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Supplier Selection in Closed Loop logistics network design using Monte Carlo simulation with Robust-Fuzzy Approach

Seyyed Hesamoddin Motevalli[1], Seyed Hamidreza Razavi[2*], Saeid Emamgholizadeh[3]

[1]*Faculty of human sciences,Ph.d in future studies, Shomal University, Amol,mazandaran,Iran*
[2]*Assistant professor, department of management, shomal university, Amol, Iran*
[3]*Associate Professor, department of management, shomal university, Amol, Iran*

Abstract

Globalization of economic activities along with the rapid growth of technology as well as limited resources have placed companies in a tight competition. Among the competitive advantages for companies is to make activities such as the supply chain more efficient and effective. Since suppliers exert a fundamental influence on the success or failure of a company, it is known as a strategic task. Considering the importance of supplier selection, in this paper a reverse logistics network model is designed for supplier selection under uncertainty. The objective functions of the designed model include minimizing the total cost, the total number of defective parts, the timely delivery of all parts to the customer, and the hazardous environmental factors associated with suppliers. In order to be closer to reality, parameters such as demand, transportation cost, product production costs, and product purchase price are considered uncertainty, and robust-fuzzy approach is used to deal with uncertainty parameters in modeling. Finally, in order to avoid weighting in multi-objective model decision making, Monte Carlo simulation has been developed to determine the total number of Pareto solutions from the presented model. The results of the evaluation of the mathematical model with the robust-fuzzy approach show that as the penalty coefficients of the objective function increase, the cost of the total supply chain network increases, but its standard deviation decreases. This issue shows the high capability of the robust method in controlling the uncertainty model of the problem.

Keywords: Closed Loop Logistics, Uncertainty, Robust-Fuzzy Approach, Monte Carlo Simulation.

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* Corresponding Author
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1. Introduction

In today's global markets, companies are not unique brand-name units that can operate independently, but instead are an important part of a supply chain. In this case, the final success of a company depends on its managerial ability to integrate and coordinate a network of business relationships among supply chain members. Since suppliers exert a fundamental influence on the success or failure of a company, purchasing, which was once considered a purely tactical tool, is now recognized as a strategic task (Amin & Zhang, 2012). The network design problem is one of the most comprehensive strategic decision-making problems that requires optimization for the long-term efficient operation of the entire supply chain (Azadeh et al., 2016, Gharachorloo et al., 2021).

In order to understand the supply chain, one should be familiar with the concept of supply chain network design. Network design specifies the number, location, capacity and types of factories, warehouses and distribution centers. It also determines the distribution channels and the number of materials and items for consumption, production and movement from the producer to the customers. On the other hand, in today's highly competitive environment, the high speed of changes and developments has increased the uncertainty governing decisions, so planning for the design of the supply chain network in an atmosphere of certainty and complete certainty is no longer the answer (Nasr et al., 2021, Nozari et al., 2012). In fact, uncertainty is one of the main characteristics of customer-facing systems. The high level of uncertainty in the supply chain hampers the chain's ability to predict future conditions. Considering this importance, the sources of uncertainty in the supply chain must be effectively managed, therefore, in order to plan better and more correctly, planning should be done in the atmosphere of uncertainty (Ren et al., 2024, Nozari, 2024).

The ever-increasing development of the competitive environment and the globalization of the product market have caused organizations to make significant efforts to optimize their company's supply chain in order to survive in the market, so that they have the ability to respond to the fast and diverse needs of customers with minimal cost and time (Rastami et al., 2023). Therefore, supply chain management emphasizes the integration of activities as well as the information and physical flow related to it through the improvement of the relationship between them, to achieve a reliable and sustainable competitive advantage (Hashemi-Amiri et al., 2023). This management includes a set of methods to integrate the effectiveness and efficiency of suppliers, manufacturing plants, warehouses, distribution centers and retailers in such a way that goods are produced and distributed in the right quantities, at the right place and at the right time, as well as system costs to meet the service level. need to be minimized (Ishizaka et al., 2023).

Supply chain management is defined as the integration of logistics services along the supply chain. In order to make the difference between supply chain management and logistics management clearer, the International Association of Logistics Management has presented a modified definition of it. In this definition: Logistics management is the process of efficient planning, execution and control that includes the storage of raw materials, work-in-progress inventory, finished products and related information from the point of origin to the point of destination, which is defined in order to meet some needs of customers or large companies (Bai et al., 2024). The terms logistics and supply chain are often used interchangeably in the transportation industry. However, the process, duties and responsibilities of each one are different and the main difference is that logistics is only a part of the entire supply chain process. In general, logistics focuses on the transportation and storage of goods and deals with features such as transportation, communication in transportation, and warehousing. While in most cases supply chain includes a bigger picture and includes all aspects of sourcing and purchasing goods. Recently, with the presence of the concept of supply chain management, more researchers, scientists and managers have realized that choosing the right supplier and managing it is a tool that can be used to increase the competitiveness of the supply chain (Yavari et al., 2020).

