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A locating model for small e-shop distribution centers in conditions of uncertainty

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Abstract

In today's world, due to the competitive nature of the market and the lack of certainty in the amount of order and also the time of ordering products, it has led to the effective response of sales centers to customers is not done properly. This is due to the lack of proper location of distribution and sales centers and optimal allocation of customers to each center. Therefore, considering the importance of locating distribution centers, in this article, the issue of locating distribution centers of e-shops in conditions of uncertainty has been developed. The main purpose is to provide a model for profit maximization and minimization of the total transfer time of electronic products between distribution centers and customer clusters. To examine the developed model, three different problem solving methods have been considered, including the epsilon constraint method, the NSGA II algorithm and the MOPSO. The results obtained from the analysis of the sample problem in small size show that NSGA II algorithm has 14 efficient answers, MOPSO algorithm has 10 efficient answers and epsilon method has obtained a limit of 8 efficient answers. The computational results show the high efficiency of the MOPSO algorithm in obtaining the optimal weight of 0.9744 in solving large size problems.

Keywords: Location of distribution centers, online stores, robust fuzzy optimization, e-shop distribution

1. Introduction

Optimal location of distribution centers and their optimal allocation to end customers to meet their demand in the shortest time and at the lowest cost, is one of the tasks of supply chain management. The main goal in supply chain management is to manage the flow of goods / services as well as information from the supplier to the end customers, taking into account economic, social and environmental goals. In the current conditions of today's business communities, the competitiveness of markets, the existence of diverse products and also the reasonable price of products while having the desired quality, requires that products be offered in the right amount, time and price to meet customer needs, which is the need for coordination. Zhou et al. (2020) show distribution centers in the form of a commodity distribution chain.

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On the other hand, attracting customers to increase sales in order to maximize the profit margins of service providers, has made the location of distribution centers such as stores more attention. Every day, a large number of goods flow between distribution centers and customers (Mokhtar et al., 2019). In most cases, it is impossible to make a direct connection between these levels of work, because it requires high costs for the construction of centers and its location, as well as the construction of communication channels (Shavarani, 2019). In fact, for this purpose, some places are considered as central hubs, in other words, as distribution centers, whose task is to meet the demand of customers within its coverage radius. These centers interact with each other to reduce their costs, and their main goal is to meet the demand of customers who can order indefinitely at any time of the day (Huang and Shi, 2021). According to the above, there are different types of location issues that can be referred to as cover location issues. In this category of coverage location issues, customers typically receive services and goods based on distance to facilitation. Most studies on hub problems consider the coverage radius to be zero and one, according to which a demand center is covered when it is inside the coverage radius and not covered if it is outside it. Such an assumption is not applicable in the real world. Because a- the quality of coverage is not necessarily constant and the closer it is to facilitation the higher it is and b- there is no definite boundary in the real world around facilitation that crosses that level of service to zero. Coverage location issues, on the other hand, focus on maximizing or completing services to the points of demand. The coverage problem locates a maximum number of facilities in order to maximize the covered demand points (Ghahremani-Nahr et al., 2021). Timely delivery of customer orders will increase their satisfaction and also reduce incidental costs. Therefore, it is necessary to locate distribution centers in areas that have the least distance from potential customers. Therefore, locating the distribution centers of small online stores is very necessary due to the uncertain demand. Proper modeling and proper network design, in addition to increasing profits for online stores, leads to reduced transfer time and increased customer satisfaction. Also, due to the online nature of orders, there is a possibility of uncertainty in demand and transfer costs, which is also modeled in this article. In order to achieve the sub-objectives and finally the general objectives of the research, first, based on library studies, the literature on the subject and the background of internal and external research will be examined. As a result, the research gap is defined. Then, based on the research gap and based on the assumptions made, first, an uncertain model of the location problem of online store distribution centers is designed and then, using the fuzzy solid optimization method, it controls two uncertain parameters of demand and transfer costs. Due to the dual purpose of the model, which is based on profit maximization and minimization of transfer time, it will use multi-objective decision making methods such as epsilon constraint method to solve the problem in small size and NSGA II and MOPSO algorithms to solve the problem in larger sizes. Since it is not possible to access real-world data, the model parameters will be quantified from random data based on the uniform distribution function. Comparisons between solution methods to select efficient solution methods will be based on criteria such as means of objective functions, number of efficient answers, maximum expansion, metric distance and computational time. In this paper, epsilon constraint method and GAMS software will be used to analyze the data in small sample problems and MOPSO and NSGA II meta-innovative algorithms and MATLAB software will be used to solve sample problems in larger sizes.

This paper is organized in 5 sections. The second part presents the theoretical foundations of the research, the background of research related to the subject and determining the research gap. In the third part, the mathematical model of research in conditions of uncertainty and the use of fuzzy stable optimization method to control uncertain parameters are presented. The fourth section presents the research results and findings related to the experiments. Finally, in the fifth section, conclusions and future research suggestions are presented.

