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Designing a green location routing inventory problem considering transportation risks and time window: a case study

Neda Manavizadeh[1*], Mahnaz Shaabani[1], Soroush Aghamohammadi-Bosjin[2]

[1]*Department of Industrial Engineering, Khatam University, Tehran, Iran*
[2] *School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran*

n.manavi@Khatam.ac.ir, m.shabaani@khatam.ac.ir, aghamohamadi.sor@ut.ac.ir

Abstract

This study introduces a green location, routing and inventory problem with customer satisfaction, backup distribution centers and risk of routes in the form of a non-linear mixed integer programming model. In this regard, time window is considered to increase the customer satisfaction of the model and transportation risks is taken into account for the reliability of the system. In addition, different factors are detected as the major factors affecting the risk of routs and a fuzzy TOPSIS method is applied to rank the related risk factors. Next, due to the complexity of the investigated model, two algorithms including multi-objective gray wolf optimization algorithms (MOGWO) and Non-Dominated Sorting Genetic algorithm (NSGA-II) are applied to solve the large-sized instances. The results prove the superiority of MOGWO in dealing with large-sized instances. In the next step, some sensitivity analysis is implemented on the model based on a case study and the related results of case study are reported as well.

Keyword: Location routing inventory**,** green supply chain**,** backup strategy**,** customer satisfaction**,** fuzzy TOPSIS**,** multi objective gray wolf optimization algorithm.

1- Introduction

Today, the role of transportation is critical in economic development of supply chains by facilitating the availability of products for the long-distance factories. Delivering process in a supply chain (SC), incorporates shipment of raw materials from suppliers to production centers (PCs) and transformation of semi-finished products between the PCs and customers. Due to the multiplicity of transportation activities, shipping costs include high percentage of logistic costs. Therefore, managing the related costs of transportation has become a major issue for the supply chain decision makers. In this regard, there is a competitive market between supply chains (SCs) to reduce their costs and enhance their profit. Many researches have considered strategic and tactical decisions in SC problems including location, routing and inventory decisions to develop integrated SCs (Zheng et al. 2019; Rabbani et al, 2017; Malladi and Sowlati 2017). Integration of these decisions is one of the most important factors that significantly reduce the cost of the chain and lead to increase of customer satisfaction. Inaccurate location of facilities and inappropriate route selection lead to high transportation costs.

*Corresponding author
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Moreover, inappropriate transportation system leads to higher amount of carbon emissions. Supply chain management (SCM) includes purchasing management, inventory control, production and distribution.

Green Supply Chain Management (GSCM) joints economic aspects of SC with environmental aspects in order to manage the environmental effects of the system besides the maximization the performance of the entire SC (Abu seman et al, 2019). The public awareness of climate change and the growing concern about the environmental conditions has made GSCM an important issue in the production and distribution cycle (Fang and azhang, 2018). This study presents a new location-routing-inventory problem by taking into consideration the environmental aspects, backup strategies, time window and transportation risks to enhance the customer satisfaction and reliability of the system simultaneously.

Clearly, strategic decisions of a SC affect the tactical decisions of the SC including inventory and routing decisions. As a result, a location- inventory-routing model covers the strategic and tactical decisions of a SC. However, combination of these issues increases the complexities of the main problem (Diabat et al, 2015). Many of developed models in the SCN consider these important decisions separately while they are dependent by nature. This study introduces a new multi objective model integrating location, routing and inventory problem issues as a joint location- routing-inventory problem (LRIP). This model considers backup distribution centers in order to decrease the shortage and time window to increase the customer satisfaction. In addition, this paper takes into account different factors affecting the stability of routs to select the best rout with the least level of risk for shipment of products. In this regard, the main contributions of this study are stated as follows:

- Developing a new multi-objective location- inventory-routing problem.
- Considering backup centers to decrease the shortage and satisfy the customers.
- Considering a hard time window for delivery process to enhance the customer satisfaction.
- Considering the transportation risks in model to enhance the reliability of the system.
- Applying a fuzzy TOPSIS method for analyzing the factors affecting the reliability of routes.
- Applying a multi-objective gray wolf optimization algorithm to efficiency solve the problem.

The remainder of this article is arranged as follows: Section 2 reviews relevant related literature. The uncertain green location- routing inventory model is proposed in section 3. The NSGA-II and MOGWO algorithms are presented in section 4. Model validation, numerical results and sensitivity analysis are reported in section 5. Comparative result from before section discuss in section 6. Sensitivity analysis is given in section 7. At last, in section 8, conclusions and future suggestions are stated.

2-Literature review

This section discusses about different studies related to location-routing-inventory problem, Green LRIP and LRIP with risk.

2-1- Location-routing-inventory problem

For the first time, Liu and Lee (2003) presented a LRIP in which they assumed heterogeneous fleet and unlimited capacity for depots. They solved model using a two-phase heuristic algorithm. Liu and Lee (2005) developed their model by using Tabu Search (TS) and Simulated Annealing (SA) algorithms to solve their model. They didn't consider shortage and ordering cost in their model. Zhang, Zujun and Jiang (2008) developed a multi-period single-item LRIP with a homogeneous fleet and uncertain demand and solved their model by a genetic algorithm. Sajjadi and Cheraghi. (2011) studied a multi- commodity, three-echelon and single-period SC with stochastic demand. In their model, warehouses had limited capacity and 3PL companies provided space in order to storage items in DCs. Seyyed Hosseini, Bozorgi-Amiri and Daraei. (2014) introduced a single-objective model for inventory, routing and location decisions. They considered stochastic demand, shortage and random disruption at distribution centers (DCs) and applied a metaheuristic algorithm to solve the proposed model. Dehghani, Behfar and Jabalameli. (2016) developed a mathematical model for LRIP and used SA algorithm for solving the problem. In their model, the demands of retailers were ucertain. Amiri aref, Klibi and Zied Babai. (2017)

presented a multi-source, multi-period, multi-echelon SC LRIP with uncertain demand. In their model, they examined the impact of shipping costs, inventory holding costs, and product referrals. They used a Sample Approximation method to solve the proposed model.

Yuchi et al. (2018) studied a LRIP in a closed-loop supply chain in which the remanufacturing centers were located. For solving their model, they used hybrid method TS and SA algorithms. Rabbani et al. (2018) formulated a multi-objective stochastic model for a locating-routing problem by considering inventory control and the risk of wastes for humans. They integrated a NSGA-II and the Monte Carlo simulation to solve the model. Momeni Kia et al. (2018) designed a two-objective model for LRIP with soft time windows. They applied three metaheuristics including MOPSO, PESA_II and NSGA-II algorithms to solve the model. Guo et al. (2018) examined the LRIP in a close loop SC and proposed a non-linear integer programming model with the aim of reducing system costs including inventory, routing and transportation costs. They used a hybrid metaheuristic comprised of SA and GA algorithms to solve the model. Zheng, Yin and zhang. (2019), formulated a nonlinear LRIP that minimized the total system costs including the inventory, shipping and opening costs of the DCs. They used exact algorithm based on the Generalized Benders Decomposition (GBD) to solve the model.

2-2- Green LRIP

In the most of researches in literature, location-routing (LR), inventory-routing (IR) and location-inventory (LI) problems have included environmental aspects in their model. Treital, Nolz and Jammerneg.(2012) proposed an IR problem with environmental aspects and applied a case study for their model. They didn't consider inventory costs in their model. In their model, emission was related to vehicle type and travelling distance. Soysal et al (2015) addressed an IRP for perishable products with environmental aspects. they assumed demand is uncertain. The environmental impacts of their model were related to reducing CO2 emission, fuel consumption and food waste. In addition, Soysal et al (2017) proposed a green IR problem by regarding Co_2 emission, total system costs and perishable goods simultaneously with uncertain demand. They applied a case study with two suppliers and showed the reduced rate of Co_2 emission is about 8-33%. Niakan and Rahimi (2015) presented an IRP in field the of medication distribution. They assumed that demand, transportation cost, and shortage cost were fuzzy parameters. Also, they showed that greenhouse gas (GHG) emission was related to transportation system. Rahimi, Babol and Rekik. (2017) developed an inventory routing problem with green considerations. Their model had three objectives and included profit of the system, service level and environmental effects of distribution operations. To solve the model, they used the NSGA-II algorithm. Rau, Budimana and Widyadanab. (2018) proposed a multi-objective IRP with environmental aspects. In their model, the Co_2 emission comes from the fuel consumption of vehicles. They proposed a discrete multi-objective particle swarm optimization (PSO) to solve the model. They showed their model reduced the total cost between 17% - 22% and total emission between 19%-22%. Guido, Michelia and Fabio Mantella. (2018) offered an inventory routing problem with uncertainty demand that simultaneously considered emissions GHG and heterogeneous fleets. In order to reduce concerns about air pollution, they consider four carbon control strategies. Dukkanci et al. (2019) addressed a green LRIP and considered the speed and weight of vehicles as the major factors affecting the fuel consumption of vehicles.

As the literature review shows, there are a few researches considering environmental aspects in LRIPs. In this regard, the green LRIPs can be divided into two categories: The LRIPs with electric vehicle (EV) that focus on green VRP and developed electric vehicle problem (EVRP). The second group decreases the emissions by paying attention the distance traveled by vehicles (Zhang et al., 2018). According to the previous section there are some gaps in the context of LRIP as follows:

- Considering the reliability of transportation system in a LRIP problem.
- Analyzing the factors affecting the risk of routs for the delivery of items in a LRIP.
- Considering hard time windows for the shipment of products in a LRIP problem.
- Considering environmental factors in a multi-objective LRIP problem.
- Considering backup centers to avoid shortage in the system.

- Applying a new multi objective metaheuristic problem for a LRIP.

Table 1 shows the summary of literature review section and highlights the research gaps.

Table 1. Summation of the literature about LRIPs.