Basically, there are two types of supplier selection issues: 1- There are no restrictions on supplier selection; In other words, each supplier is able to meet the needs of the buyer, including the amount of demand, quality, delivery time, etc., and 2-supplier selection in a situation where there are limitations in the capacity of the supplier, the quality of the supplier's product, etc. In other words, a supplier is not able to meet the buyer's needs, and the buyer must produce part of his demand from one supplier and another part from another supplier in order to compensate for the lack of capacity or low quality of the first supplier. Regarding the first case, one supply meets all the needs of the buyer, (single sourcing), in which case the management makes only one decision and which supplier is the best (Hejazi & Khorshidvand, 2024). While in the second case, none of the suppliers are able to meet all the needs of the buyer. Therefore, in this case, more than one supplier should be selected (multiple sourcing). In this case, the management must make two decisions: First, which suppliers are the best? And second, how much should be purchased from each of the selected suppliers? Considering the importance of supplier selection in closed-loop logistics, this article has presented a new model of this problem in the conditions of uncertainty, in which different strategic and tactical decisions are taken simultaneously.

Considering the multiple objective functions of the mathematical model, Torabi-Hassini method with Monte Carlo has been proposed to clarify the effect of the robust-fuzzy approach on the objective functions.

2. Literature Review

Govindan et al. (2020) developed a hybrid approach of fuzzy analysis network process (FANP), fuzzy decision-making trial and evaluation laboratory (FDEMATEL), and multi-objective mixed-integer linear programming (MOMILP) models for circular supplier selection and order allocation in a multi-product circular closed-loop supply chain (C-CLSC) considering multi-depot, capacitated green routing problem using heterogeneous vehicles. Tirkolaee et al. (2020) considered three levels of the supply chain, i.e., suppliers, central warehouses, and wholesalers. They used a novel hybrid approach based on the fuzzy logic to address the sustainable supplier selection problem. To assess the applicability of the suggested methodology, a case study of the lamp supply chain was considered and solved using GAMS/CPLEX solver and optimal policies based on suppliers' sustainability. Chen et al. (2020) proposed a novel framework to identify smart-sustainable SCMP (supply chain management practices) as supplier selection criteria for a smart supply chain. They used a hybrid rough-fuzzy DEMATEL-TOPSIS approach to sustainable supplier selection for a smart supply chain. The proposed method combines the strength of the fuzzy set in handling internal uncertainty and the advantages of the rough set in manipulating external uncertainty.

Boronoos et al. (2021) developed a novel multi-objective mixed integer nonlinear programming model for a closed-loop green supply chain network design problem. The proposed model aims to minimize the total costs, total CO2 emissions, and robustness costs in both forward and reverse directions, simultaneously. To cope with flexible constraints and epistemic uncertainty in the model's parameters, a robust flexible-possibilistic programming approach is tailored. Baghizadeh et al. (2021) developed a supply chain network based on a multi-period and multi-product Mixed-Integer Non-Linear Programming (MINLP) model in which the objective is to maximize the profit, minimize detrimental environmental effects, improve social effects, and minimize the number of lost demands. Because of the presence of uncertainty in some parameters, the proposed model, they formulated and optimized under uncertainty using the hybrid robust possibilistic programming (HRPP-II) approach. Shang et al. (2022) proposed a novel fuzzy MULTIMOORA-based method for SSS. The proposed method, firstly, obtains weights by both groups Best Worst Method (subjective method) and fuzzy Shannon Entropy Method (objective method), respectively. Nasrollahi et al. (2023) identified resilient supplier selection criteria in the desalination supply chain and analyze the interactions between them. They used two different multi-criteria decision-making techniques, i.e. interpretive structural modeling (ISM) and fuzzy decision-making testing and evaluation laboratory (fuzzy-DEMATEL), to identify driving criteria. Bathaee et al. (2023) designed a new closed-loop supply chain (CLSC) network model, including economic, social and environmental goals. This paper's primary purpose is to meet customers' uncertain demands in different scenarios where the new robust-fuzzy-probabilistic method has been used to estimate the exact demand. Also, they used NSGA II and MOPSO to solve the problem. Khalili-Fard et al. (2024) designed a multi-objective closed-loop supply chain model to develop sustainable objectives, where the most important objective was supplier selection. In this article, meta-heuristic and epsilon algorithms are used to form the Pareto front. Ala et al., (2024) proposed a novel optimization model to optimize multiple objectives, including minimizing the total costs and environmental impacts, while maximizing the social factors by creating jobs simultaneously. To address the effects of uncertain parameters, a fuzzy optimization method alongside the MOGWO, NSGA-II, MODEA, and ε-constraint are applied to optimize the model.

The review of the literature shows that the issue of supplier selection has attracted the attention of many researchers. However, in this paper, a new model of supplier selection in closed loop logistics under uncertainty is presented. The main feature of this model is to consider a discount with an uncertain selling price in the selection of the supplier. Also, the use of robust-fuzzy approach to control the uncertainty parameters is one of the other features of this paper.