2- Literature review

Changes in the competitive market environment, as well as the shift of companies to offer products globally, has led organizations to optimize their company's supply chain in order to survive in the market and gain more share of product sales in global markets to be able to respond quickly to needs. Have the shortest time, the lowest cost and the highest quality. Therefore, all levels of the supply chain from raw material suppliers to product distribution to customers must be carefully monitored, monitored, planned and controlled. Therefore, supply chain management can be defined as a process consisting of planning, execution and control of all operations related to the supply, production, warehousing and distribution of products to customers (Zahiri et al., 2014). Simply put, supply chain management focuses on the integration of activities / flows of information / finance and materials between chain levels to achieve a sustainable competitive advantage. Rapid developments in technology and the emergence of new industrial products, as well as shortening the product life cycle, have led to an increase in the number of discarded products and growing environmental problems. Governments' concerns about the increase in waste products, as well as government laws and regulations on environmental issues, have forced companies to collect waste products. This has led to the emergence of a new concept called reverse supply chain (Srivastava, 2008). In the environmental factor, which is considered as the main motivation in the reverse supply chain network, factors such as market and customer pressures and ethical motivations in improving the environmental conditions are discussed. These include forcing companies to return products under government law, economic benefits such as reducing production costs, and increasing public awareness of the environment. In the commercial factor, the reuse and recycling of waste products in the reverse supply chain, the returned economic capital, can create direct and indirect benefits for the organization (Soleimani et al., 2013). Therefore, the cost of raw materials, part of the cost of transportation as well as production costs are reduced and leads to a reduction in the cost of the product and thus increase profits and other economic benefits. With the globalization and emergence of large corporate affiliates in the 21st century, there has been an increasing trend in the supply of raw materials, parts and services (Nozari and Aliahmadi, 2022).

This trend has forced companies to pay more attention to purchasing operations and related decisions. Under the pressure of global competition, companies strive to provide high quality and low cost products and services to their customers in a timely manner and to achieve their supply chain superiority in order to achieve a competitive advantage (Ahmadi and Amin, 2019). Since distributors are among the most important levels in the supply chain network. Therefore, choosing the most suitable place for the construction of distribution centers to distribute products with appropriate quality and lower cost, in the shortest time is important. There are several criteria in choosing the location of distribution centers, which can be low prices of raw materials, offering different levels of discounts, sufficient capacity of distribution centers to distribute products, supply of materials in the shortest time and high quality, low costs of selection and contract with supply Are raw material suppliers, etc. (Ghayebloo et al., 2015). Uncertainties in the location of distribution centers, such as demand parameters and operating and transportation costs, lead to the model being closer to the real world and is an integral part of supply chain network issues (Tavakkoli Moghaddam et al., 2015). The concept of uncertainty can be defined as conditions in which data and information are incomplete. In mathematical programming, problems are usually solved by assuming data is definite, while in the real world, most data are uncertain. Uncertainty can affect the optimality and justification of problems. Usually, the best data estimation is used for application in mathematical models (Farrokh et al., 2018). In real-world problems, changing one of the data may violate a large number of constraints and the result obtained may be non-optimal or even impossible.

In recent years, a combination of methods to deal with uncertainty control such as fuzzy robust (possibility robust) has been used by several authors, which covers the shortcomings of each of the random, fuzzy and robust optimization methods alone. Among these authors we can name (Liu et al., 2021; Habib et al., 2021; Hamidieh et al., 2017). Since the economic and social aspects of distribution center location issues are addressed simultaneously, the optimization of the above issue is multi-objective. Each of these aspects is in conflict with the other and cannot be aligned with each other. Therefore, to optimize such problems, multi-objective problem-solving methods are used, which can include such things as the comprehensive benchmark method, Maxmin method, ideal planning method, ideal achievement method, etc. By examining the literature, the subject can be seen. However, a lot of research has been done in this field in recent years. Nickel et al. (2001) proposed a mathematical model for the hub location problem in which the fixed cost of creation, in addition to the demand centers, was also considered for the connection nodes of the demand nodes and the connection edges of the demand centers. Hub location plays a key role in the design of the network of demand centers and hubs. Because the total cost of transportation affects the capacity of the intermediate centers and therefore the service time and the amount of congestion in the system. There are several overviews of hub location issues, the most recent of which is Alumur et al.'s paper, which compiled all network hub location models up to 2007 (Alumur & Kara, 2008).

Özceylan and Paksoy (2013) proposed a mixed-integer programming model for the closed-loop supply chain network. In this paper, a new model of multi-cycle, multi-product and multi-level closed-loop supply chain network is presented, which simultaneously optimizes the amount of product transfer, production and reproduction, as well as the location of retailers. By designing various problems, they measured the effect of important parameters of the problem, such as demand, on the total costs of supply chain network design and showed that as the demand increases, the total costs of network design increase.

Rodríguez et al. (2014) considered a hub location-routing problem by considering hub location decisions and allocating hubs to each other. They used AP and CAB data to solve their problem and used the branch and cut algorithm to solve their problem. Zhai et al. (2016) examined a two-level model of location-oriented location in conditions of uncertainty that demand is in conditions of uncertainty and has been analyzed with a fuzzy approach. Silva et al. (2017) proposed an innovative method based on forbidden search to solve the problem of single-allocation coverage P hub. They performed their problem with a 200-node AP data set and showed that the method presented by them was highly efficient in finding the answer.

Ghahremani Nahr et al. (2018) designed a closed-loop supply chain network with three levels of production center, end customers, collection centers and destruction centers. Their goal in this article was to reduce the total cost of location and allocation. To solve their model, they used a Champions League algorithm by presenting a modified priority-based chromosome and tested their chromosome performance against different types of chromosomes. The results showed the very high efficiency of the Champions League algorithm by providing priority-based chromosomes in solving small to large sample size problems.

Pourjavad and Mayorga (2019) presented an optimal model of closed-loop supply chain network design for the glass industry. In this model, the integration of facility location decisions and optimal flow distribution decisions between facilities, the optimal amount of production is considered. Sadeghi et al. (2021) used an evolutionary multi-objective optimization algorithm to solve the problem of locating the distribution centers of basic goods in the event of earthquakes and natural disasters. Pourghader et al. (2021) modeled a problem of locating tourist centers to provide essential goods. Their main goal was to reduce logistics costs and reduce greenhouse gas emissions. To solve this problem, they used the NSGA II meta-heuristic algorithm.