Author	**Network routing**	Inventory control			**Co_2 emission and environmental impacts**	**Backup center**	**Route risk**	**Customer satisfaction**	**Time window**	**objective**	**Uncertain demand**	**Solution Approach**
		Shortage	Ordering	Safety stock								
Sajjadi and Cheraghi (2011)	✓	✓	✓							Single-objective	✓	SA algorithm
Ahmadi-Javid and Seddighi (2012)	✓		✓							Single-objective	✓	Hybrid metaheuristic Ant Colony system-SA
Tavakoli moghddam et al (2013)			✓	✓						Multi-objective	✓	Lingo
Seyed Hosseni et al (2014)	✓	✓	✓							Single-objective	✓	GA algorithm
Dehghani et al (2016)		✓	✓							Single-objective	✓	SA algorithm
Zhaleh chian et al (2016)	✓		✓		✓					Multi-objective	✓	hybrid meta-heuristic algorithm
Tang et al (2016)	✓		✓	✓	✓					Multi-objective	✓	multi-objective particle swarm optimization (MOPSO) algorithm
Tavakoli moghaddam and Raziei (2016)	✓	✓			✓					Multi-objective	✓	Cplex
Amiri aref et al (2017)	✓		✓	✓						Single-objective	✓	2-phase method based on average approximation approach (SAA)
Momeni kia et al (2018)	✓		✓	✓					Soft TW	Multi-objective	✓	NSGA-II MOPSO PESA_II
Zheng et al (2019)	✓		✓	✓					✓	Single-objective	✓	Exact solution (GBD)
This study	✓	✓	✓	✓	✓	✓	✓	✓	✓	Multi-objective	✓	MOGWO

3-Problem description

In this model a three-level SC consisted of suppliers, distribution/backup centers and customers, is designed. The products are transferred directly from the suppliers to the distribution and backup centers. The model aims to minimize the total cost, risk of routes and CO_2 emission, while selecting and locating a set of DCs, allocating customers to DCs and timing the shipments of vehicles to fulfill the customer demand. The main assumptions of the model are as follows:

3-1- Assumptions

- Inventory review of DCs is continuous. When inventory level of distribution center K'reaches its reorder point $ROP_{k'}.Q_{k'}$ units are ordered
- Each retailer is visited by only one vehicle.
- Transportation fleet is heterogeneous and vehicles capacities are not equal.
- Each retailer is served by only one DC.
- Time window is hard. In other word, customer demand must be met within a specific time interval.
- After serving customer demand allocated to a DC, the vehicle returns back to the DC.
- Customer demand is uncertain and follows normal distribution.
- Network risk parameter is a combination of factors including road security, weather conditions and traffic which are considered as triangular fuzzy numbers.

Figure 1 illustrates the overview of the supply chain network.

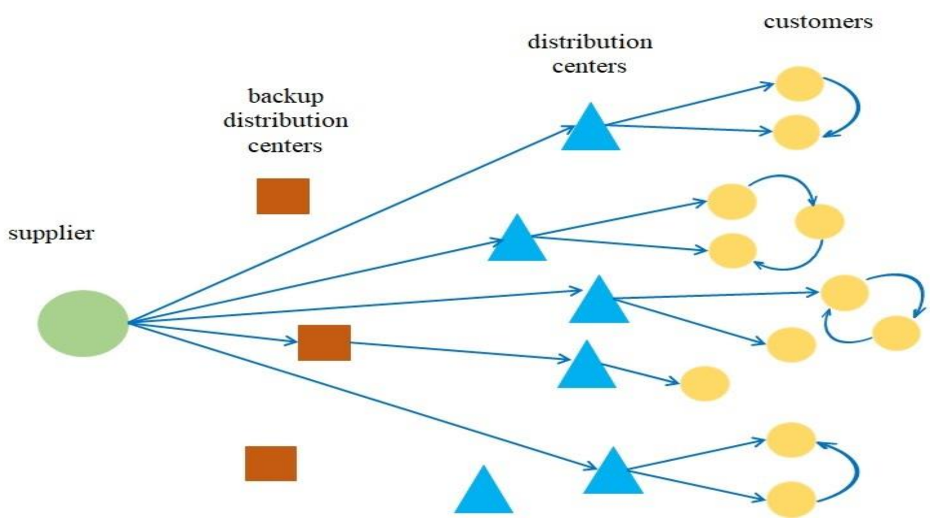

Fig 1. The supply chain network examined

3-2- Fuzzy TOPSIS

According to assumption, the risk of transportation system increases by traffic, situation of roads and weather conditions. It should be note that each of mentioned risk factors have different degree of importance. Converting these factors to a single factor is applied utilizing fuzzy TOPSIS (refer to Abbasi Parizi et al (2018) for more details). Assume that r and l indicate alternatives and decision factors, respectively. The Risk of rout $(\alpha_{II'v2})$ is calculated based on the instruction stated as follows:

1- Determining effective factors on risk of the route (like traffic, weather conditions, and situations of the roads) and weighting them,
2- Determining weights of each factor using average.

3- Computing risk of each route using sum of weights allocated to route risk factors.
4- Composing a matrix for risk of the routes from node i to node j.
5- Selecting the route with the lowest risk.

The proposed fuzzy TOPSIS approach is defined as follows:
The Fuzzy factors must be defined before the optimization of the model, so they are calculated according to the related various features. For the first time, Yoon and Hwang in 1981 developed The TOPSIS method. TOPSIS is a multi-criterion decision-making (MCDM) method for ranking a number of alternatives with respect to their various criteria. The fuzzy TOPSIS is applicable when the weight of proposed criteria is unknown. In this regard, the closest Fuzzy Positive Ideal Solution (FPIS) and the farthest Fuzzy Negative Ideal Solution (FNIS) are selected as the factor range. According to (abbasi-parizi, 2018), the procedure of fuzzy TOPSIS can be expressed in following steps:

Definition 1: It is assumed that $\tilde{a} = (a_1 . a_2 . a_3)$ is a triangular fuzzy number (TFN). The membership function of $\tilde{a}$ described the following relation:

$$trn(x: a_1 . a_2 . a_3) = \begin{cases} 0 & c \\ \dfrac{x - a_1}{a_2 - a_1} & a_1 < x \leq a_2 \\ \dfrac{a_3 - x}{a_3 - a_2} & a_2 < x \leq a_3 \\ 0 & x > a_3 \end{cases} \tag{1}$$

Definition 2: If the $\tilde{a} = (a_1 . a_2 . a_3)$ and $\tilde{b} = (b_1 . b_2 . b_3)$ are two fuzzy number, then the distance between $\tilde{a} . \tilde{b}$ is calculated as:

$$d(\tilde{a} . \tilde{b}) = (|b_1 - a_3|, |b_2 - a_2|, |b_3 - a_1|) \tag{2}$$

Step1: *D* denotes a fuzzy decision matrix as follows:

$$D = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots \cdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \quad \text{and} \quad \tilde{x}_{rl} = (a_{rl} . b_{rl} . c_{rl}) \tag{3}$$

Step2: The fuzzy decision matrix is normalized as follows:

$$\tilde{R} = [\tilde{r}_{rl}]_{M \times N} \tag{4}$$

$$r_{rl} = \left({}^{a_{rl}}/_{c^*_{rl}} . {}^{b_{rl}}/_{c^*_{ij}} . {}^{c_{rl}}/_{c^*_{rl}} \right) \quad . \quad c^*_{rl} = \max c_{rl} \qquad \text{benefit criteria} \tag{5}$$

$$r_{rl} = \left({}^{a^-_{rl}}/_{c_{rl}} . {}^{a^-_{rl}}/_{b_{rl}} . {}^{a^-_{rl}}/_{a_{rl}} \right) \quad . \quad a^-_{rl} = \min a_{rl} \qquad \text{cost criteria} \tag{6}$$

Step3: The weighted normalized decision matrix is calculated. $\widetilde{w}_{rl}$ is the weight factor of fuzzy parameters as follows:

$$V = [\tilde{v}_{rl}]_{M \times N} \tag{7}$$

$$V=\begin{bmatrix}\tilde{v}_{11} & \tilde{v}_{12} & \cdots & \tilde{v}_{1n}\\ \tilde{v}_{21} & \tilde{v}_{22} & \cdots & \tilde{v}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \tilde{v}_{m1} & \tilde{v}_{m2} & \cdots & \tilde{v}_{mn}\end{bmatrix}=\begin{bmatrix}\tilde{w}_{11}\tilde{r}_{11} & \tilde{w}_{12}\tilde{r}_{12} & \cdots & \tilde{w}_{1n}\tilde{r}_{1n}\\ \tilde{w}_{21}\tilde{r}_{21} & \tilde{w}_{22}\tilde{r}_{22} & \cdots & \tilde{w}_{2n}\tilde{r}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \tilde{w}_{m1}\tilde{r}_{m1} & \tilde{w}_{m2}\tilde{r}_{m2} & \cdots & \tilde{w}_{mn}\tilde{r}_{mn}\end{bmatrix} \tag{8}$$

Step4: The fuzzy ideal (positive) and fuzzy negative-ideal solutions are determined as follows.

$$A^{*}=(\tilde{v}_1^{*}.\tilde{v}_2^{*}.\tilde{v}_3^{*})=\{(max v_{rl}|r=1.2.\cdots.m).l=1.2.\cdots.n\} \tag{9}$$

$$A^{-}=(\tilde{v}_1^{-}.\tilde{v}_2^{-}.\tilde{v}_3^{-})=\{(min v_{rl}|r=1.2.\cdots.m).l=1.2.\cdots.n\} \tag{10}$$

Step5: The total fuzzy distance between each component, the positive and negative ideal solutions are calculated as follows:

$$\tilde{d}_r^{*}=\sum_{l=1}^{n} d(\tilde{v}_{rl}.\tilde{v}_l^{*}) \qquad r=1.2.\ldots.m \tag{11}$$

$$\tilde{d}_r^{-}=\sum_{l=1}^{n} d(\tilde{v}_{rl}.\tilde{v}_l^{-}) \qquad r=1.2.\ldots.m \tag{12}$$

Step 6: Convert the similarity index to the Ideal Solution as follows:

$$\tilde{C}_r^{*}=\frac{\tilde{d}_r^{-}}{\tilde{d}_r^{-}+\tilde{d}_r^{*}} \qquad r=1.2.\ldots.m \tag{13}$$

It is obvious that fuzzy parameters are obtained as $\tilde{a}=(a_1.a_2.a_3)$. For example, for the risk factor; $\tilde{\alpha}_{II'v}=(\alpha_{1II'v}.\alpha_{2II'v}.\alpha_{3II'v})$; the relative closeness to the Ideal Solution is calculated as follow as:

Table 3. Linguistic variables for fuzzy rating

Fuzzy number	Weight of each criteria	alternative	QA weight
(0,0,2)	(0,0,0.2)	Very poor (VP)	Very low (VL)
(0,2,3)	(0,0.2,0.3)	Poor (P)	Low (L)
(2,3,6)	(0.2,0.3,0.6)	Medium (M)	Medium (M)
(3,6,9)	(0.3,0.6,0.9)	Good (G)	High (H)
(6,9,10)	(0.6,0.9,1.0)	Very good (VG)	Very high (VH)

Table 3 shows the importance weight risk factors and the related rating of qualitative criteria. In the next step, the results of each factor are achieved using the decision maker's opinions. The related results are reported in table 4.

Table 4. fuzzy decision and weight matrix

alternative	C_1	C_2	C_3
A_1	(3,6,10)	(5,8,10)	(7,9,10)
A_2	(2,5.7,10)	(0,6,9)	(5,8.4,10)
A_3	(4,7,10)	(7,9,10)	(5,9,10)
weight	(0.65,0.82,1)	(0.5,0.71,0.93)	(0.5,0.74,1)

According to relations (5)- (9), the fuzzy weighted normalized decision matrix described in table 5.