3. Problem definition and modeling

The closed loop logistics network studied in this paper includes suppliers, production/reproduction centers, separation centers and disposal centers according to Figure (1). In this network, the suppliers send the parts needed for the production of products to the production centers. Production centers also produce and supply various products according to customer demand. In this network, a percentage of the products after use are collected by the separation center and usable parts are sent to the reproduction centers. In this stage, the parts that cannot be used are sent to the disposal centers. Usable parts are sent to reproduction centers to produce new products and are stored there. Then, based on the customer's demand, some of these parts are converted into new products and the rest are purchased from suppliers with a quantity discount. The selection of the supplier along with the level of discount offered and the price it offers for the sale of parts are among the important decisions of the network.

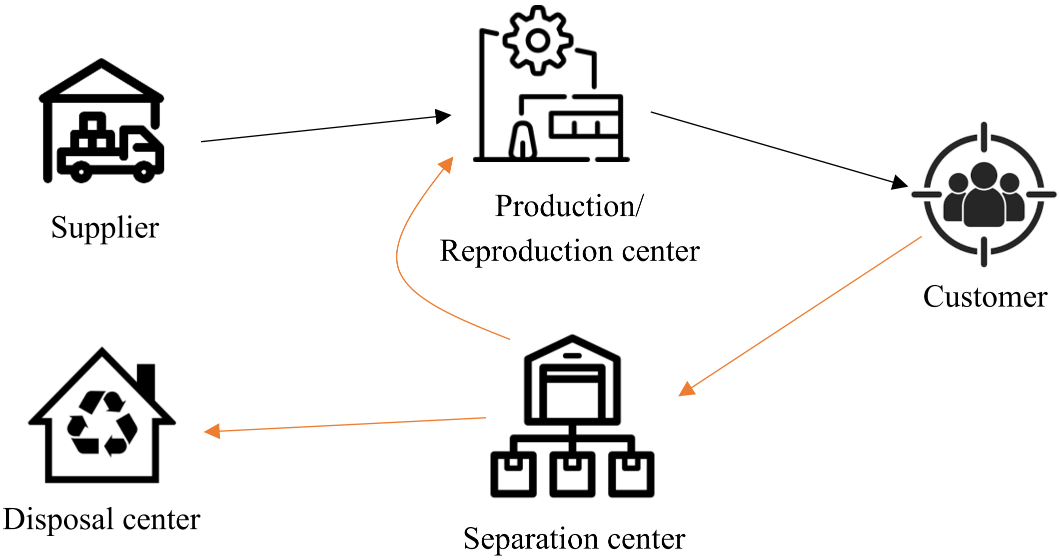


Figure 1. Closed loop logistics network model for supplier selection

To model the investigated problem, the following assumptions are considered:

- The proposed model includes several different products.
- The supplier sells the parts needed to manufacture the products at a discount.
- The capacity of potential suppliers is limited and specific.
- The parameters of demand, transportation and operating costs and purchase price of parts are considered uncertain (Trapezoidal fuzzy data).
- The control of the uncertainty model has been done using the robust fuzzy approach.

Considering the above assumptions, the most important issue mentioned in this paper is the selection and location of suppliers, determining the optimal amount of flow between the centers and the appropriate level of discount.

To model the problem, the set, parameter and decision variables are defined as follows:

Sets

I	Suppliers
J	Production/Reproduction Centers
M	The pieces
N	Products
T	Time Periods
H	Discount Level

Parameters

$Cost_{jnt}$	Production cost of product $n \in N$ at production center $j \in J$ in period $t \in T$
Pr_{ihmt}	Price of piece $m \in M$ purchased from supplier $i \in I$ at discount level $h \in H$ in period $t \in T$
$Ship_{ijm}$	Transportation cost of piece $m \in M$ between supplier $i \in I$ and production center $j \in J$
inv_{jmt}	Inventory cost of piece $m \in M$ at production center $j \in J$ in period $t \in T$
$setdis_n$	The fixed cost of opening separation center for product $n \in N$
$openS_i$	The fixed cost of opening supplier $i \in I$
$disa_{mt}$	Separation cost for a piece $m \in M$

$disp_{mt}$	Disposal cost for a piece $m \in M$
$refc_{jmt}$	Reproduction cost for a piece $m \in M$ at production center $j \in J$ in period $t \in T$
qua_{imt}	Fraction of low-quality piece $m \in M$ purchased from supplier $i \in I$ in period $t \in T$
del_{imt}	Fraction of piece $m \in M$ with delayed delivery purchased from supplier $i \in I$ in period $t \in T$
eco_{it}	Environmental risk factors associated with supplier $i \in I$ in period $t \in T$
dem_{nt}	Demand of product $n \in N$ in period $t \in T$
req_{mn}	The number of part $m \in M$ needed to produce a product $n \in N$
$smax_{im}$	The maximum available capacity of piece $m \in M$ provided by supplier $i \in I$
$smin_{im}$	Minimum purchase amount of piece $m \in M$ from supplier $i \in I$
$reuse_{m}$	The maximum usable percentage of piece $m \in M$
ret_{nt}	Percentage of product $n \in N$ returned in period $t \in T$
low_{ihmt}	The lower limit of the discount interval for the purchase of piece $m \in M$ from supplier $i \in I$ at the discount level $h \in H$ in period $t \in T$
α	Uncertainty rate