3- Modeling and problem definition

This section develops a model for locating small e-shop distribution centers. According to figure (1), the intended network includes a set of distribution centers and customer clusters that aim to meet customer demand in the shortest possible time with the maximum profit. Therefore, locating distribution centers among potential centers is very important. Each center can only allocate clusters of customers that are located within the coverage radius of the distribution center.

After determining the optimal location of distribution centers, it is possible to assign customers to one or more online stores. After receiving customer orders by each distribution center, orders are queued and answered in order. Therefore, the cost of waiting time in the order queue is also considered as one of the network costs. After summarizing the orders, it is possible to send them to the demand points (customer clusters) based on the various vehicles that have been considered. Distribution centers are also in contact with each other and can send electronic components to each other to complete customer orders, if needed.

Accordingly, the most important strategic and tactical decisions in this article include strategic decisions such as locating distribution centers and tactical decisions such as allocating customers to distribution centers, choosing the best means of transportation.

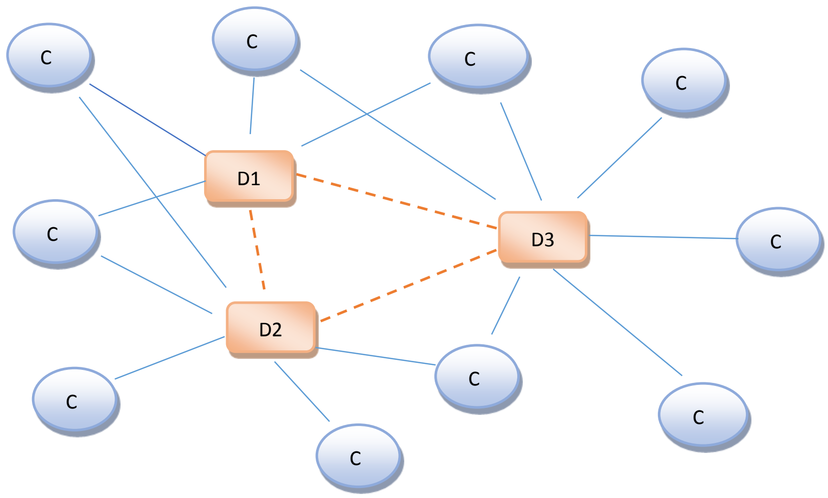


Fig 1. Developmental model for locating e-shop distribution centers

Making tactical and strategic decisions in order to achieve two functions simultaneously, the goal is to maximize the profit from networking and minimize the total time of transfer of electronic products from distribution centers to customers. Therefore, in order to develop the location model of online store distribution centers under conditions of uncertainty, the following assumptions should be considered:

- The number of distribution centers of online stores is already known and their only location is unknown.
- Cost and demand in the considered model are uncertain and triangular fuzzy numbers.
- The capacity of vehicles is pre-determined.
- Each distribution center can cover a specific range of customers.
- The number of employees in each distribution center is known.
- The transfer time depends on the type of vehicle.

3-1- Problem modeling

According to the above goals and assumptions, the symbols used in modeling will be as follows:

Sets:

C	Customer cluster set for $c \in C$ network
D	Set of distribution centers of potential small e-shops $d, e \in D$
P	Set of electronic products $p \in P$
N	Set of types of means of transport $n \in N$

Parameters:

f_d	The cost of building an e-shop on the site $d \in D$
g_n	Cost of using any type of vehicle $n \in N$
$capD_{dp}$	Maximum distribution capacity of $p \in P$ electronic product by $d \in D$ e-shop
$capN_n$	Maximum vehicle capacity $n \in N$ of transmission of all electronic products
$\widetilde{dem}_{cp}$	Demand for customer $c \in C$ clusters of electronic product $p \in P$
ρ	Total number of e-shops to be located.
φ	Coverage radius of customer clusters by online stores
dis_{dc}	Distance between $d \in D$ e-shop and $c \in C$ customer cluster
dis_{de}	Distance between $d \in D$ e-shop and $c \in C$ customer cluster
sp_n	Speed of vehicle $n \in N$
pr_p	Selling price of product $p \in P$
$\widetilde{tr}_{dcp}$	The cost of transferring the electronic product $p \in P$ between the e-shop $d \in D$ and the customer cluster $c \in C$
$\widetilde{tr}_{dep}$	The cost of transferring the electronic product $p \in P$ between the e-store $d \in D$ and $e \in D$
c_d	Cost of waiting time to serve in the e-shop $d \in D$
μ_d	service rate of e-shop $d \in D$ (exponential distribution)
B_d	Upper bound of queue length for service in $d \in D$ e-shop
θ_d	High probability for queue length exceeding service limit in $d \in D$ e-shop
ϑ_d	Number of servers in the e-shop $d \in D$
M	A very large number

Decision variables:

Y_d	If the e-shop is set up at $d \in D$, it will be 1 and otherwise it will be 0.
U_n	If the vehicle $n \in N$ is used to transport electronic products, the value is 1 and otherwise it is 0.
X_{dcpn}	Amount of electronic product $p \in P$ transferred from $d \in D$ e-store to customer $c \in C$ cluster with $n \in N$ vehicle
V_{depn}	Amount of electronic product $p \in P$ transferred between $d \in D$ and $e \in D$ e-shop with $n \in N$ vehicle
Q_{dp}	Amount of $p \in P$ electronic product distributable by $d \in D$ e-shop
R_{dcn}	If the $d \in D$ e-store is assigned to the $c \in C$ customer cluster by $n \in N$ vehicle, it takes 1 and otherwise 0.
W_{den}	If the e-store $d \in D$ and $e \in D$ are assigned to the vehicle $n \in N$, the value is 1 and otherwise it is 0.
λ_d	Customer order entry rate to $d \in D$ e-shop
π_{0d}	Probability of occurrence of $d \in D$ e-shop
ω_d	Waiting time for customer order in $d \in D$ e-shop