Table 5. The results of the fuzzy weighted normalized decision matrix

alternative	C_1	C_2	C_3
A_1	(0.42, 0.69,1)	(0.5,0.8,1)	(0.65,0.55,0.71)
A_2	(0.35,0.77,1)	(0,0.6,0.9)	(0.5,0.6,1)
A_3	(0.3,0.7,1)	(0.52,0.82,1)	(0.5,0.55,1)

Then the FPIS and FNIS are determined:
$A^{*} = \{(1.1.1).(1.1.1).(0\cdot5.0\cdot5.0\cdot5)\}$
$A^{-} = \{(0\cdot3.0\cdot3.0\cdot3).(0.0.0).(1.1.1)\}$
Finally, the distance between each component, the positive and negative ideal solutions are reached and the closest factor to ideal solution is reported in table 6.

Table 6: fuzzy distance and closeness coefficient

	A^{*}	A^{-}	$\widetilde{C}_r^{*}$
d(A₁,)	2.57	2.78	0.517
d(A₂,)	1.84	2.34	0.559
d(A₃,)	2.18	1.95	0.472

Based on the above mentioned, the merged risk is calculated and will be used in the model.

3-3- Mathematical model

Symbols	Definition
Index sets	
k'	Set of potential DCs
k	Set of backup DCs
i	Set of customers (or retailers)
$I = \{k' \cup i\}$	Set of customers and DCs
v_i	Set of available vehicles from supplier O to DC k'
v_2	Set of available vehicles from DC k' to retailers and between them
$V = v_1 \cup v_2$	Set of vehicles
O	supplier
parameters	
$ff_{k'}$	establishing cost of candidate $DC_{k'}$
f_k	establishing cost of candidate backup DC_k
μ_i	mean yearly demand of retailer i
σ_i^2	yearly demand variance at retailer i
D_i	demand of retailer i
f_k'	pollution cost of candidate backup DC_k
$h_{k'}$	inventory holding cost per unit of product at $DC_{k'}$
$c'_{ok'}$	fixed administrative cost of ordering to supplier O by $DC_{k'}$
$safety_{\ k}$	holding cost of safety stock at backup DC_k
tr_{okv1}	transportation cost from supplier O to backup center $DC_k$by vehiclv_1e
$mo_{kk'}$	fixed cost of transportation from backup center $DC_k$to $DC_{k'}$
$cost_{ok'v1}$	Shipment cost per unit from supplier O to $DC_{k'}$ by vehicle v_1
γ_v	pollution cost of vehicle v
ρ_v	amount of fuel consumption of vehicle v while loaded full
ρ_{ov}	amount of fuel consumption of vehicle v while unloaded
$d_{1ok'}$	distance between $DC_{k'}$ and supplier O
d_{2ok}	distance between backup center DC_k and supplier O
d_{3ij}	distance between nodes i and j
$d'_{kk'}$	distance between backup center DC_k and $DC_{k'}$
$c_{II'}$	transfer cost of product from DCs to retailers i and between them
cap_{1v1}	capacity of vehicles v_1
$cap_{2k'}$	capacity of $DC_{k'}$
cap_{3v2}	capacity of vehicles v_2
$cost'_{k'}$	shortage cost at $DC_{k'}$
L	number of backup centers, if needed

Symbols	Definition
U	A big number
$\tilde{t}_{II'v2}$	time needed to travelling from node I to node I' by vehicle v_2
$\widetilde{st}_{I'}$	time needed to serve node I'
$\tilde{e}_{I'}$	earliest start time to serve node I'
$\tilde{l}_{I'}$	latest start time to serve node I'
L'	upper level of inventory
z_{α}	confidence level for inventory
$\widetilde{lt}_{k'}$	lead time of $DC_{k'}$
$\tilde{\alpha}_{II'v2}$	Route risk of driving from node I to node I' using vehicle v_2

Decision variables:

$x_{kk'} = \begin{cases}1\\0\end{cases}$	In case of shortage at $DC_{k'}$, if products are transferred from backup center DC_k otherwise
$x'_k = \begin{cases}1\\0\end{cases}$	if backup center DC_k selected otherwise
$s'_{k'} = \begin{cases}1\\0\end{cases}$	If distribution center $DC_{k'}$ is opened otherwise
$Q'_{ok'v1} = \begin{cases}1\\0\end{cases}$	If order from supplier O for $DC_{k'}$is delivered by vehicle v_1 otherwise
$R_{k'v2} = \begin{cases}1\\0\end{cases}$	If vehicle v_2 is used in distribution center $DC_{k'}$ otherwise
$w_{II'v2} = \begin{cases}1\\0\end{cases}$	If product is transported from node I to node I' by using vehicle v_2 otherwise
$y_{ik'} = \begin{cases}1\\0\end{cases}$	If distribution center $DC_{k'}$ is selected by retailer i otherwise
$ba_{k'}$	amount of shortage at distribution center $DC_{k'}$
ss_k	safety stock at backup center DC_k
N_{10kv_1}	count of orders from supplier O for distribution center $DC_{k'}$ using vehicle v_2
$Q_{1ok'v1}$	quantity of order from supplier o for backup center DC_kusing vehicle v_1
N_{2okv1}	count of orders from supplier O for backup center DC_k using vehicle v_1
$y'_{kk'}$	quantity of products sent to $DC_{k'}$ from backup center DC_k in case of shortage
M_{iv}	auxiliary variable to eliminate sub-tour
At_{Iv1}	start time for serving node I using vehicle v_1

The proposed non-linear uncertain model of this problem is described as follows.
Yearly demand of $DC_{k'}$, is equal to the summation of mean yearly demand of all retailers allocated to that DC. Hence:

$$\text{Mean yearly demand at } DC_{k'} = \sum_i \mu_i y_{ik'} \tag{14}$$

$$\text{Variance of yearly demand at } DC_{k'} = \sum_i \sigma_i^2 y_{ik'} \tag{15}$$

Given that $N_{1ok'v1}$ is number of orders and $Q_{ok'v1}$ is quantity of each order at $DC_{k'}$, yearly demand for $DC_{k'}$can be obtained from : $N_{1ok'v1} \cdot Q_{1ok'v1}$.

Thus, if $N_{1ok'v1} \cdot Q_{1ok'v1} \leq \sum_i \mu_i \cdot y_{ik\prime}$, then safety stock will be equal to $\sqrt{\widetilde{lt}_{k\prime} \sum_i \sigma_i^2 y_{ik\prime}}$

Let $D_{k\prime}$ be demand of $DC_{k'}$. If $\boldsymbol{k'}$ places $N_{1ok'v1}$ orders with quantity of $Q_{1ok'v1}$ for each time, with $c'_{ok\prime}$ as fixed order cost for this DC, inventory holding cost, ordering cost and safety stock holding cost can be formulated as relation 16:

$$h_{k\prime}\left(\frac{N_{1ok'v1} \cdot Q_{1ok'v1}}{2}\right) + c'_{ok\prime}\left(\frac{D_{k\prime}}{N_{1ok'v1} \cdot Q_{1ok'v1}}\right) + h_{k\prime} z_\alpha \sqrt{\widetilde{lt}_{k\prime} \sum_i \sigma_i^2 y_{ik\prime}} \tag{16}$$

On the other hand:

Inventory cost for all DCs is determined using Equation (17):

$$h_{k\prime}\left(\frac{N_{1ok'v1} \cdot Q_{1ok'v1}}{2}\right) + \sum_{k\prime} c'_{ok\prime}\left(\frac{\sum_i \mu_i y_{ik\prime}}{N_{1ok'v1} \cdot Q_{1ok'v1}}\right) + \sum_{k\prime} h_{k\prime}\, z_\alpha \sqrt{\widetilde{lt}_{k\prime} \sum_i \sigma_i^2 y_{ik\prime}} \tag{17}$$

The non-linear uncertain multi-objective mathematical model is formulated as follows:

- ***Total costs***

$$\begin{aligned} minZ_1 = {} & \sum_k f_k \cdot x'_k + \sum_{k'} ff_{k'} \cdot s'_{k'} + \sum_k f'_k \cdot x'_k + \sum_k ss_k \cdot safety_k \\ & + \sum_O \sum_{k'} \sum_{v \in v_1} (cost_{0k'v} \cdot d_{1Ok'} \cdot N_{1Ok'v} \cdot Q_{1Ok'v}) + \sum_O \sum_{k'} \sum_{v \in v_1} c'_{ok'} \\ & \cdot \left(\frac{\sum_i \mu_i \cdot y_{ik'}}{N_{1Ok'v} \cdot Q_{1Ok'v}}\right) + \sum_O \sum_{k'} \sum_{v \in v_1} \frac{h_{k'} \cdot N_{1Ok\prime v} \cdot Q_{1Ok\prime v}}{2} \\ & + \sum_{k'} h_{k'} \cdot Z_\alpha \sqrt{\widetilde{lt}_{k\prime} \sum_i \sigma_i^2 \cdot y_{ik'}} + \sum_o \sum_k \sum_{v \in v_1} tr_{okv} \cdot N_{2okv} \cdot Q_{2okv} \cdot d_{2ok} \\ & + \sum_k \sum_{k\prime} mo_{kk\prime} \cdot d'_{kk\prime} \cdot y'_{kk} + \sum_I \sum_{v \in v_2} \sum_{I'} C_{II'} \cdot w_{II'} \cdot R_{k'v} + \sum_{k'} ba_{k'} \cdot cost'_{k'} \end{aligned} \tag{18}$$

$$\begin{aligned} \omega = {} & \sum_k f_k \cdot x'_k + \sum_{k'} ff_{k'} \cdot s'_{k'} + \sum_k f'_k \cdot x'_k + \sum_k ss_k \cdot safety_k \\ & + \sum_O \sum_{k'} \sum_{v \in v_1} (cost_{0k'v} \cdot d_{1Ok'} \cdot N_{1Ok'v} \cdot Q_{1Ok'v}) + \sum_O \sum_{k'} \sum_{v \in v_1} c'_{ok'} \\ & \cdot \left(\frac{\sum_i \mu_i \cdot y_{ik'}}{N_{1Ok'v} \cdot Q_{1Ok'v}}\right) + \sum_O \sum_{k'} \sum_{v \in v_1} \frac{h_{k'} \cdot N_{1Ok\prime v} \cdot Q_{1Ok\prime v}}{2} \\ & + \sum_o \sum_k \sum_{v \in v_1} tr_{okv} \cdot N_{2okv} \cdot Q_{2okv} \cdot d_{2ok} + \sum_k \sum_{k\prime} mo_{kk\prime} \cdot d'_{kk\prime} \\ & \cdot y'_{kk} + \sum_I \sum_{v \in v_2} \sum_{I'} C_{II'} \cdot w_{II'} \cdot R_{k'v} + \sum_{k'} ba_{k'} \cdot cost'_{k'} \end{aligned}$$

The related costs are associated with distribution and backup center establishment, holding safety stock in distribution and backup centers, transporting products from suppliers to distribution and backup centers and from backup centers to DCs, inventory holding in DCs, holding safety stock in DCs, transferring products from DCs to retailers, shortage of inventory, and fixed order cost.