Decision variables

X_{ijmt}	Number of piece $m \in M$ purchased from supplier $i \in I$ by production center $j \in J$ in period $t \in T$
Y_{jnt}	Number of product $n \in N$ produced by production center $j \in J$ in period $t \in T$
r_{nt}	Number of returned product $n \in N$ for disassembly at the separation center in period $t \in T$
O_{mt}	The number of usable piece $m \in M$ obtained at the separation center in period $t \in T$
D_{mt}	The number of unusable piece $m \in M$ obtained in the separation center in period $t \in T$
ref_{jmt}	The number of piece $m \in M$ reproduced in production center $j \in J$ in period $t \in T$
Q_{imt}	The total purchase amount of piece $m \in M$ from supplier $i \in I$ in period supplier $i \in I$
S_{i}	1; if the supplier $i \in I$ is selected, and 0; otherwise
bd_{n}	1; if the separation center for product $n \in N$ is opening, and 0; otherwise
A_{ihmt}	1; if supplier $i \in I$ is selected with discount level $h \in H$ for piece $m \in M$ in period $t \in T$, and 0; otherwise

According to the stated sets, parameters and decision variables, the problem of supplier selection in closed loop logistics network is modeled as follows:

$$Minf_1 = E[f_1] + \xi\left(f_{1(\max)} - f_{1(\min)}\right) + \sum_{n=1}^{N}\sum_{t=1}^{T} \eta\left(dem_{nt}^{4} - (1-\alpha)dem_{nt}^{3} - \alpha dem_{nt}^{4}\right) \quad (1)$$

$$Minf_2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} qua_{imt}X_{ijmt} \quad (2)$$

$$Minf_3 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} del_{imt}X_{ijmt} \quad (3)$$

$$Minf_4 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} eco_{it}X_{ijmt} \tag{4}$$

$s.t.$:

$$E[f_1] = \sum_{j=1}^{J}\sum_{n=1}^{N}\sum_{t=1}^{T}\left(\frac{cost_{jnt}^1 + cost_{jnt}^2 + cost_{jnt}^3 + cost_{jnt}^4}{4}\right)y_{jnt}$$
$$+\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}\left(\left(\frac{ship_{ijm}^1 + ship_{ijm}^2 + ship_{ijm}^3 + ship_{ijm}^4}{4}\right) + inv_{jmt}\right)X_{ijmt}$$
$$+\sum_{n=1}^{N} setdis_n bd_n + \sum_{i=1}^{I} openS_i S_i + \sum_{m=1}^{M}\sum_{t=1}^{T}(disa_{mt}O_{mt} + disp_{mt}D_{mt}) \tag{5}$$
$$+\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} refc_{jmt}ref_{jmt} +$$
$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{h=1}^{H}\left(\frac{Pr_{ihmt}^1 + Pr_{ihmt}^2 + Pr_{ihmt}^3 + Pr_{ihmt}^4}{4}\right)A_{ihmt}\,X_{ijmt}$$

$$f_{1(\max)} = \sum_{j=1}^{J}\sum_{n=1}^{N}\sum_{t=1}^{T} cost_{jnt}^4 y_{jnt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}(ship_{ijm}^4 + inv_{jmt})X_{ijmt}$$
$$+\sum_{n=1}^{N} setdis_n bd_n + \sum_{i=1}^{I} openS_i S_i + \sum_{m=1}^{M}\sum_{t=1}^{T}(disa_{mt}O_{mt} + disp_{mt}D_{mt}) \tag{6}$$
$$+\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} refc_{jmt}ref_{jmt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{h=1}^{H} Pr_{ihmt}^4\,A_{ihmt}\,X_{ijmt}$$

$$f_{1(\min)} = \sum_{j=1}^{J}\sum_{n=1}^{N}\sum_{t=1}^{T} cost_{jnt}^1 y_{jnt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}(ship_{ijm}^1 + inv_{jmt})X_{ijmt}$$
$$+\sum_{n=1}^{N} setdis_n bd_n + \sum_{i=1}^{I} openS_i S_i + \sum_{m=1}^{M}\sum_{t=1}^{T}(disa_{mt}O_{mt} + disp_{mt}D_{mt}) \tag{7}$$
$$+\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T} refc_{jmt}ref_{jmt} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{h=1}^{H} Pr_{ihmt}^1\,A_{ihmt}\,X_{ijmt}$$

$$\sum_{j=1}^{J} y_{jnt} \geq (1-\alpha)dem_{nt}^3 + \alpha dem_{nt}^4, \quad \forall n,t \tag{8}$$

$$\sum_{n=1}^{N} req_{mn}y_{jnt} = \sum_{i=1}^{I} X_{ijmt} + ref_{jmt}, \quad \forall j,m,t \tag{9}$$

