paper presented a multi-period, multi-product, multi-echelon CLSC network under discount on the purchase of raw materials, possibility of demand backorder, and indigenous and exogenous uncertain parameter. The material flow structure in our problem statement includes the returned items (in both upgradable and recyclable inputs); and therefore, the model incorporates the reverse logistics in addition to the conventional forward flow of the raw material in a supply chain. This pattern reflects the real-world practices in several sectors where the chain is of high raw material intensity and/or complex products are consumed/produced, such as automotive, aerospace, and electronic industries, among others. Besides sustainability motives and carbon footprint concerns, the importance of the returned items (for upcycling or recycling) is more eminent when sourcing of the raw materials becomes a significant challenge due to scary of the components/material and price/availability uncertainty of the materials, among other causes which make the reverse logistics in such situations of an extremely high importance to the success or survival of the entire chain. For instance, both high-tech electronic and automobile industries in Iran have been repetitively subject to international sanctions in the last two decades and as such the local manufacturers in these industries encounter difficulties in supply of certain raw materials or components for sustaining the production lines. Thus, the returned faulty or end-of-cycle products can be valuable for the manufacturer for recycling/upcycling some of the material or components before disposing the rest. In such conditions design of a supply network cannot afford to ignore the closed-loops flows, and thus inclusive models like what is presented in this paper seem essential for optimizing the dynamic of the chain.

A mathematical programming model was developed for the aforementioned closed-loop supply chain and a robust fuzzy formulation counterpart was developed to address the effects of uncertainty parameters, including uncertainty on periodic customer demand, raw material costs, transportation costs, shortage cost, and availability of return goods and materials. This wide implementation of uncertain parameters in our model makes it more realistic and closer to the real-world practice. However, approaches in confronting with uncertain parameters vary in the nature and scope of the studies. For instance, estimation of demand or backorder can be investigated as a separate problem with probabilistic, simulation or other fuzzy techniques (see Rodger 2014). To comment on how efficient each of these approaches may be, one requires to compare them in real case studies, which can be suggested as one direction for the future studies. From the solution method perspective, we have contributed with proposing a priority based encoding method to be integrated with the whale optimization algorithm. Thus, we equipped this algorithm to solve the problems in discrete spaces by converting the continuous space into discrete one. The numerical experiment presented in this paper provides with some further insights. For example, we observe the proposed meta-heuristic can perform 13 time faster than a well known general-purposed solver while its solution deviates only at most 3.33%. The computational time of WOA algorithm was significantly less than that of the exact solution for relatively big size problem instances and it is likely for the off-the-shelf optimization package to be incapable of solving large scale problems even with longer computation times. Besides, replicating different instances revealed that the algorithm provides consistent solutions with similar qualities without parameter-dependent behavior which is an advantage for a meta-heuristic algorithm. In addition, our sensitivity analysis over the penalty coefficient parameters (ρ, θ), showed an insensitive objective values to these parameters which indicates that the parameters are chosen sufficiently large and the algorithm performs correctly.

Besides the proposed methodology, other numerical methods, such as neural networks, genetic algorithms, Tabu search, particle swarm, ant colony optimization, and expert system applications may be applied and incorporated into the decision support systems (DSS) of big companies with similar supply chain structure to aid their decision makers in strategic location selection. Hence, there are some rooms for improvement in both theoretical and practical aspects and the current work can be further studied either for a more customized supply chain with the specific configurations such as waste and sustainability issues, pricing and regulations, etc. or with the aforementioned solution methodologies, and modeling approaches.