- ***Greenhouse emission***

Carbon emissions are generated by fuel consumption of vehicles during the transportation of products between nodes:

$$\begin{aligned} minZ_2 = &\sum_{o}\sum_{k'}\sum_{v\in v_1} N_{1ok'v} d_{1ok'}\gamma_v \left(Q_{1ok'v}\frac{\rho_v-\rho_{ov}}{cap_v}\right) \\ &+\sum_{o}\sum_{k}\sum_{v\in v_1} N_{2okv} d_{2ok}\gamma_v \left(Q_{2okv}\frac{\rho_v-\rho_{ov}}{cap_v}\right) \\ &+\sum_{0}\sum_{k\prime}\sum_{i}\sum_{j}\sum_{v\in v_2} N_{1ok\prime v} d_{3ij}\gamma_v \left(Q_{1ok\prime v}\frac{\rho_v-\rho_{ov}}{cap_v}\right) \end{aligned} \tag{19}$$

- ***Risk of routs***

Since, risk parameters are defined as triangular fuzzy numbers, the offered model is reformulated as:

$$Z_3 = minmax_{II\prime v\in v_2}\tilde{\alpha}_{II\prime v} w_{II\prime v} \tag{20}$$

Subject to:

$y_{ik\prime} \le s'_{k\prime}$	$\forall i.k'$	(21)
$\sum_{k\prime} y_{ik\prime} = 1$	$\forall i$	(22)
$\sum_{v\in v2}\sum_{I} w_{II'v2} = 1$	$\forall I'$	(23)
$\sum_{v\in v2}\sum_{I} w_{II'v} \le 1$	$\forall I'$	(24)
$\sum_{I} w_{II\prime v} - \sum_{I} w_{I\prime Iv} = 0$	$\forall v \in v_2.I'$	(25)
$M_{Iv} - M_{I\prime v} + (\lvert I\rvert w_{II\prime v}) \le \lvert I\rvert - 1$	$\forall v \in v_2.I'.I$	(26)
$\sum_{k}\sum_{i} w_{kiw} \le 1$	$\forall v \in v_2$	(27)
$\sum_{I} w_{k\prime Iv} + \sum_{I} w_{Iiv} \le 1 + y_{ik\prime}$	$\forall v \in v_2.i.k'$	(28)
$R_{k\prime v} = \sum_{i} w_{k\prime iv}$	$\forall v \in v_2.k'$	(29)
$s'_{k'} \ge ba_{k'}$	$\forall k'$	(30)
$\sum_{o}\sum_{v\in v_1} N_{1ok\prime v} Q_{1ok\prime v} \le cap_{k\prime} s'_{k\prime}$	$\forall k'$	(31)
$x_{kk\prime} \le s'_{k\prime}$	$\forall k'.k$	(32)

$$x'_k \geq x_{kk'} \qquad \forall k'.k \qquad (33)$$

$$\sum_k x'_k \leq L \qquad (34)$$

$$\sum_o \sum_{v\in v1} (N_{1ok'v} Q_{1ok'v}) + ba_{k'} + ss_{k'} \leq \sum_i (y_{ik'} \mu_i) \qquad \forall k' \qquad (35)$$

$$y'_{kk'} \leq x_{kk'} \qquad \forall k'.k \qquad (36)$$

$$\sum_k y'_{kk'} \geq ba_{k'} \qquad \forall k' \qquad (37)$$

$$\sum_i \mu_i y_{ik'} - \sum_o \sum_{v\in v1} N_{1ok'v} Q_{1ok'v} = ba_{k'} \qquad \forall k' \qquad (38)$$

$$U \cdot Q'_{ok'v} \geq Q_{1ok'v} \qquad \forall k'.o.v \in v_1 \qquad (39)$$

$$N_{1ok'v} \leq Q_{1ok'v} \cdot U \qquad \forall k'.o.v \in v_1 \qquad (40)$$

$$N_{1ok'v} \geq Q'_{ok'v} \qquad \forall k'.o.v \in v_1 \qquad (41)$$

$$x'_{okv} \cdot U \geq Q_{2okv} \qquad \forall k.o.v \in v_1 \qquad (42)$$

$$N_{2okv} \leq Q_{2okv} \cdot U \qquad \forall k.o.v \in v_1 \qquad (43)$$

$$Q_{1ok'v} \leq s'_{k'} \cdot U \qquad \forall k'.o.v \in v_1 \qquad (44)$$

$$ba_{k'} \leq L' \qquad \forall k' \qquad (45)$$

$$At_{Iv} + \tilde{t}_{II'v} + \widetilde{St}_t - At_{I'v} \leq U \cdot w_{II'v} \qquad \forall I.I'.v \in v_{1.2} \qquad (46)$$

$$\tilde{e}_{I'} \leq At_{I'v} + \widetilde{St}_{I'} \leq \tilde{l}_{I'} \qquad \forall I'.v \in v_2 \qquad (47)$$

$$(1 - w_{II'v}) \cdot \left(At_{Iv} + \tilde{t}_{II'v} + \widetilde{St}_t - At_{I'v}\right) \leq 0 \qquad \forall I.I'.v \in v_{1.2} \qquad (48)$$

$$ba_{k'}.ss_k.Q_{1ok'v1}.Q_{2okv1}.At_{Iv2}.M_{iv} \geq 0 \qquad (49)$$

$$y_{ik'}.R_{k'v2}.y'_{kk'}.w_{II'v2}.x_{kk'}.x'_k.s'_{k'}.Q'_{ok'v1} \in \{0.1\} \qquad (50)$$

$$N_{1ok'v1}.N_{2okv2}: integer \qquad (51)$$

The constraint (21) ensures that customer ***i*** will be allocated to $DC_{k'}$ if this DC is established. Constraint (22) indicates that each retailer is exactly allocated to one DC. Constraints (23) and (24) make sure that each customer is assigned exactly to one route. Constraint (25) represents when a vehicle visits a customer or DC, the vehicle should leave the place. Constraint (26) is designed to eliminate the sub-tours and constraint (27) ensures that each route involves only one DC. Constraint (28) indicates that customer ***i*** will be allocated to $DC_{k'}$ if the vehicle ***v*** visiting customer ***i*** starts it's travel from the same DC. Constraint (29) enforces that vehicle ***v*** will not be allocated to DC k' unless it satisfies the demand of customer ***i*** allocated to $DC_{k'}$. Constraint (30) obliges the model to set $S'_{k'}$ equal to 1, if shortage happens in the DC. Constraint (31) indicates capacity limitation at DCs and enforces the order size to be less than capacity of DC. Constraints (32) and (33) represent binary variables of distribution and backup centers. Constraint (34) implies that in case of shortage, L backup centers will be active. Equation (35) indicates the inventory balance at DC. Constraint (36) expresses the flow of products from backup center to DC in case of shortage. Constraint (37) restricts the quantity of products transferred from a backup center to a DC to be more than shortage amount. Relation (38) is the mathematical implication of inventory shortage amount. Constraint (39) is designed to determine the value of $Q'_{ok'v}$. Constraints (40) and (41) indicate that, if $Q'_{ok'v}$ is set to 1, order quantity will be meaningful. Constraint (42) represents the allocation of orders to backup centers and constraint (43) restricts the value of orders from suppliers to backup centers. Constraint (44) indicates the allocation of $DC_{k'}$by setting a binary variable. If $DC_{k'}$is allocated, an order equal to $Q_{1ok'v}$ is placed for this DC. Relation (45) determines the upper limitation of the shortage. Constraints (46), (47) and (48) are considered for hard time windows. Constraints (49), (50) and (51) indicate negative, binary, and integer variables, respectively.

3-5- Equivalent linear and crisp form of the model

Due to the uncertain nature of the parameters mentioned in the model and lack of knowledge about the variability range of these parameters, the uncertain parameters are assumed to be in the form of fuzzy parameters. Since some parameters of the model are regarded as triangular fuzzy numbers, therefore, the first and third objective functions show an uncertain behavior. In this regard, according to (Torabi and Hassini, 2008), the crisp form of the proposed model is reached. So, the cost function (18) and constraints (46) to (48) are reformulated as equivalent deterministic relations. In addition, the objective function (20) is linearized. Thus, the final linear and deterministic model is as follows:

$$minZ_1^2 = \omega + \sum_{k'} h_{k'} \cdot Z_\alpha \sqrt{lt_{2k'} \sum_i \sigma_i^2 \cdot y_{ik'}} + \sum_o \sum_k \sum_{v \in v_1} tr_{okv} \cdot N_{2okv} \cdot Q_{2okv} \cdot d_{2ok} \tag{52}$$

$$maxZ_1^{2-1} = \omega + \sum_{k'} h_{k'} \cdot Z_\alpha \sqrt{(lt_{2k'} - lt_{1k'}) \sum_i \sigma_i^2 \cdot y_{ik'}} \tag{53}$$

$$minZ_1^{3-2} = \omega + \sum_{k'} h_{k'} \cdot Z_\alpha \sqrt{(lt_{3k'} - lt_{2k'}) \sum_i \sigma_i^2 \cdot y_{ik'}} \tag{54}$$

$$minZ_3 = \varphi \tag{55}$$

Subject to: (21) - (45), (49) -(51)

Relations (56) to (64) ensure hard time window constraints of the problem and constraints (65) to (67) indicate linearization constraints of the third objective function.

$$At_{Iv} + t_{1II'v} + St_{1t} - At_{I'v} \leq U \cdot w_{II'v} \qquad \forall II'v \in v_{1.2} \tag{56}$$

$$At_{Iv} + t_{2II'v} + St_{2t} - At_{I'v} \leq U \cdot w_{II'v} \qquad \forall II'v \in v_{1.2} \tag{57}$$

$$At_{Iv} + t_{3II'v} + St_{3t} - At_{I'v} \leq U \cdot w_{II'v} \qquad \forall II'v \in v_{1.2} \tag{58}$$

$$e_{1I'} \leq At_{I'v} + St_{1I'} \leq l_{1I'} \qquad \forall I'v \in v_2 \tag{59}$$

$$e_{2I'} \leq At_{I'v} + St_{2I'} \leq l_{2I'} \qquad \forall I'v \in v_2 \tag{60}$$

$$e_{3I'} \leq At_{I'v} + St_{3I'} \leq l_{3I'} \qquad \forall I'v \in v_2 \tag{61}$$

$$(1 - w_{II'v}) \cdot (At_{Iv} + t_{1II'v} + St_{1t} - At_{I'v}) \leq 0 \qquad \forall II'v \in v_{1.2} \tag{62}$$

$$(1 - w_{II'v}) \cdot (At_{Iv} + t_{2II'v} + St_{2t} - At_{I'v}) \leq 0 \qquad \forall II'v \in v_{1.2} \tag{63}$$

$$(1 - w_{II'v}) \cdot (At_{Iv} + t_{3II'v} + St_{3t} - At_{I'v}) \leq 0 \qquad \forall II'v \in v_{1.2} \tag{64}$$

$$\varphi \geq \alpha_{1II'v} \cdot w_{II'v} \qquad \forall II'v \in v_{1.2} \qquad (65)$$

$$\varphi \geq \alpha_{2II'v} \cdot w_{II'v} \qquad \forall II'v \in v_{1.2} \qquad (66)$$

$$\varphi \geq \alpha_{3II'v} \cdot w_{II'v} \qquad \forall II'v \in v_{1.2} \qquad (67)$$

4-Solution Approach

As the related studies show, the problem is comprised of three NP-hard problems including location, routing and inventory problems (Ahmadi-javid and seddighi, 2011). In addition, considering contradicting objective functions, uncertainty and non-linear nature of the problem increases the complexity of the model. Thus, two multi-objective metaheuristic algorithms namely MOGWO and NSGA-II are applied to solve the large-sized instances.