According to the defined symbols, the uncertain model of the location problem of e-shop distribution centers is as follows:

$$max\, Z_1 = \sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N} pr_p . X_{dcpn} - \sum_{d\in D} f_d . Y_d - \sum_{n\in N} g_n . U_n - \tag{1}$$

$$\sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N}\widetilde{tr}_{dcp}.X_{dcpn}-\sum_{d\in D}\sum_{e\in D}\sum_{p\in P}\sum_{n\in N}\widetilde{tr}_{dep}.V_{depn}$$

$$min\,Z_2=\sum_{d\in D}\sum_{c\in C}\sum_{n\in N}\frac{dis_{dc}}{sp_n}.R_{dcn}+\sum_{d\in D}\sum_{e\in D}\sum_{n\in N}\frac{dis_{de}}{sp_n}.W_{den} \tag{2}$$

$s.t.$:

$$\sum_{d\in D}\sum_{n\in N}X_{dcpn}=\widetilde{dem}_{cp}, \qquad \forall c\in C,p\in P \tag{3}$$

$$\sum_{d\in D}Y_d=\rho \tag{4}$$

$$Q_{dp}\le capD_{dp}.Y_d, \qquad \forall d\in D,p\in P \tag{5}$$

$$\sum_{p\in P}X_{dcpn}\le capN_n.U_n, \qquad \forall c\in C,d\in D,n\in N \tag{6}$$

$$Q_{dp}+\sum_{e\in D}\sum_{n\in N}V_{edpn}-\sum_{e\in D}\sum_{n\in N}V_{depn}=\sum_{c\in C}\sum_{n\in N}X_{dcpn}, \quad \forall d\in D,p\in P \tag{7}$$

$$R_{dcn}\le\sum_{p\in P}X_{dcpn}\le M.R_{dcn}, \quad \forall d\in D,c\in C,n\in N \tag{8}$$

$$W_{den}\le\sum_{p\in P}V_{depn}\le M.W_{den}, \quad \forall d\in D,e\in E,n\in N \tag{9}$$

$$\sum_{c\in C}\sum_{p\in P}\sum_{n\in N}X_{dcpn}\le M.Y_d, \qquad \forall d\in D \tag{10}$$

$$dis_{dc}.R_{dcn}\le\varphi, \quad \forall d\in D,c\in C,n\in N \tag{11}$$

$$P\{d\text{ Store queue length}>B_d\}\le\theta_d, \quad \forall d\in D \tag{12}$$

$$Y_d,U_n,W_{den}\in\{0,1\} \tag{13}$$

$$X_{dcpn},V_{depn},Q_{dp}\ge 0\ and\ integer \tag{14}$$

Equation (1) maximizes profits from the sale of electronic products to customer clusters. Equation (2) Minimizes the total transmission time of electronic products between networks based on vehicle speed. Equation (3) shows the amount of electronic product transferred from e-shops to customer clusters by multiple vehicles. Equation (4) shows the total number of small e-shops to be located. Equation (5) shows the maximum possibility of using the distribution capacity of the located e-shop. Equation (6) ensures that the amount of electronic products transferred between e-shops and customer clusters is less than the capacity of the vehicle. Equation (7) shows the amount of electronic products transferred between online stores. Equation (8) shows the vehicle allocation between online stores and customer clusters. Equation (9) shows the allocation of vehicles between online stores. Equation (10) ensures that various products cannot be sent from that center to customer clusters until an online store is established. Equation (11) ensures that each online store can meet the demand of customer clusters up to a radius. Equation (12) shows the limit on the length of a store order queue. Equations (13) and (14) express the type of decision variables.

According to constraint (12), it is necessary to convert the model to a definite state, so a $M/M/m/C$queue model is used to convert this constraint to a definite constraint. In this model, the $M/M/m/C$ queue for the store is defined as the input rate equal to λ (Poisson distribution) and the service time at μ (exponential distribution). The entry rate in this model is defined according to Equation (15) (Zahedi and Ghahremani, 2020):

$$\lambda_d=\sum_{c\in C}\sum_{p\in P}\sum_{n\in N}X_{dcpn}, \qquad \forall d\in D \tag{15}$$

The queue model includes m server with limited capacity C. It is assumed that the distribution center has ϑ_d servers, so the constraint (12) becomes:

$$\sum_{d'=\vartheta_d+B_d+1}^{C} Pr_{d'd} \leq \theta_d \;\; or \;\; 1-\sum_{d'=0}^{\vartheta_d+B_d} Pr_{d'd} \leq \theta_d, \qquad \forall d \in D \tag{16}$$

The first expression indicates the constraint (16) of the probability that more than n orders in the $d \in D$ store service queue with ϑ_d server is less than θ_d, and the second expression indicates that the sum of all probabilities is 1. In other words, equation (16) indicates the probability of having n orders in the service queue. Therefore, the service rate is obtained as follows:

$$\mu_{nd} = \begin{cases} n\mu_d & n \leq \vartheta_d \\ \vartheta_d\mu_d & \vartheta_d < n < C \end{cases}, \qquad \forall d \in D \tag{17}$$

By combining the above constraints π_{0d} (the probability of the construction of a $d \in D$ store) will be transformed as follows:

$$\pi_{0d} = \left[\sum_{d'=0}^{\vartheta_d-1} \frac{1}{d'!}\left(\frac{\lambda_d}{\mu_d}\right)^{d'} + \frac{1}{\vartheta_d!}\left(\frac{\lambda_d}{\mu_d}\right)^{\vartheta_d}\left(\frac{\vartheta_d\mu_d}{\vartheta_d\mu_d-\lambda_d}\right)\right]^{-1} Y_d, \qquad \forall d \in D \tag{18}$$