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Table 8: Sensitivity analysis on constraints satisfaction $\vartheta_n, n = 1, 2$; $\rho = \tau = 400$

Instance	$\vartheta_1 = \vartheta_2 = 0.5$			$\vartheta_1 = \vartheta_2 = 0.8$			$\vartheta_1 = \vartheta_2 = 1$		
no.	Exact sln.	WOA	dev.%	Exact sln.	WOA	dev.%	Exact sln.	WOA	dev.%
	13941354.6	14170665.9	1.6	14301344.0	14485117.0	1.3	15152529.6	15338808.9	1.2
	13959384.8	14089937.6	0.9	14358137.6	14489158.0	0.9	15171443.6	15256525.6	0.6
1	13647495.0	13809931.3	1.2	14024170.2	14148818.0	0.9	14795317.2	14999398.3	1.4
	14254736.4	14341577.5	0.6	14588111.2	14726523.0	0.9	15407680.2	15465874.5	0.4
	13750608.3	13871036.9	0.9	14062490.1	14189029.0	0.9	14780755.1	15042614.9	1.8
	13874031.7	13982072.1	0.8	14216932.0	14342359.0	0.9	15106791.6	15132830.1	0.2
	23482945.7	23930943.2	1.9	23851372.5	24272419.0	1.8	24555970.5	25101151.2	2.2
	24304126.3	24655455.8	1.4	24658085.1	24988196.0	1.3	25389169.1	25832023.8	1.7
2	23947025.6	24273058.4	1.4	24333818.4	24636302.0	1.2	25164606.4	25480090.4	1.3
	24336561.3	24625579.3	1.2	24679723.3	24959943.0	1.1	25433441.3	25841517.3	1.6
	27175934.5	27725097.6	2.0	27539829.2	28106536.0	2.1	28384790.2	28868825.6	1.7
	27213024.0	27627282.1	1.5	27600701.9	27983786.0	1.4	28494232.9	28765684.1	1.0
	47405920.2	48446157.7	2.2	47757355.5	48787591.0	2.2	48480915.5	49546037.7	2.2
	47048331.2	47970171.5	2.0	47401886.5	48272553.0	1.8	48158541.5	49082229.5	1.9
3	47600631.0	48632438.1	2.2	47931708.9	48972971.0	2.2	48686297.9	49679398.1	2.0
	47920224.8	48739594.9	1.7	48262990.6	49061752.0	1.7	49020295.6	49881166.9	1.8
	47726848.6	48569693.7	1.8	48037319.8	48956153.0	1.9	48881135.8	49700684.7	1.7
	47410875.2	48507454.8	2.3	47790428.0	48811230.0	2.1	48649947.7	49622252.8	2.0
	78053516.2	79436204.1	1.8	78386933.2	79738576.0	1.7	79095664.2	80486497.1	1.8
	77364006.8	78951388.8	2.1	77713143.8	79280658.0	2.0	78513493.8	80054466.8	2.0
4	79559143.3	81168000.7	2.0	79939904.3	81553417.0	2.0	80746427.3	82423499.7	2.1
	79482290.1	81583551.3	2.6	79792082.1	81884694.0	2.6	80588521.1	82621415.3	2.5
	69847185.5	71345749.2	2.1	70203506.5	71681793.0	2.1	70908087.5	72533125.2	2.3
	69633012.6	71857794.6	3.2	70027578.6	72167927.0	3.1	70921754.6	72884422.3	2.8
	99634420.5	102876783.3	3.3	100029552.0	103202277.3	3.2	100762644.9	103977132.3	3.2
	109412906.7	111670412.5	2.1	109777803.7	112038649.5	2.1	110562722.7	112918354.5	2.1
5	100114878.4	103489995.1	3.4	100476705.4	103799111.1	3.3	101257512.4	104577233.1	3.3
	100011631.6	102894600.6	2.9	100326206.6	103271171.6	2.9	101161355.6	104007119.6	2.8
	99583690.9	102934308.2	3.4	99958729.9	103294321.2	3.3	100755581.9	104065223.2	3.3
	109295585.5	111684590.3	2.2	109693222.5	111995260.3	2.1	110566737.5	112732082.3	2.0

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Table 9: Sensitivity analysis on penalty coefficient ρ, τ; $\vartheta_1 = \vartheta_2 = 0.8$