4-1- NSGA-II

NSGA-II is a population-based metaheuristic algorithm introduced by Deb in 2001. This algorithm starts by generating an initiative population and ranking the results of the initial group. NSGA-II uses crossover and mutation operators for the exploration and exploitation of the search area. Figure 2 show the summary of the NSGA-II.

Procedure of next generation(P_{t+1})

$R_t = P_t \cup Q_t$	*combine parent and offspring population*
F=fast-non-dominated-sort(R_t)	*F=(F_1,F_2,...), all non-dominated fronts of R_t*
$P_{t+1} = \emptyset$ *and* $i = 1$	
until $\lvert P_{t+1}\rvert + \lvert F_i\rvert \leq N$	*until the parent population is not filled*
crowding-distance-assignment(F_i)	*calculate crowding-distance in F_i*
$P_{t+1} = P_{t+1} \cup F_i$	*include ith non-dominated front in parent*
pop	
i=i+1	*check the next front for inclusion*
sort($F_i, \prec_n$)	*sort in descending order using* $\prec_n$
$P_{t+1} = P_{t+1} \cup F_i[1:(N - \lvert P_{t+1}\rvert)]$	*choose the first* $(N - \lvert P_{t+1}\rvert)$ *elements of F_i*
Q_{t+1}=make-new-pop(P_{t+1})	*use selection, crossover and mutation to create a new population Q_{t+1}*
t=t+1	*increment the generation counter*

Fig 2. Pseudo code of NSGA-II algorithm

4-2- Grey wolf optimization algorithm

The GWO or Gray Wolf Optimizer algorithm is a metaheuristic method inspired from social leadership and hunting technique of grey wolves, developed by Mirjalili et al (2014). In GWO, optimization is directed by α, β, δ wolves and the rest of the wolves (ω) follow them. Grey wolves besiege their prey during hunting. Grey wolves are able to identify the hunt position and besiege it. Hence, the first three best solutions are provided to be saved. The Pseudo code of MOGWO algorithm is provided in figure 3.

```
Initialize the gery wolf population Xi (i=1, 2, ..., n)
Initialize a,A and C
Calculate the fitness of each search agent,
Xα=the best search agent,
Xβ= the second best search agent,
Xδ= the third best search agent,
While (t< max number of iteration)
For each search agent;
Update the position of the current search agent by equation (5-4) to (7-4).
End for
Update a,A and C
Calculate the fitness of all search agent,
Do fast Non-dominated sorting,
Update Xα, Xβ and Xδ,
T=t+1,
End while,
 Return Xα
```

Fig 3. Pseudo code of MOGWO algorithm

5- Numerical results

5-1- Model validation

In this section, the feasibility of the model is assessed by solving the model with exact solvers. In this regard, the linearized version of the model is solved by GAMS using CPLEX solver. Due to the multi objective nature of the problem, the model is divided into three sub-problems. Each sub- problem is comprised of a single objective function; the rest of constraints are included in the proposed sub-problems. The number of distribution centers is equal to 3, backup centers are numbered 4, 5, 6, and finally, there exist 3 customers numbered from 7 to 9. Other related data are generated randomly with the upper and lower limits specified in table 7.

Table 7. Validation problem data

Parameters	Lower bound	Upper bound
f_k	1000	8000
$ff_{k'}$	1000	8000
σ_i^2	10	20
$h_{k'}$	10	30
f_k'	10	50
$\cos t_{ok'v_1}$	10	30
tr_{okv_1}	10	30
$C_{II'}$	50	80
$mo_{kk'}$	50	100
$\cos t_{k'}'$	10	30
$safety_k$	0.1	0.3
$\tilde{\alpha}_{IIv_2}$	0	1
L'	5	15

The optimal values of objective functions are reported in table 8.

Table 8. Optimal values of objective functions

Objective function	Optimal value
Distribution and storage costs	12,945,675
Environmental pollutions cost	6,485,266
Transportation risk	127,951

Figure 4 illustrates the optimal solution of the problem. According to the results, the relationships between the nodes in the network are logical. The model assigns only one backup center to the system and connects the retailers to two distribution centers. This structure makes a balance between different costs of the system.

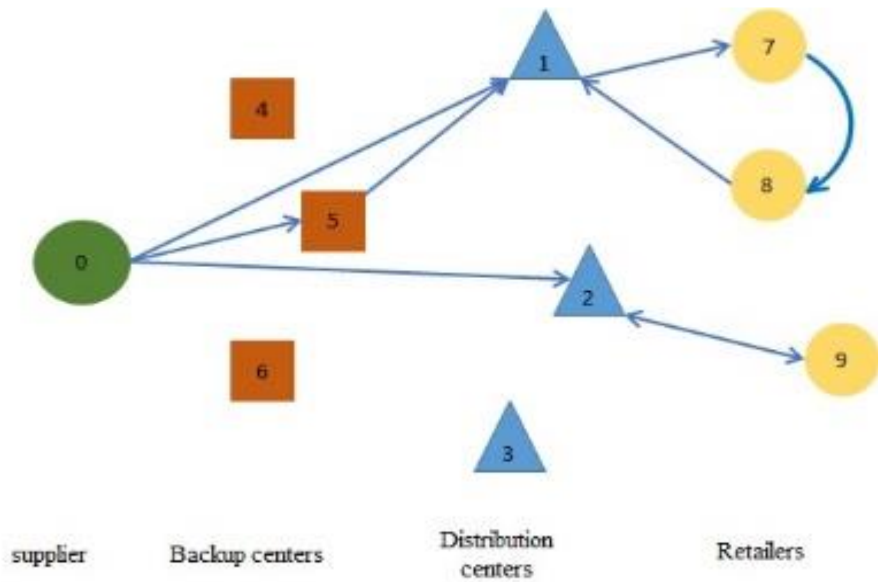

Fig 4. Optimal solution of the problem

5-2- Solution representation scheme in metaheuristic algorithms

To use a metaheuristic algorithm for solving a given problem, the definition of the nominated solutions in the proposed algorithm is an important issue. In the proposed problem, each solution is composed of 6 vectors named from x1 to x6, containing continuous values between 0 and 1.

Vector X_1: Shows the visiting priority of customers.
Vector X_2: Demonstrates the customer allocation to DCs.
Vector X_3 : Is related with the allocation of customers to vehicles. Cells with value from 0 to 1/V are allocated to vehicle 1, cells with value from $1/V$ to $2/V$ are allocated to vehicle 2.
Vector X_4: Shows the allocation of DCs to backup centers.
Vector X_5: Indicates the number of visiting conducted by a vehicle. Each cell contains a value implying a DC has been visited.
Vector X_6: Determines which vehicle is allocated to each DC in level one.
By Determining the vector X_4 and X_6, the number of items sent to each DC is calculated taking into consideration the vehicle capacity. Thereafter, the shortage possibility is calculated. Figure 5 illustrates an instance of the designed chromosome.

X_1	0.74	0.12	0.48	0.96	0.27	0.35
X_2	0.83	0.62	0.48	0.53	0.86	0.79
X_3	0.43	0.27	0.33	0.89	0.73	0.04
X_4	0.62	0.57	0.19	0.64		
X_5	0.27	0.43	0.49	0.14		
X_6	0.97	0.39	0.27	0.88		

Fig 5. Representation of a chromosome of problem solution

5-3- Parameter tuning

To tune the parameters of the algorithms and improve the performance of the algorithms, a Taguchi method is utilized. The nominated values for the major factors of NSGA-II are provided in table 9 according to (Rabbani et al, 2018).

Table 9. value levels of Parameters for NSGA-II algorithm

algorithm	**parameter**	Quantity of level		
		Level1	Level2	Level3
NSGA-II	Percentage of Crossover (P_c)	0.7	0.8	0.9
	Percentage of Mutation (P_m)	0.05	0.1	0.15
	Number of Solutions in the Population (N_p)	50	100	150
	Max_iteration	100	200	300

Figure 6 provides the results of Taguchi method.
In addition, the suggested values for parameters of MOGWO are provided in table 10.

Table 10. Parameters and their value levels for MOGWO algorithm

algorithm	**parameter**	Quantity of level		
		Level1	Level2	Level3
MOGWO	Number of search agent (N_s)	10	20	50
	Change position rate (P_r)	0.1	0.2	0.3
	Max_iteration	100	200	300

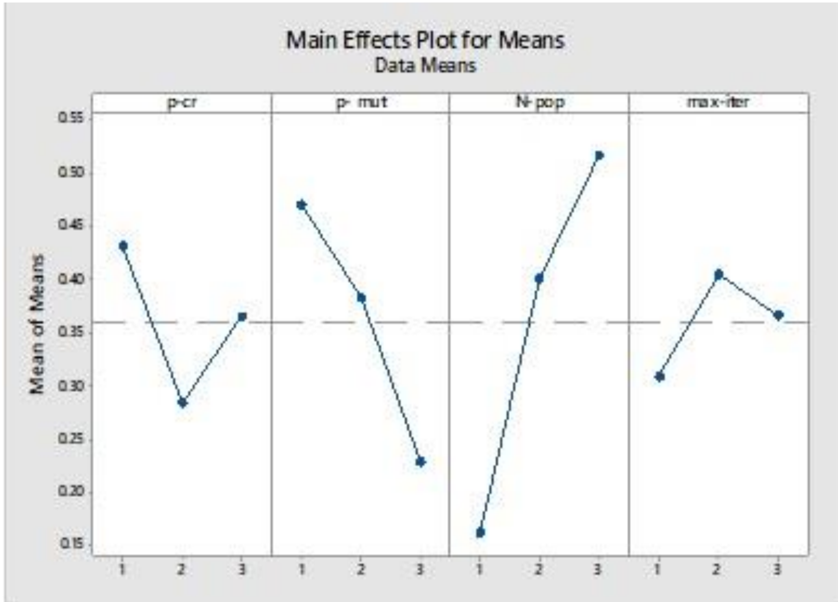

Fig 6. Comparison of the mean of the answers for the NSGA-II algorithm

Figure 7 depicts the related results of Taguchi method for MOGWO algorithm too.