In the results, the probability of a steady state for n orders in the service queue of distribution center d (constraint 11) is as follows:

$$Pr_{nd} = \begin{cases} \dfrac{\lambda_d^n}{n!\,\mu_d^n}\pi_{0d} & 1 \leq n \leq \vartheta_d \\ \dfrac{\lambda_d^n {\vartheta_d}^{n-\vartheta_d}}{n!\,\mu_d^n}\pi_{0d} & \vartheta_d < n \leq C \end{cases} \qquad \forall d \in D \tag{19}$$

$$Pr_{d'd} = \sum_{d'=0}^{\vartheta_d} \frac{\lambda_d^{d'}}{d'!\,\mu_d^{d'}}\pi_{0d}\,Y_d + \sum_{d'=\vartheta_d+1}^{\vartheta_d+B_d} \frac{\lambda_d^{d'}{\vartheta_d}^{d'-\vartheta_d}}{d'!\,\mu_d^{d'}}\pi_{0d}\,Y_d \geq (1-\theta_d)Y_d, \forall d \in D \tag{20}$$

$$Pr_{d'd} = \left(\sum_{d'=0}^{\vartheta_d} \frac{\lambda_d^{d'}}{d'!\,\mu_d^{d'}} + \sum_{d'=\vartheta_d+1}^{\vartheta_d+B_d} \frac{\lambda_d^{d'}{\vartheta_d}^{d'-\vartheta_d}}{d'!\,\mu_d^{d'}}\right)\pi_{0d}Y_d \geq (1-\theta_d)Y_d, \qquad \forall d \in D \tag{21}$$

Also, according to the above, the customer waiting time in the $d \in D$ store is obtained as described in relation (21):

$$\omega_d = \left[\frac{\pi_{0d}}{\vartheta_d!}\left(\frac{\lambda_d}{\mu_d}\right)^{\vartheta_d!} \frac{\vartheta_d\mu_d}{(\vartheta_d\mu_d-\lambda_d)^2} + \frac{1}{\mu_d}\right].Y_d, \qquad \forall d \in D \tag{22}$$

Therefore, in the new model, the amount of the cost of waiting time for the order in the $d \in D$ store is added to the first objective function as an additional cost, so the modified model will be as follows:

$$max\,Z_1 = \sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N} pr_p.X_{dcpn} - \sum_{d\in D} f_d.Y_d - \sum_{n\in N} g_n.U_n - \sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N} \widetilde{tr}_{dcp}.X_{dcpn} - \sum_{d\in D}\sum_{e\in D}\sum_{p\in P}\sum_{n\in N} \widetilde{tr}_{dep}.V_{depn} - \sum_{d\in D} c_d.\omega_d \tag{23}$$

$s.t.$:

$$\lambda_d = \sum_{c\in C}\sum_{p\in P}\sum_{n\in N} X_{dcpn}, \qquad \forall d \in D \tag{24}$$

$$\pi_{0d} = \left[\sum_{d'=0}^{\vartheta_d - 1} \frac{1}{d'!} \left(\frac{\lambda_d}{\mu_d} \right)^{d'} + \frac{1}{\vartheta_d!} \left(\frac{\lambda_d}{\mu_d} \right)^{\vartheta_d} \left(\frac{\vartheta_d \mu_d}{\vartheta_d \mu_d - \lambda_d} \right) \right]^{-1} Y_d, \qquad \forall d \in D \tag{25}$$

$$\omega_d = \left[\frac{\pi_{0d}}{\vartheta_d!} \left(\frac{\lambda_d}{\mu_d} \right)^{\vartheta_d!} \frac{\vartheta_d \mu_d}{(\vartheta_d \mu_d - \lambda_d)^2} + \frac{1}{\mu_d} \right] . Y_d, \qquad \forall d \in D \tag{26}$$

$$Pr_{d'd} = \left(\sum_{d'=0}^{\vartheta_d} \frac{\lambda_d^{d'}}{d'!\,\mu_d^{d'}} + \sum_{d'=\vartheta_d+1}^{\vartheta_d+B_d} \frac{\lambda_d^{d'} \vartheta_d^{\,d'-\vartheta_d}}{d'!\,\mu_d^{d'}} \right) \pi_{0d} Y_d \geq (1-\theta_d) Y_d, \qquad \forall d \in D \tag{27}$$

$$Eqs\ (3-11) \tag{28}$$

$$Y_d, U_n, W_{den} \in \{0,1\} \tag{29}$$

$$X_{dcpn}, V_{depn}, Q_{dp}, \geq 0\ and\ integer \tag{30}$$

Also, due to the dynamic nature of some important parameters (including transportation costs and demand) which are beyond planning, as well as the unavailability and even unavailability of historical data required at the design stage, these parameters are mainly based on opinions and experiences. Therefore, the above ambiguous parameters are formulated as uncertain data in the form of trapezoidal fuzzy numbers. It is worth noting that for long-term decisions, estimating transportation costs, demand and capacity of the production facility is definite, difficult and sometimes even impossible. Even if one can estimate a distribution function for these parameters, they may not behave similarly to previous data. Therefore, these parameters, which change in a long-term planning horizon, are considered as fuzzy data. Given the general form of indefinite finite programming, the expected value of the objective function and the pessimistic fuzzy to obtain the objective function and the indefinite constraint, respectively. Now, according to the abbreviated form, the basic pessimistic fuzzy model is as follows (Ghahremani-Nahr et al., 2020):

$$\begin{aligned} & max\ Z_1 = E[Z] = p.X - (f.Y + E[\tilde{c}].X) \\ & s.t.: \\ & NEC\{aX \geq \tilde{d}\} \geq \alpha \\ & Ex \leq sY \\ & Y \in \{0,1\}, \qquad X \geq 0 \end{aligned} \tag{31}$$