Instance	$\rho = \tau = 100$			$\rho = \tau = 10000$			$\rho = \tau = 1000000$		
no.	Exact sln.	WOA	dev.%	Exact sln.	WOA	dev.%	Exact sln.	WOA	dev.%
	14301344.0	14485116.9	1.3	14301344.0	14485116.9	1.3	14301344.0	14485116.9	1.3
	14358137.6	14489157.6	0.9	14358137.6	14489157.6	0.9	14358137.6	14489157.6	0.9
1	14024170.2	14148818.3	0.9	14024170.2	14148818.3	0.9	14024170.2	14148818.3	0.9
	14588111.2	14726522.5	0.9	14588111.2	14726522.5	0.9	14588111.2	14726522.5	0.9
	14062490.1	14189028.9	0.9	14062490.1	14189028.9	0.9	14062490.1	14189028.9	0.9
	14216932.0	14342359.1	0.9	14216932.0	14342359.1	0.9	14216932.0	14342359.1	0.9
	23851372.5	24272419.2	1.8	23851372.5	24272419.2	1.8	23851372.5	24272419.2	1.8
	24658085.1	24988195.8	1.3	24658085.1	24988195.8	1.3	24658085.1	24988195.8	1.3
2	24333818.4	24636302.4	1.2	24333818.4	24636302.4	1.2	24333818.4	24636302.4	1.2
	24679723.3	24959943.3	1.1	24679723.3	24959943.3	1.1	24679723.3	24959943.3	1.1
	27539829.2	28106535.6	2.1	27539829.2	28106535.6	2.1	27539829.2	28106535.6	2.1
	27600701.9	27983786.1	1.4	27600701.9	27983786.1	1.4	27600701.9	27983786.1	1.4
	47757355.5	48787590.7	2.2	47757355.5	48787590.7	2.2	47757355.5	48787590.7	2.2
	47401886.5	48272552.5	1.8	47401886.5	48272552.5	1.8	47401886.5	48272552.5	1.8
3	47931708.9	48972971.1	2.2	47931708.9	48972971.1	2.2	47931708.9	48972971.1	2.2
	48262990.6	49061751.9	1.7	48262990.6	49061751.9	1.7	48262990.6	49061751.9	1.7
	48037319.8	48956152.7	1.9	48037319.8	48956152.7	1.9	48037319.8	48956152.7	1.9
	47790428.0	48811229.8	2.1	47790428.0	48811229.8	2.1	47790428.0	48811229.8	2.1
	78386933.2	79738576.1	1.7	78386933.2	79738576.1	1.7	78386933.2	79738576.1	1.7
	77713143.8	79280657.8	2.0	77713143.8	79280657.8	2.0	77713143.8	79280657.8	2.0
4	79939904.3	81553416.7	2.0	79939904.3	81553416.7	2.0	79939904.3	81553416.7	2.0
	79792082.1	81884694.3	2.6	79792082.1	81884694.3	2.6	79792082.1	81884694.3	2.6
	70203506.5	71681793.2	2.1	70203506.5	71681793.2	2.1	70203506.5	71681793.2	2.1
	70027578.6	72167927.4	3.1	70027578.6	72167927.4	3.1	70027578.6	72167927.4	3.1
	100029552.0	103202277.3	3.2	100029552.0	103202277.3	3.2	100029552.0	103202277.3	3.2
	109777803.7	112038649.5	2.1	109777803.7	112038649.5	2.1	109777803.7	112038649.5	2.1
5	100476705.4	103799111.1	3.3	100476705.4	103799111.1	3.3	100476705.4	103799111.1	3.3
	100326206.6	103271171.6	2.9	100326206.6	103271171.6	2.9	100326206.6	103271171.6	2.9
	99958729.9	103294321.2	3.3	99958729.9	103294321.2	3.3	99958729.9	103294321.2	3.3
	109693222.5	111995260.3	2.1	109693222.5	111995260.3	2.1	109693222.5	111995260.3	2.1

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