Fig 7. Comparison of the mean of the answers for the MOGWO algorithm

6- Comparative results

Considering the multi-objective nature of the problem, some factors are defined to compare the results of proposed metaheuristic algorithms described as follows.

Max spread (DM): This metric show how the pareto answers are scattered. Larger values of this metric, indicate that algorithm have high efficiently:

$$DM = \sqrt{\sum_{i=1}^{n} (minf_i - maxf_i)^2} \tag{71}$$

Mean ideal distance (MID): The value of this metric is related to the distance between pareto points and the ideal point. The lower value of this metric show that algorithm have better performance:

$$MID = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f_{1i}-f_1^{best}}{f_{1total}^{max}-f_{1total}^{min}}\right)^2 + \left(\frac{f_{2i}-f_2^{best}}{f_{2total}^{max}-f_{2total}^{min}}\right)^2}}{n} \tag{72}$$

The rate of achievement to objective simultaneously (RAS): This metric makes a balance between goals.

$$RAS = \frac{\left[\left|\frac{f_{1i}(x)-f_{1i}^{beat}(x)}{f_{1i}^{beat}(x)}\right| + \left|\frac{f_{2i}(x)-f_{2i}^{beat}(x)}{f_{2i}^{beat}(x)}\right|\right]}{n} \tag{73}$$

To compare the performance of the developed algorithms based on the given metrics, 19 problem instances (numerical examples) in different sizes are generated and the related results are included in Appendix A. Tables 11 and 12 summarize the results of NSGA-II and MOGWO respectively.

Table 11. NSGA-II algorithm output for 19 numerical examples

	NSGA-II						Solution time
No#	MID	Max spread	SM	NPS	RAS	SNS	
1	2128.402	1948.62643	388.3026	99	0.451629	337.138	19.6
2	9901.841	2994.92402	947.1654	97	0.343909	1327.495	24.8
3	14960.24	4251.83043	1626.795	97	0.183981	1424.479	26.9
4	26614.19	4859.99894	656.5366	100	0.224434	2013.4	34.8
5	43885.55	7192.19064	3292.813	95	0.268187	2982.944	39.7
6	65925.99	5793.68036	1670.296	98	0.033118	3692.972	45.6
7	170150.2	27237.3369	7986.59	98	0.161788	6394.361	51.7
8	252032.8	13156.2508	5583.598	99	0.105741	4870.001	62.7
9	284951.5	34799.2004	16779.53	95	0.212974	9177.958	63.8
10	381924	10841.6594	15844.87	96	0.083745	4170.522	67.4
11	407187.7	15401.8929	13023.62	97	0.169853	5017.187	73.5
12	511353.5	31636.8040	22114.78	96	0.111687	6296.453	78.9
13	564882.1	19289.8738	23743.56	96	0.084279	5480.24	84.9
14	1018173	13870.8791	21063.69	98	0.082837	4831.171	95.1
15	1135045	38126.7724	46694.52	96	0.116901	6484.229	102.1
16	1384478	48452.8222	57609.56	96	0.124858	11310.78	116.3
17	1843051	29375.6547	6594.312	100	0.110827	7245.205	121.9
18	2187982	122226.418	74481.82	97	0.203288	25578.92	127.3
19	2324567	30865.7246	25490.3	99	0.076859	8181.96	138.6
Average	664694.4	24332.7652	18189.09	97.31579	0.165837	6148.285	72.4

The results for MOGWO are provided in table 12, as well.

Table 12. MOGWO algorithm output for 19 numerical examples

			MOGWO				Solution time
No#	MID	Max spread	SM	NPS	RAS	SNS	
1	2392.871	1229.484	387.0695	29	0.501259	62.36729	21.9
2	10025.83	5984.361	2126.98	7	0.226547	811.6118	22.2
3	17064.71	2621.545	1115.375	12	0.202768	630.3547	23.5
4	29887.93	263.0591	71.44966	11	0.021221	36.73556	34.4
5	43253.99	5162.052	1438.363	19	0.122953	1676.061	38.6
6	65007.11	9463.854	3411.264	13	0.096517	2778.861	42.3
7	172745.8	15061.96	3498.732	35	0.147178	2442.37	55.3
8	256509.7	19706.37	5928.794	27	0.113406	4474.071	57.5
9	273177.9	32119.22	6887.26	30	0.094122	4848.212	65.1
10	367442.1	27278.38	8144.148	37	0.080044	10614.28	74.2
11	396215.3	12784.23	3333.181	20	0.05852	2116.804	76.5
12	500211	19204.24	5713.979	18	0.081107	7539.665	79.9
13	535189.2	45799.99	10652.97	22	0.109507	5908.288	87.8
14	1007010	41500.52	9102.659	33	0.067525	5083.914	93.8
15	1118785	29107.15	5011.775	56	0.04178	2630.089	109.7
16	1346664	72629.74	14150.27	42	0.079241	8890.723	121.4
17	1888444	46733.89	12186.75	23	0.082087	6959.926	133.2
18	2163074	61189.45	14309.2	35	0.050732	8877.949	146.1
19	2392.871	1229.484	387.0695	29	0.501259	62.36729	150.5
Average	566283.4	24879.97	5970.568	26.05556	0.120918	4243.46	75.5

Figure 8 illustrates that that MOGWO outperforms NSGA-II in terms of MID metric.

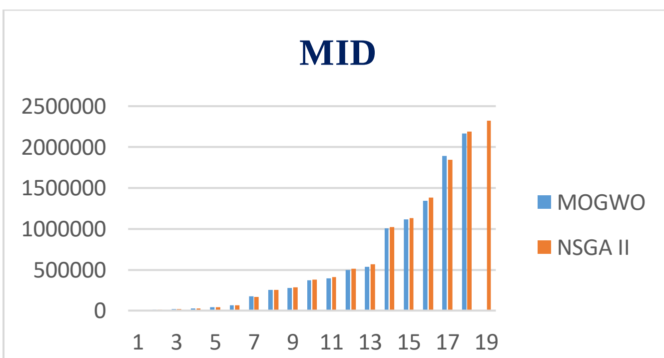

Fig 8. Comparison between the algorithms in terms of MID metric

The average of DM metric is equal to 5162 and 24879 for NSGA-II and MOGWO, respectively. Figure 9 provides the values of this metric for all the problem instances solved by both of the algorithms. Due to the characteristics of DM, MOGWO algorithm has a better performance than NSGA-II in terms of this metric. The data of table 10 and 11 show that the mean value of RAS metric for NSGA-II is 0.165 and for MOGWO algorithm is 0.12. As evident from the figure 10, MOGWO gives lower values for most of the test problems which demonstrates it has better performance in comparison with NSGA-II algorithm, regarding RAS metric formulation.

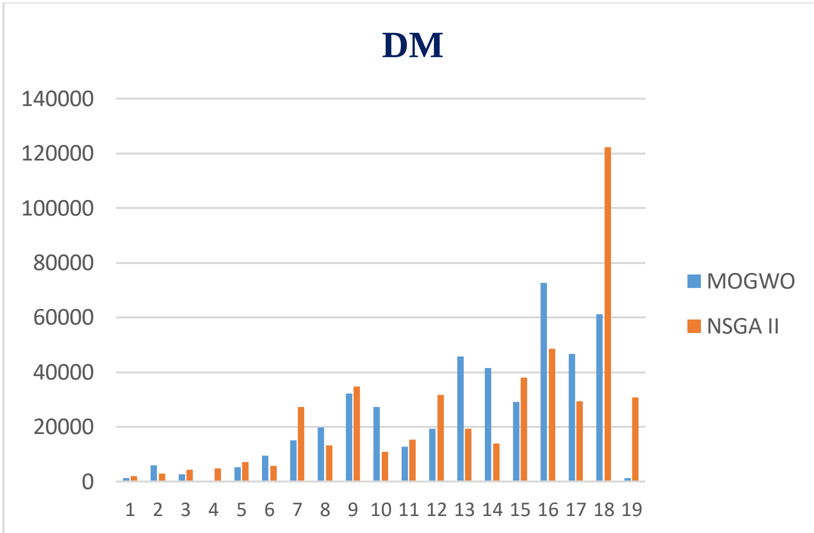

Fig 9. Comparison between the algorithms in terms of DM metric

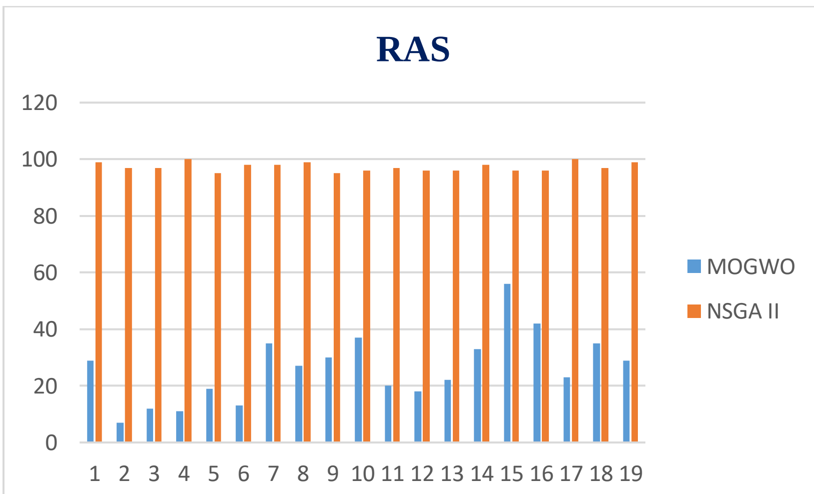

Fig 10. Comparison between the algorithms in terms of RAS metric

The results show that the mean of run time for NSGA-II algorithm is 72.4 seconds, while MOGWO takes 75.5 seconds to solve the problem in average. Figure 11 compares the solving time for NSGA-II against MOGWO algorithm.