Where α controls the minimum degree of certainty of indefinite constraint with a (pessimistic) decision-making approach. Given the trapezoidal probability distribution for the ambiguous parameters, the general form of the relations (31) is as follows:

$$\begin{aligned} & max\ Z_1 = p.X - \left(f.Y + \left(\frac{c^1 + c^2 + c^3 + c^4}{4} \right).X \right) \\ & s.t.: \\ & aX \geq (1-\alpha) d^3 + \alpha d^4 \\ & eX \leq sY \\ & Y \in \{0,1\}, \qquad X \geq 0 \end{aligned} \tag{32}$$

In indefinite models, the minimum level of confidence for establishing indefinite constraints must be determined in terms of decision preferences. As can be seen, in the proposed models, the objective function is not sensitive to deviation from its expected value, which means that the achievement of solid solutions in the base model is not guaranteed. In such cases, high risk may be imposed on decision-making in many real cases, especially in strategic decisions where solution consolidation is largely critical. Hence, to deal with this inefficient situation, the fixed-fuzzy indefinite programming approach to the problem is used. This approach benefits from the significant advantages of both robust and fuzzy programming, which clearly distinguishes it from other uncertainty programming approaches. In this paper, solid-fuzzy uncertainty programming is applied to the proposed model, which is as follows:

$$\begin{aligned}
&max\, Z_1 = E[Z] - \xi\big(Z_{(max)} - Z_{(min)}\big) - \eta[d^4 - (1-\alpha)d^3 - \alpha d^4]\\
&s.t.:\\
&aX \geq (1-\alpha)d^3 + \alpha d^4\\
&eX \leq sY\\
&Y \in \{0,1\}, \quad X \geq 0
\end{aligned} \tag{33}$$

Where M is a very large positive number and $Z_{(max)}$ و $Z_{(min)}$ and $E[Z]$ can be expressed as follows:

$$\begin{aligned}
&Z_{(max)} = p.X - (f.Y + c^1X)\\
&Z_{(min)} = p.X - (f.Y + c^4X)\\
&E[Z] = p.X - \left(f.Y + \left[\left(\frac{c^1 + c^2 + c^3 + c^4}{4}\right)\right].X\right)
\end{aligned} \tag{34}$$

In the first objective function of equation (34), the first expression refers to the expected value of the first objective function using the mean values of the uncertain parameters of the model. The second statement refers to the cost of the penalty for deviating more than the expected value of the first objective function (optimality stability). The third sentence also shows the total cost of the demand deviation penalty (uncertain parameter). Hence, the parameter ξ weighted coefficient of the objective function is the cost of the penalty for not estimating demand. The parameter α indicates the minimum degree of confidence in the value of the fuzzy surfaces of the numbers, which must be between 0.1 and 0.9. According to the above, the controlled model of the problem is as follows.

In the first objective function of equation (34), the first expression refers to the expected value of the first objective function using the mean values of the uncertain parameters of the model. The second statement refers to the cost of the penalty for deviating from the expected value of the first objective function (Robust optimality). The third sentence also shows the total cost of the demand deviation penalty (uncertain parameter). Therefore, the parameter ξ is the weight coefficient of the objective function and η is the cost of the penalty for not estimating the demand. The parameter α indicates the minimum degree of confidence in the value of the fuzzy surfaces of the numbers, which must be between 0.1 and 0.9. According to the above, the controlled model of the problem is as follows.

$$max\, Z_1 = E[Z] - \xi(Zmax - Zmin) - \eta \sum_{c\in C}\sum_{p\in P}\left[dem_{cp}^4 - (1-\alpha)dem_{cp}^3 - \alpha dem_{cp}^4\right] \tag{35}$$

$$min\, Z_2 = \sum_{d\in D}\sum_{c\in C}\sum_{n\in N}\frac{dis_{dc}}{sp_n}.R_{dcn} + \sum_{d\in D}\sum_{e\in D}\sum_{n\in N}\frac{dis_{de}}{sp_n}.W_{den} \tag{36}$$

$s.t.:$

$$\begin{aligned}
&E[Z] = \sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N} pr_p.X_{dcpn} - \sum_{d\in D} f_d.Y_d - \sum_{n\in N} g_n.U_n -\\
&\sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N}\left(\frac{tr_{dcp}^1 + tr_{dcp}^2 + tr_{dcp}^3 + tr_{dcp}^4}{4}\right).X_{dcpn} -\\
&\sum_{d\in D}\sum_{e\in D}\sum_{p\in P}\sum_{n\in N}\left(\frac{tr_{dep}^1 + tr_{dep}^2 + tr_{dep}^3 + tr_{dep}^4}{4}\right).V_{depn} - \sum_{d\in D} c_d.\omega_d
\end{aligned} \tag{37}$$

$$\begin{aligned}
&Zmax = \sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N} pr_p.X_{dcpn} - \sum_{d\in D} f_d.Y_d - \sum_{n\in N} g_n.U_n -\\
&\sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N} tr_{dcp}^1.X_{dcpn} - \sum_{d\in D}\sum_{e\in D}\sum_{p\in P}\sum_{n\in N} tr_{dep}^1.V_{depn} - \sum_{d\in D} c_d.\omega_d
\end{aligned} \tag{38}$$

$$Zmin = \sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N} pr_p.X_{dcpn} - \sum_{d\in D} f_d.Y_d - \sum_{n\in N} g_n.U_n - \sum_{d\in D}\sum_{c\in C}\sum_{p\in P}\sum_{n\in N} tr^4_{dcp}.X_{dcpn} - \sum_{d\in D}\sum_{e\in D}\sum_{p\in P}\sum_{n\in N} tr^4_{dep}.V_{depn} - \sum_{d\in D} c_d.\omega_d \tag{39}$$