$$\sum_{j=1}^{J} ref_{jmt} + D_{mt} = O_{mt}, \quad \forall m,t \tag{10}$$

$$O_{mt} = \sum_{n=1}^{N} req_{mn}r_{nt}, \quad \forall m,t \tag{11}$$

$$\sum_{j=1}^{J} X_{ijmt} \leq smax_{im}S_i, \quad \forall i,m,t \tag{12}$$

$$\sum_{j=1}^{J} X_{ijmt} \geq smin_{im}S_i, \quad \forall i, m, t \tag{13}$$

$$\sum_{j=1}^{J} ref_{jmt} \leq reuse_m O_{mt}, \quad \forall m, t \tag{14}$$

$$D_{mt} \leq (1 - reuse_m)O_{mt}, \quad \forall m, t \tag{15}$$

$$\sum_{j=1}^{J} ret_{nt} y_{jnt} \geq r_{nt}, \quad \forall n, t \tag{16}$$

$$r_{nt} \leq Mbd_n, \quad \forall n, t \tag{17}$$

$$A_{ihmt} low_{ihmt} \leq Q_{imt}, \quad \forall i, h, m, t \tag{18}$$

$$\sum_{h=1}^{H} A_{ihmt} = S_i, \quad \forall i, m, t \tag{19}$$

$$Q_{imt} = \sum_{j=1}^{J} X_{ijmt}, \quad \forall i, m, t \tag{20}$$

$$X_{ijmt}, y_{jnt}, r_{nt}, O_{mt}, D_{mt}, ref_{jmt}, Q_{imt}, B_{ijmth} \geq 0, \quad \forall i, j, m, t \tag{21}$$

$$A_{ihmt}, S_i, bd_n \in [0,1], \quad \forall i, h, m, t \tag{22}$$

Equation (1) minimizes the total network design costs. The costs of network design include (production costs, transportation and maintenance costs, costs of establishing centers, the cost of buying discounted parts and other operating costs). Equation (2) minimizes the number of defective parts that is equal to the highest quality of the total parts purchased from suppliers. Equation (3) minimizes the total number of parts purchased from suppliers that deliver late. Equation (4) minimizes the total environmental risk factors associated with suppliers. Relations (5) to (7) show the equations related to the robustness of the uncertainty model. Constraint (8) guarantees that the total number of products produced of each type in each period is equal to the demand of customers. Constraint (9) states, the total number of parts used to produce a final product is equal to the number of remanufactured parts from the disassembly department and new purchased parts from suppliers. Constraint (10) expresses the equilibrium constraint resulting from the equality of separated parts with the sum of reconstructed and destroyed parts. Constraint (11) shows the relationship between the number of parts obtained from returned products. Constraint (12) ensures that the total number of parts purchased from suppliers does not exceed its maximum capacity. Constraint (13) shows the minimum purchase of each piece from suppliers in each period. Constraints (14) and (15) limit, respectively, the usable and destroyed percentage of parts obtained from returned products in each period at the separation center. Constraints (16) and (17) show the percentage of products returned from the total products produced. Constraint (18) shows the total number of parts purchased from each discount level in each period. Constraint (19) guarantees that if a certain supplier is selected, parts can be purchased only from the discount level of that supplier. Constraint (20) shows the equilibrium equation between the purchased parts and the production of products in each period. Constraints (21) and (22) also show the type of decision variables

4. Computational Results

In this section, the computational results are presented in order to show the performance of the proposed model in the robust-fuzzy approach. The proposed model has been solved and analyzed using the multi-objective decision-making method of Torabi-Hassini and Monte Carlo. In order to examine the results and comparisons of the proposed model in a robust feasibility approach, a sample problem with 4 suppliers, 4 production centers, 3 types of pieces, 2 types of products in three time periods and 3 discount levels is considered. The parameters related to the model are also created by MATLAB software and according to the uniform distribution presented in Table (1).

Table 1. Interval limits of parameters

Parameter	*Value*	*Parameter*	*Value*
inv_{jmt}	$\sim U(0.5,1.2)$	$quality_{imt}$	$\sim U(0.3,0.5)$
$setdis_n$	$\sim U(100000,120000)$	$delivery_{imt}$	$\sim U(0.6,0.8)$
$openS_i$	$\sim U(100000,120000)$	$econrisk_{it}$	$\sim U(6,10)$
$reuse_m$	$\sim U(0.2,0.4)$	$return_{nt}$	$\sim U(0.3,0.4)$
$disa_{mt}$	$\sim U(0.5,1.5)$	req_{mn}	$\sim U(1,3)$
$disp_{mt}$	$\sim U(0.8,1.5)$	$supmax_{im}$	$\sim U(1000,1500)$
$refcost_{jmt}$	$\sim U(0.2,0.4)$	$supmin_{im}$	$\sim U(50,100)$
$\widetilde{cost}_{jnt}$	$\sim U(1,2), \sim U(3,4), \sim U(5,6), \sim U(7,8)$		
$\widetilde{Ship}_{ijm}$	$\sim U(1,2), \sim U(3,4), \sim U(5,6), \sim U(7,8)$		
$\widetilde{Dem}_{nt}$	$\sim U(100,125), \sim U(125,200), \sim U(200,250), \sim U(250,400)$		
$\widetilde{Price}_{ihmt}$	$\sim U\left(\frac{2}{h},\frac{3}{h}\right), \sim U\left(\frac{3}{h},\frac{4}{h}\right), \sim U\left(\frac{4}{h},\frac{5}{h}\right), \sim U\left(\frac{6}{h},\frac{8}{h}\right)$		

Analysis of the results and values obtained as a result of 20 repetitions in the combined method of Torabi-Hassini and Monte Carlo and by changing the α. Table (2) shows the number of optimal locations of selected suppliers in different α. According to the results, it can be seen that the optimal number of facility locations does not change with the increase of α. Meanwhile, the average cost of the total supply chain network has increased. With this analysis, it can be seen that with the increase of α, total network costs, including transportation costs, operating costs, purchase of parts, and inventory costs have increased.