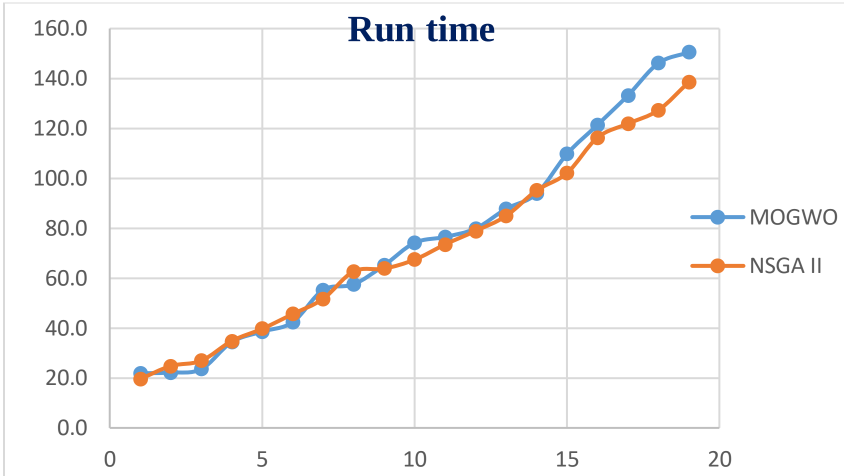

Fig11. Comparison between solving time of the both algorithms

As figure 12 represents, solving time metric is similar for both of the algorithms in the most of the test problems. However, MOGWO takes more run time for large-sized instances.

7- Discussion

In this section the behavior of the model is assessed to extract managerial insights for the model. In this regard, a Beverage production and distribution company around the Tehran is selected to implement the model in a real situation. The introduced company has about 300 personnel. Decreasing the related costs, reliability of delivery system and environmental issues due to governmental legislation are the major concerns of the company. The proposed company is comprised of 10 major customers, 3 DCs, and 3 backup centers. Considering the features of the company, the demand of items follows a normal distribution with range of [20,150] and [10,20]. Also, Transportation and ordering costs are generated randomly between [10,80] and [10,30]. The main parameters of the mathematical model include the risk of route, emission coefficient as well as cost parameters and lead time. Hence, the effects of changing the given parameters on the objective functions, is assessed. Figure 12 depicts the location of suppliers, retailers, DCs and BDCs in the proposed case.

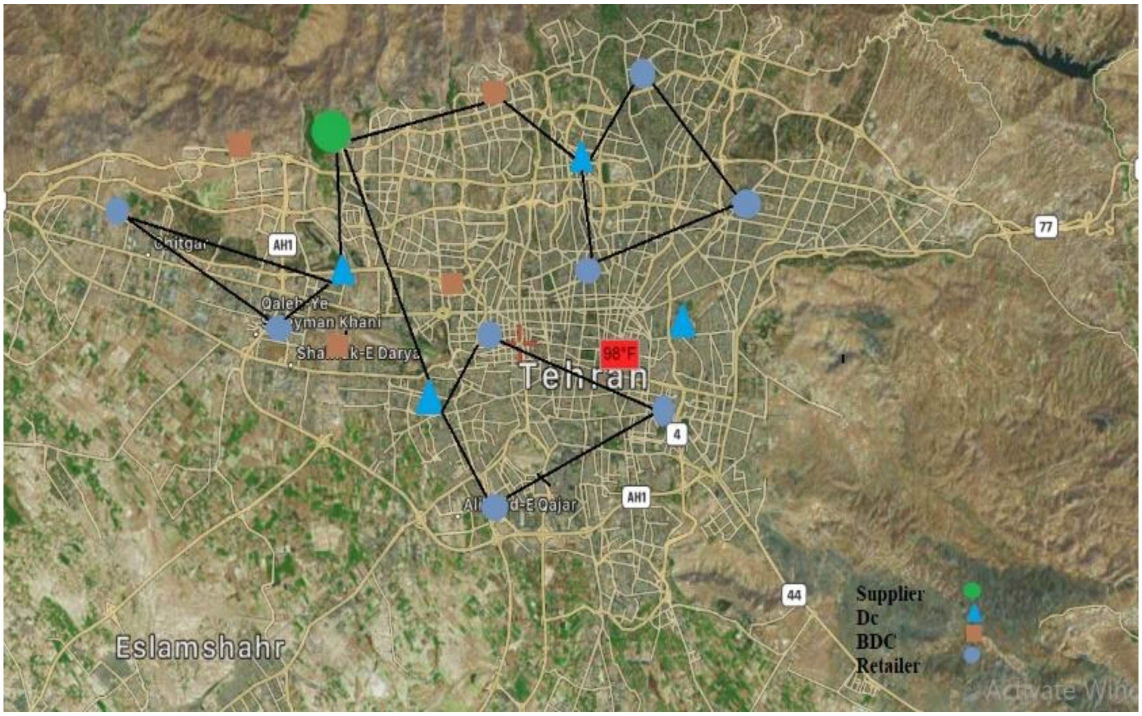

Fig 12. The number of routes, DCs and BDCs

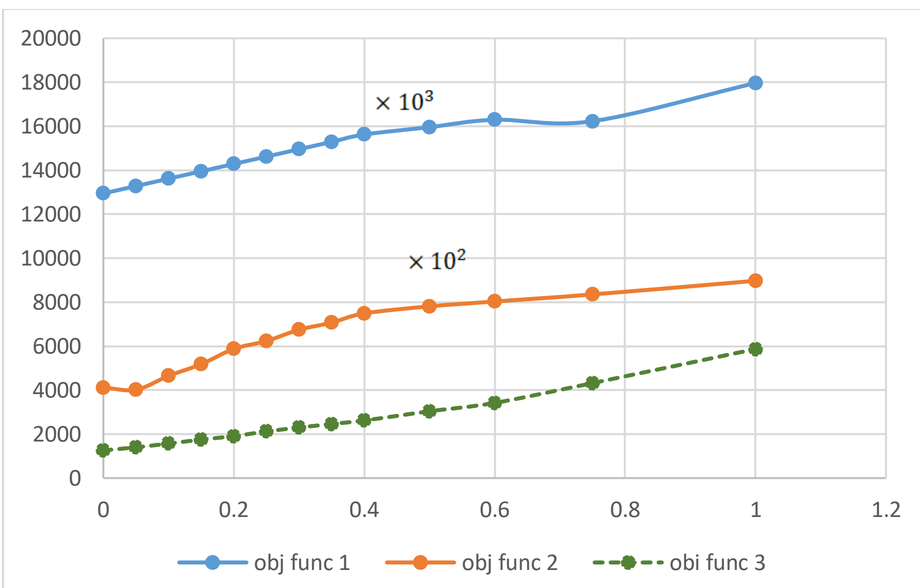

Fig 13. Trend of the objective functions under changes to risk of the route

Figure 13 represents the effect of changing the risk of the route on three objective functions simultaneously. According to the results, increasing the value of risk of the route parameter leads to a sharp increment of the third objective function. The slope of the increase in the third objective function reaches its highest value when the parameter enhances from 20 percent to higher values. By increasing the risk factor, the fuel consumption of vehicles increases and the amount of emission enhances during the shipment of items. In addition, the transportation cost between nodes increases leading to raise in the total cost of the system.

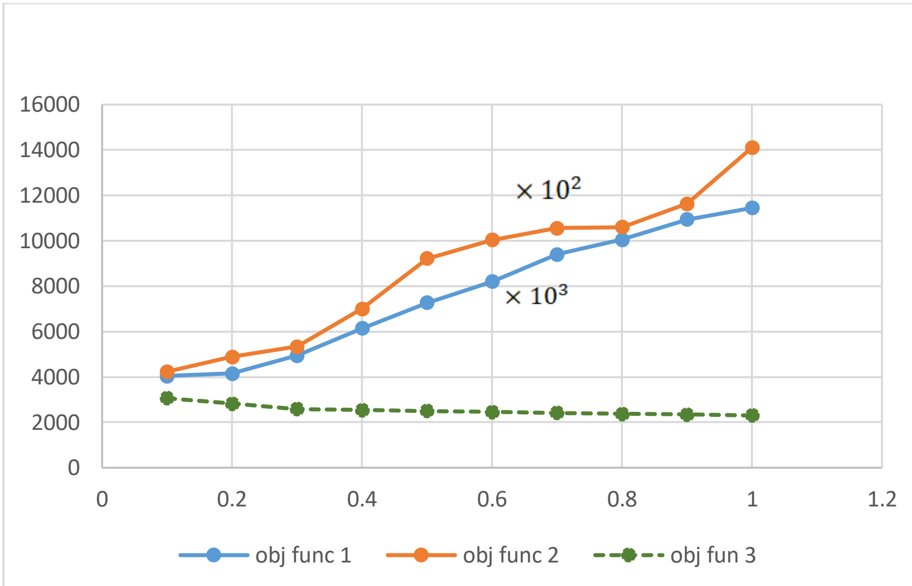

Fig 14. Trend of the objective functions under changes to the pollutants emission coefficient

Figure 14 shows the increasing trend for the second objective function under changing the emission parameter. The sharpest slope of the second objective function is when the parameter increases to 90 percent. The reason for this behavior is that the considered parameter is regarded in different sections of the second objective function. There are two main reasons for increasing the pollution parameters, firstly the number of vehicles has reduced and their carrying capacity has increased. Secondly, the routes with less distance are selected. The model tends to reduce the route risk, so the total cost of the system shows an increasing trend.

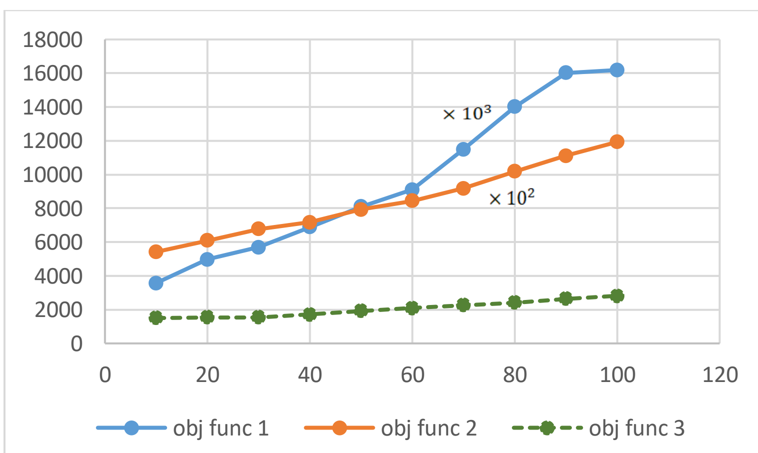

Fig 15. sensitive analysis for holding cost changes on objective functions

Figure 15 indicates that increasing the holing cost of the model leads to higher values of total cost. Since enhancing the holing cost, leads to higher amounts of service level and vehicle number.