$$Eqs(4-11)\ \&\ Eqs(24-27) \tag{40}$$

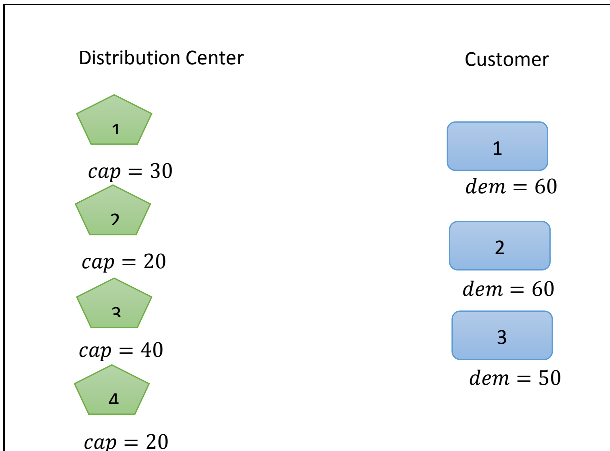
$$\sum_{d\in D}\sum_{n\in N} X_{dcpn} = (1-\alpha)dem^3_{cp} + \alpha dem^4_{cp}, \qquad \forall c\in C, p\in P \tag{41}$$

$$Y_d, U_n, W_{den} \in \{0,1\} \tag{42}$$

$$X_{dcpn}, V_{depn}, Q_{dp} \geq 0 \text{ and integer} \tag{43}$$

3-2- Initial display of the answer (encryption)

The most important part in using meta-heuristic algorithms is how to display the initial solution and decode it in a way that can solve the problem under study. The issue of supply chain network consists of different types of decision-making strategies. According to figure (2) in a two-tier supply chain network (distribution-customer center), the most important decisions related to the location of supply centers and the optimal allocation of flow between the two facilities. Figure (2) shows how to display the initial answer for 3 customers and 4 distribution centers, 3 types of vehicles (Szmelter-Jarosz et al., 2021).



tr	i_1	i_2	i_3	i_4	cap
j_1	15	7	12	10	60
j_2	9	13	10	14	60
j_3	10	12	18	20	50
dem	30	20	40	20	

Node	$\lvert I\rvert + \lvert J\rvert$						
	i_1	i_2	i_3	i_4	j_1	j_2	j_3
$Rand()$	6	1	3	4	2	5	7
V	3	2	1	3	-	-	-

Fig 2. Showing the initial answer (primary chromosome)

Figure (2) shows how to display the initial answer in a $2 * (|I| + |J|)$ matrix. To decrypt, we will follow the steps in each section:

1. The highest priority is selected from the modified chromosome as the starting part of the allocation (Customer No. 3 with priority 7)
2. The distribution center / customer is selected based on the lowest shipping cost with the customer / distribution center obtained from step (1) (distribution center 1 with shipping cost 10)
3. The vehicle required to transfer materials between the two levels is selected (vehicle 3).
4. The optimal flow allocation between the selected levels is achieved based on the minimum value (distribution center supply, customer demand and vehicle capacity) $min\{36.120,30,50\} = 30$).

5. The supply of the distribution center and the customer demand will be updated $\boldsymbol{\psi}_3 = 36.120 - 30 = 6.120$ و $\boldsymbol{\varpi}_1 = 30 - 30 = 0$
6. If the supply center demand or customer demand is zero, the priority associated with that center will be reduced to 0.
7. Steps 1 to 6 continue until the total priority of the distribution centers is reduced to 0.
8. If all customer priorities are not set to zero, that customer will face a shortage.
9. Distribution centers are used to their capacity, are selected as optimal supply chain network centers.

Considering the use of two algorithms NSGA II and MOPSO to solve the problem, the following criteria are used to evaluate the performance of the proposed algorithms (Ghahremani-Nahr et al., 2019):
A) Computation time: An algorithm that has less computation time will be more desirable.
B) Number of efficient answers: The number of undefeated answers in the Pareto set shows the obtained for each problem and the greater the number of these points, it means that the algorithm is more efficient.
C) Maximum Expansion: This criterion shows how many of the answers of a Pareto set are distributed in the answer space, which is calculated from the following equation. The larger the value of this criterion, the more appropriate the diversity of Pareto set answers.

$$MSI = \sqrt{\sum_{m=1}^{M} \left(max_{i=1:|Q|} f_m^i - max_{i=1:|Q|} f_m^i\right)^2} \quad (44)$$

D) Metric distance: indicates the degree to which the answers are evenly spaced, which is calculated from the following equation.

$$SM = \sqrt{\frac{1}{|Q|}\sum_{i=1}^{|Q|} \left(d_i - \bar{d}\right)^2} \quad (45)$$

In the above relation, $|Q|$ Indicates the size of the Pareto archive, and the values d_i and d. Can be calculated from the following equations, respectively. An algorithm that is less than this criterion will be more desirable.

$$d_i = min_{k \in Q \cap k \neq i} \sum_{m=1}^{M} \left|f_m^i - f_m^k\right| \quad (46)$$

$$\bar{d} = \sum_{i=1}^{|Q|} \frac{d_i}{|Q|} \quad (47)$$

4- Analysis of experiments

4-1- Numerical example analysis by epsilon constraint method

At the beginning of this chapter, a numerical example including 10 customers, 8 distribution centers (potential e-shops), 4 products and 6 types of means of transportation is designed and the constraint is solved using the epsilon method. Also, due to the lack of access to real data, random data in accordance with the uniform distribution function as described in table (1) has been used.