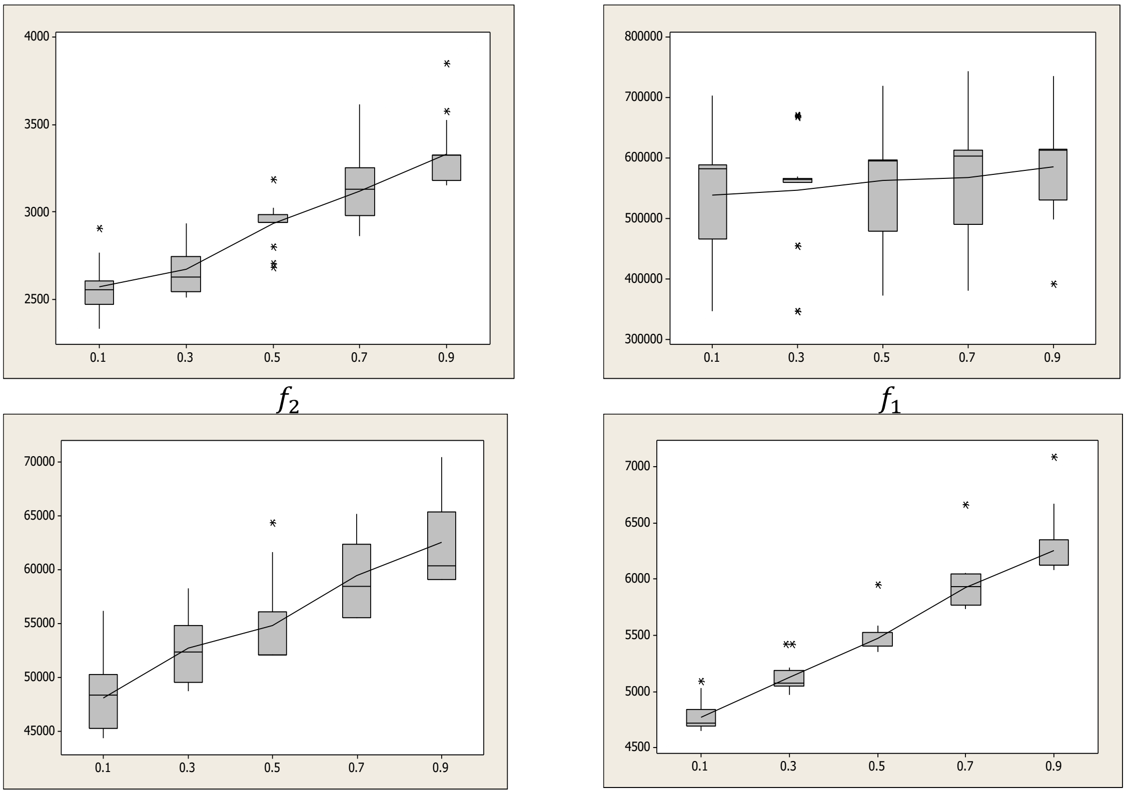
Table 2. Selected suppliers in the robust-fuzzy approach in different $\boldsymbol{\alpha}$

α	The optimal number of locations obtained	The cost of selecting a supplier	1	2	3	4
0.1	2	223564.00	-	-	*	*
0.3	2	227640.90	*	-	*	-
0.5	2	223564.00	-	-	*	*
0.7	2	227640.90	*	-	*	-
0.9	2	223564.00	-	-	*	*

Tables (3) show the average of the objective functions and the standard deviation of the results obtained from 20 Monte Carlo iterations. According to the results of Table (3), the average cost of network design has increased with the increase of α value, while that the standard deviation of the first objective function has decreased. These results are also true for other objective functions and with the increase of α, the average size of the objective functions has also increased. For a detailed analysis of the results, Figure (2) shows the box-plot diagrams of the objective functions separately with increasing α.

Table 3. Average values of objective functions with different $\boldsymbol{\alpha}$ (*1000)

α	f_1		f_2		f_3		f_4	
	Average	STD	Average	STD	Average	STD	Average	STD
0.1	538.110	86.68	2.571	0.187	4.77	0.207	48.087	4.130
0.3	546.992	80.204	2.675	0.164	5.12	0.207	52.789	3.501
0.5	562.586	74.765	2.935	0.139	5.47	0.128	54.801	3.400
0.7	568.170	68.214	3.121	0.128	5.92	0.120	59.475	3.074
0.9	586.075	65.439	3.333	0.103	6.25	0.117	62.547	2.872



f_4 f_3

Figure 2. Boxplot diagrams of average objective functions

Figure (3) also shows the Pareto diagram of the objective functions relative to each other. For this purpose, the Pareto front of objective functions relative to each other is shown at $\alpha = 0.1$ and in 200 Monte Carlo iterations.