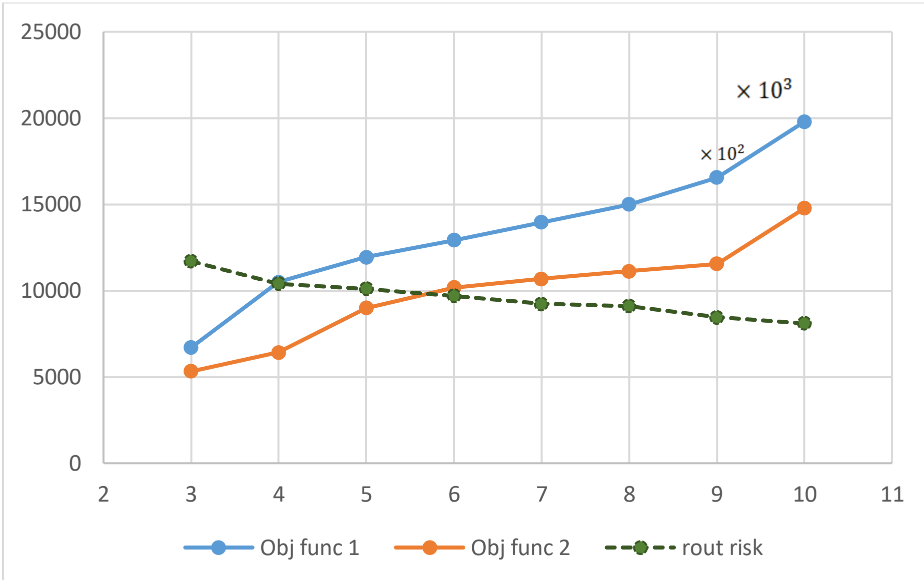

Fig 16. Sensitivity analysis for the number of DCs

The results of figure 16 show that, with a raise in the number of DCs, the total cost of the system increases. But the slope of increment is slowly and the reason is that by increasing the number of DCs, the model decides to ship the items to more near DCs. Thus, the shipping costs are decreased and as a result, with increasing the number of DCs, the risk of the route shows an increasing trend while reducing the emissions behaves conversely.

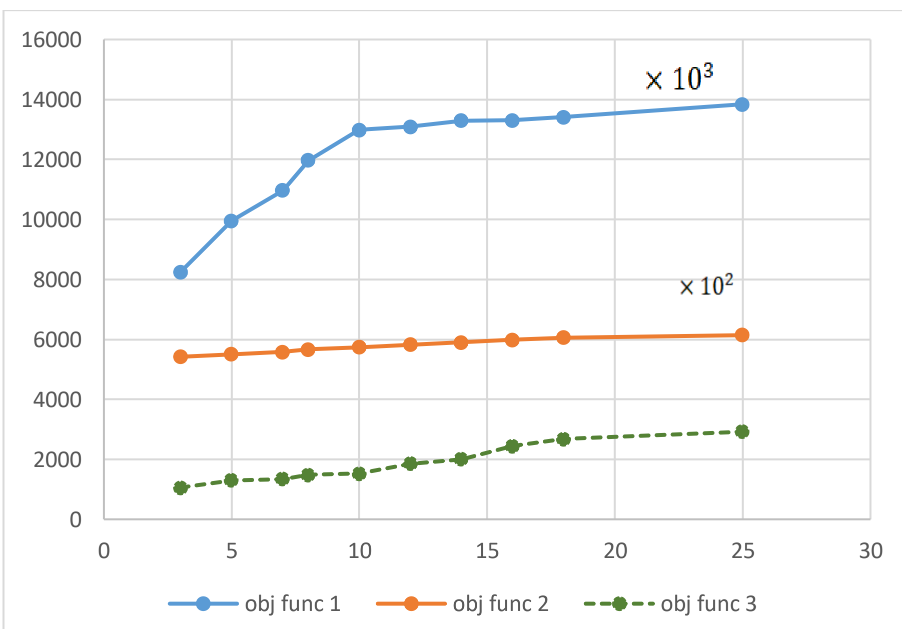

Fig 17. Sensitivity analysis for change of lead time

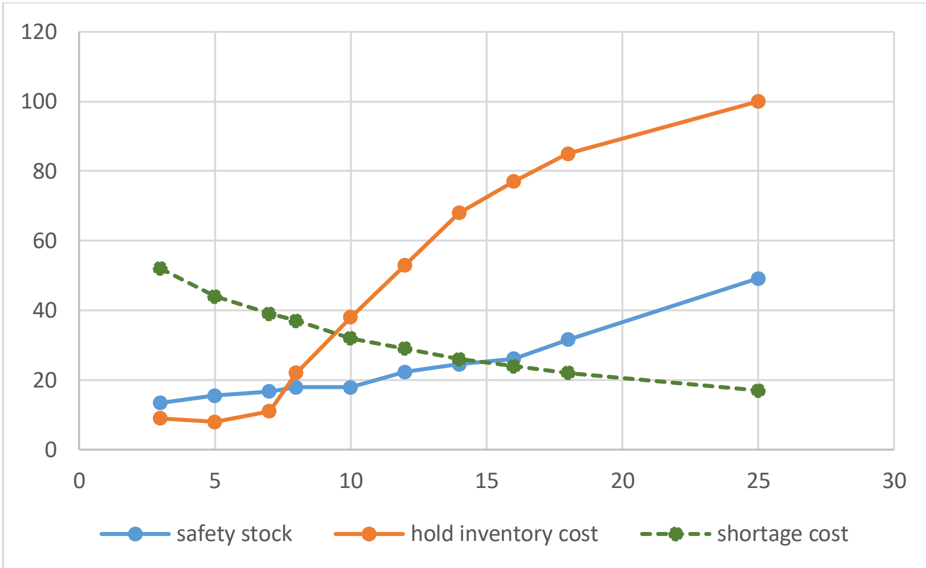

Fig18. effect of lead time changing on inventory holding cost, safety stock, shortage cost

Figure 17 and 18 illustrate the effect of increasing the lead time on the changing trend of inventory holding, safety stock, shortage and total costs. Based on the results, one can see that enhancing the value of safety stock leads to higher amounts of inventory holding cost and lower amount of shortage cost. As a result, the total cost and service level of the system show an increasing trend. In addition, the risk of the routes has increased too.

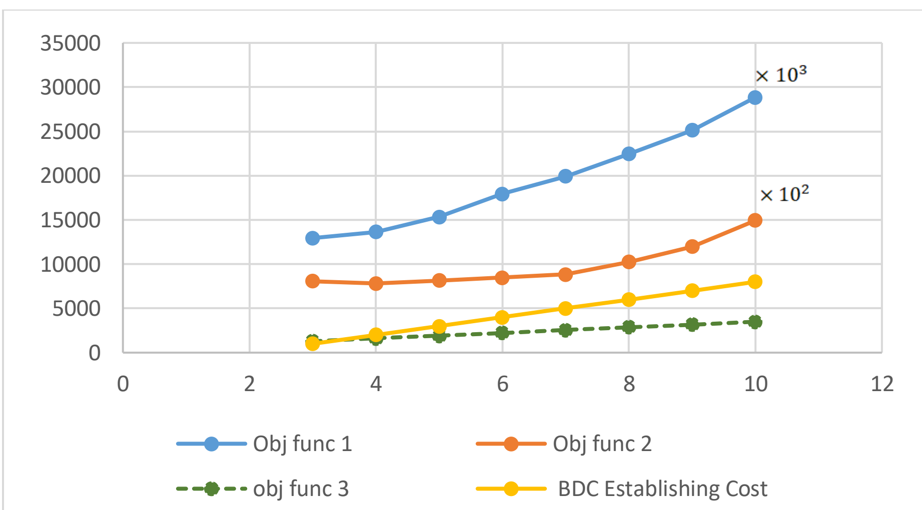

Fig19. Sensitivity analysis for the number of BDCs

The results of figure 19 show that, with increase in the number of BDCs, the total cost of the system enhances. The main reason is that with raise in the number of BDCs, the cost of deploying these centers, and the transportation cost of BDCs increases simultaneously. On the other hand, the cost of pollution caused by the establishment and operational actions of these centers has also increased. In addition, the inventory holding costs in these centers should be considered. As a result, with increasing the number of BDCs, the emission and risk of the route shows an increasing trend.

Based on the results, it can be concluded that the establishment of BDCs is economically justified if the products are appealing for the customers and their related shortage causes high costs to the organization. On the other hand, inventories are the important factor in an organization and due to relatively high investment; inventories need more careful planning and control. Thus, decision makers should set a balance in the system considering according to the level of inventories. Since decision makers and managers cannot control the demand under normal circumstances, the best way to manage the inventory costs is by paying attention to the time and amount of new orders and number of items that should be held for the next periods.

8- Conclusion

In this study, a SCN comprising of suppliers, distribution centers and customers (or retailers) is designed. In addition, this study introduces a new location-inventory-routing model for supply chain network design by determining the related decisions of distribution and backup centers establishment. The proposed multi objective model includes shortage of inventory, allocation of customers to distribution centers, routing decisions, establishing new centers, and backup strategies. The model aims to reduce the related costs, environmental pollutions and transportation risks at the same time. As on of the main contributions of the current study, different factors were detected affecting the shipment risks of the system. In this regard a fuzzy TOPSIS method was applied to rank the related factors of shipment risks. Considering the time windows was another contribution of the proposed the model. In the next step, the results of the exact solver were compared with the results of the proposed metaheuristic algorithms for small-sized test problems to ensure about the performance of the metaheuristic algorithms and feasibility of the model. In addition, large-scale problems were solved by two metaheuristic algorithms namely NSGA-II and MOGWO and the results were compared. According to the comparative results, the MOGWO algorithm was able to reach results with better qualities, however, the NSGA-II had shorter run time for large-sized test problems. In addition, a sensitivity analysis was conducted on a real case to assess the behavior of the model and shows the applicability of the model in the real cases. According to the results, increasing the holding cost affects the model with grater slope compared to increasing the number of DCs. For future studies, considering soft and hard time window simultaneously or separately, regarding direct transportation from supplier to customer in case of large demand of the customer are suggested.

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Appendix A:

Numerical examples information

NO#	Number of customers	Number of DCs	Number of vehicles in level 2	Number of vehicles in level 1	Number of BDCs
1	6	4	2	1	1
2	8	5	2	1	2
3	10	5	2	1	2
4	12	7	2	1	3
5	14	8	3	1	3
6	16	8	3	1	4
7	18	10	3	2	4
8	20	12	3	2	5
9	22	12	4	2	5
10	24	15	4	2	6
11	26	16	4	2	6
12	28	18	5	2	7
13	30	20	6	3	7
14	35	24	7	3	8
15	40	25	8	3	8
16	50	30	9	3	9
17	60	35	10	4	9
18	70	40	11	4	10
19	80	45	12	4	10