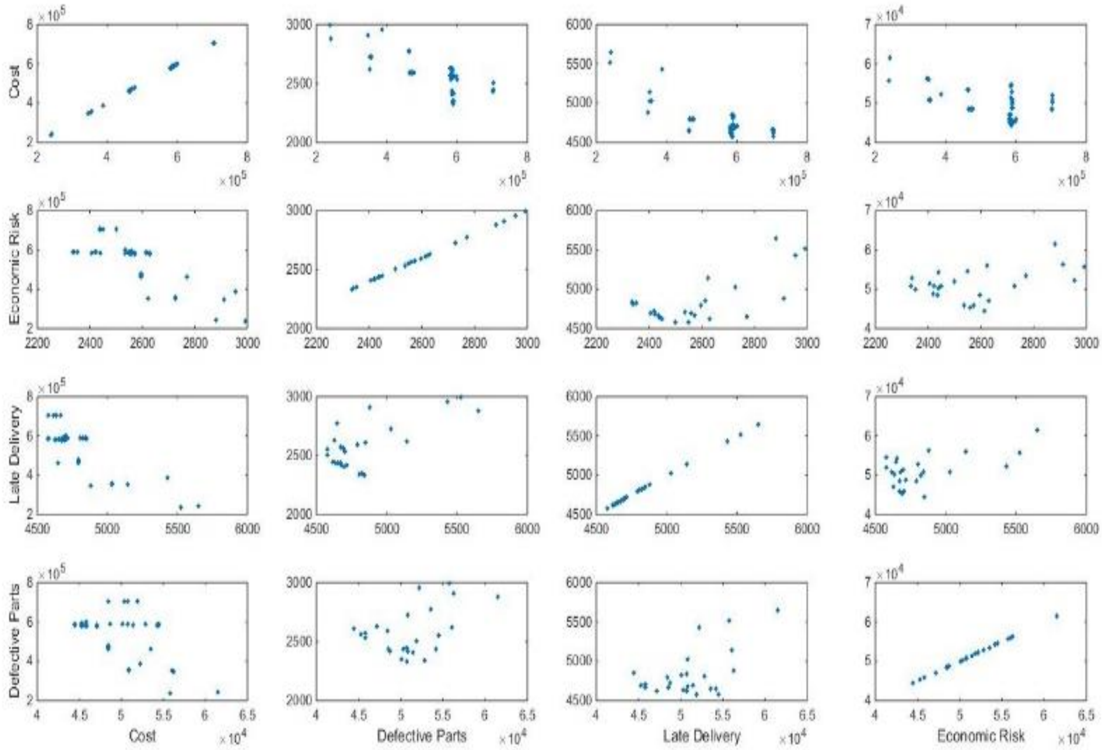


Figure 4. Pareto front of objective functions

In the following, by changing other effective parameters on the proposed model based on possibility, the results have been compared. Therefore, the parameters of the degree of importance (ξ) and the penalty cost of deviation from the unmet demand unit (η) are considered equal to 10 and 100, the changes of these values should be investigated in the model. The results and values obtained as a result of 20 Monte Carlo repetitions and by changing the α parameter (0.1,0.3,0.5,0.7,0.9) are shown in Tables (4).

Table 4. Average calculation results with different α and penalty cost

$\xi = \eta$	α	f_1	f_2	f_3	f_4
10	0.1	1078713.90	2595.53	4706.30	47550.79
10	0.3	1154885.03	2695.90	5127.69	51769.31
10	0.5	1207420.95	2903.74	5421.39	53570.97
10	0.7	1237150.44	3111.29	5823.51	57792.11
10	0.9	1315420.03	3293.10	6132.25	61952.61
100	0.1	6654008.04	2539.88	4683.17	46516.95
100	0.3	7159855.10	2729.17	5026.81	50178.89
100	0.5	7471288.33	2881.55	5409.86	54391.91
100	0.7	7780742.26	3112.39	5742.95	57317.08
100	0.9	8265650.41	3272.68	6114.11	62295.45

The results show that with the increase in the cost of the penalty function, the value of the first objective function has increased, while the other objective functions have not changed much. Tukey's multiple test with a confidence level of 95% has been used to check the significance of the difference between the averages of penalty costs. The results of the analysis are shown in Table (5).

Table 5. Tukey's multiple test with different cost penalty coefficients (*1000)

Objective function	Comparison of the penalty factor	mean difference	95% CI	F-Value	P-value
f_1	1-10	638.331	(612.575, 664.088)	2.388	0.00
	1-100	6905.92	(6783.62, 7028.21)	124.01	0.00
	10-100	6267.59	(614.47, 6390.47)	10.115	0.00
f_2	1-10	7.6	(-90.8, 75.8)	0.03	0.859
	1-100	20.4	(-103.4, 62.7)	0.23	0.630
	10-100	12.8	(-89.9, 64.3)	0.11	0.744
f_3	1-10	69	(-219.2, 81.2)	0.82	0.366
	1-100	115.8	(-266, 34.4)	2.31	0.130
	10-100	46.8	(-189.5, 95.9)	0.42	0.518
f_4	1-10	1016	(-2073, 677)	1.4	0.239
	1-100	1400	(-3103, 303)	2.63	0.107
	10-100	387	(-2067, 1293)	0.21	0.650

According to the results of the above tables, the P-value is less than 0.05, which shows that there is a significant difference between the average value of the first objective functions with the change of the cost penalty.

Next, in order to examine the proposed model in large size scales, 3 sample problems have been designed according to Table (6). For this purpose, the average of each of the sample problems is calculated by considering the penalty cost factor (1-10-100) and α parameter (0.1,0.3,0.5,0.7,0.9) and its results are shown in Table (7).

Table 6. Size of sample problems in large size scales

Sets	Sample Problem 1	Sample Problem 2	Sample Problem 3
Supplier	6	8	12
Production center	6	8	12
Pieces	4	6	8
Products	3	4	5
Time Period	4	5	6
Discount Level	4	4	5

Table 7. Average computational results of sample problems in large size scales (*1000)

Sample Problem	$\xi = \eta$	α	f_1	f_2	f_3	f_4
1	1	0.1	1120	5.351	9.937	100
	1	0.3	1138	5.568	10.67	109.8
	1	0.5	1171	6.11	11.38	114
	1	0.7	1182.6	6.497	12.33	123.7
	1	0.9	1219	6.938	13.01	130.1
	10	0.1	2245	5.402	9.796	98.97
	10	0.3	2403	5.611	10.67	107.7
	10	0.5	2513	6.044	11.28	111.5
	10	0.7	2575	6.476	12.12	120.2
	10	0.9	2738	6.854	12.76	128.9
	100	0.1	13850	5.286	9.74	96.82
	100	0.3	14903	5.68	10.463	104.4
	100	0.5	15551	5.997	11.26	113.2
	100	0.7	16195	6.478	11.95	119.3
	100	0.9	17204	6.811	12.726	129.6
2	1	0.1	1663	7.946	14.75	148.61
	1	0.3	1690	8.267	15.84	163.15
	1	0.5	1738	9.072	16.909	169.36
	1	0.7	1755	9.648	18.32	183.8
	1	0.9	1811	10.3	19.33	193.3
	10	0.1	3333	8.021	14.54	146.95
	10	0.3	3569	8.331	15.84	159.9
	10	0.5	3731	8.974	16.755	165.56
	10	0.7	3823	9.615	17.99	178.61
	10	0.9	4065	10.17	18.95	191.46
	100	0.1	20564	7.849	14.47	143.76
	100	0.3	22128	8.434	15.53	155
	100	0.5	23090	8.905	16.719	168.1
	100	0.7	24047	9.619	17.74	177.1
	100	0.9	25545	10.11	18.896	192.5
3	1	0.1	2643	12.631	23.45	236.23
	1	0.3	2687	13.14	25.18	259.3
	1	0.5	2763	14.42	26.878	269.22
	1	0.7	2791	15.336	29.12	292.1
	1	0.9	2879	16.376	30.72	307.2
	10	0.1	5299	12.75	23.12	233.6
	10	0.3	5673	13.24	25.19	254.3
	10	0.5	5931	14.265	26.633	263.17
	10	0.7	6077	15.28	28.609	283.9
	10	0.9	6462	16.17	30.12	304.3
	100	0.1	32689	12.47	23	228.5
	100	0.3	35174	13.4	24.69	246.5
	100	0.5	36704	14.15	26.57	267.2
	100	0.7	38224	15.29	28.21	281.5
	100	0.9	40606	16.07	30.03	306

The results of the evaluation of the mathematical model with the robust-fuzzy approach show that as the penalty coefficients of the objective function increase, the cost of the total supply chain network increases, but its standard deviation decreases. This issue shows the high capability of the robust method in controlling the uncertainty model of the problem.

5. Conclusion

In this paper, in the continuation of the articles in the suppliers selection in the closed loop logistics network, taking into account some important factors, to design a selection of suppliers in the multi-objective, multi-product and multi-echelon closed loop logistics network, taking into account the discount obtained from the purchase We have discussed raw materials as well as uncertainty of parameters such as transportation cost, purchase price of pieces, demand and return rate of products. At first, a supplier selection model was designed in the mixed integer non-linear inverse logistic network, and then the possibility robust optimization model was also designed in the integer non-linear mode. To solve the proposed model, a combined Monte Carlo simulation method and Torabi-Hassini multi-objective decision-making method were developed. In the phase of analyzing the results of the proposed model, a small example was fully described and analyzed. By doing the calculations, it was observed that with the increase of the penalty cost, the value of the first objective function increases, while the other objectives do not change. Also, with the increase in the size of the problem, the computing time also increases exponentially, so heuristic and meta-heuristic methods should be used to solve problems with a larger size than mentioned. For future articles, the following are suggested for researchers:

- Using heuristic and meta-heuristic algorithms to solve problems
- Using priority-based encoding to decode the problem
- Combining goals with each other to clarify the issue
- Considering a group discount instead of a general discount

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