Table 1. Definitive and non-definite parameters of the distribution model location model in terms of uniform distribution function

Parameter	Approximate interval	Parameter	Approximate interval
f_d	$\sim U[5000,8000]$	dis_{dc}, dis_{de}	$\sim U[10,20]$
g_n	$\sim U[800,950]$	sp_n	$\sim U[70,100]$
$capD_{dp}$	$\sim U[300,450]$	pr_p	$\sim U[40,70]$
$capN_n$	$\sim U[40,80]$	c_d	$\sim U[2,3]$
ρ	5	ϑ_d	3
φ	15		
$\widetilde{dem}_{cp}$	$\sim U[(35,40),(40,45),(45,50),(50,55)]$		
$\widetilde{tr}_{dcp}$	$\sim U[(10,15),(15,20),(20,25),(25,30)]$		
$\widetilde{tr}_{dep}$	$\sim U[(5,10),(10,15),(15,20),(20,25)]$		

Before solving the problem using the constraint epsilon, the best and worst values of the first and second objective functions must be obtained by the individual optimization method. This requires solving each of the objective functions separately. Table (2) shows the best and worst value of the objective functions of the small sample size problem, assuming an uncertainty rate ($\alpha = 0.5$).

Table 2. The best answer to the sample problem in small size

Efficient solution	Z1	Z2	Efficient solution	Z1	Z2
1	69658.572	5.580	5	69590.796	4.736
2	69654.694	5.288	6	69477.658	4.503
3	69601.845	4.983	7	69372.849	4.389
4	69594.997	4.894	8	68579.576	4.098

According to the obtained efficient answers, in order to reduce the transfer time, vehicles with higher speeds and also higher costs should be used. This will increase the cost of transportation and the use of the vehicle in the distribution network of electronic products. Therefore, with the constant amount of total sales of products, the amount of profit from the design of such a network decreases. Figure (3) shows the Pareto front obtained from solving a small numerical example by the epsilon constraint method.

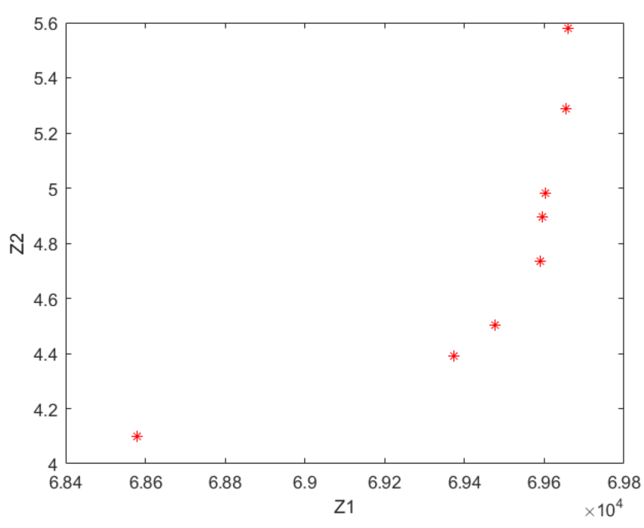


Fig 3. Pareto front obtained from solving a small sample size problem by the epsilon constraint method

As shown in figure (3), the epsilon method has obtained a limit of 8 efficient answers, which can be expressed by analyzing the efficient answers. Since in this model the uncertainty rate has a significant effect on the values of the objective functions, table (4) shows the values of the first and second objective functions under different rates of uncertainty.

Table 4. Changes in the values of the objective functions of the problem under different rates of uncertainty

α	Z1	Z2	α	Z1	Z2
0.1	69677.63	3.723	0.6	64395.52	3.829
0.2	68993.73	3.739	0.7	63344.36	3.914
0.3	68195.50	3.752	0.8	62998.89	4.015
0.4	67087.48	3.794	0.9	61366.18	4.154
0.5	65603.38	3.818			

According to the results obtained from the sensitivity analysis of the problem under different rates of uncertainty is observed with increasing uncertainty rate, due to increasing the amount of electronic products transferred and also increasing the queue length of customer orders, shipping costs and waiting for orders increase as a result, the total profit of the network has decreased. Also, with the increase of uncertainty rate in the network due to more use of vehicles to transfer electronic products, the total transfer time of electronic products in the network has increased. In the following, in table (5), by changing the number of potential centers, its effect on the profit objective function and transfer time is investigated.

Table 5. Changes in the values of the objective functions of the problem constructed under different distribution centers

ρ	Z1	Z2	ρ	Z1	Z2
3	85122.03	5.264	6	54241.16	3.267
4	74909.42	4.355	7	43798.44	2.497
5	65603.38	3.818			

According to table (5), it is observed that with the increase in the number of distribution centers built, due to the proximity of the distance of e-shops to customer clusters, transfer costs have decreased and in return the costs associated with the construction of centers have increased. This has led to a reduction in total profits. On the other hand, by reducing the distance between distribution centers and customer clusters, the total transfer time of electronic products has decreased. Table (6) also examines the effect of the number of employees in each distribution center on the profit objective function and the total transfer time. Considering that the number of employees in each center is equal to 3. Table (6) shows the rate of decrease or increase in profits as well as the total transfer time of electronic products, assuming the number of employees 1, 2, 3, 4 and 5.

Table 6. Changes in the values of the objective functions of the problem under the number of different servers

ϑ	Z1	Z2
1	64012.74	3.818
2	64932.15	3.818
3	65603.38	3.818
4	66147.24	3.818
5	66597.49	3.818

According to table (6), it is observed that with the increase in the number of service providers, the amount of waiting time for orders in the queue of e-store distribution centers decreases and as a result, the waiting cost also decreases. Total costs increase as costs of waiting time decrease. It is also observed that with the decrease or increase of the number of servers, the total transmission time of electronic products in the network has not changed. Figure (4) also shows the sensitivity analysis performed on various parameters of the problem.

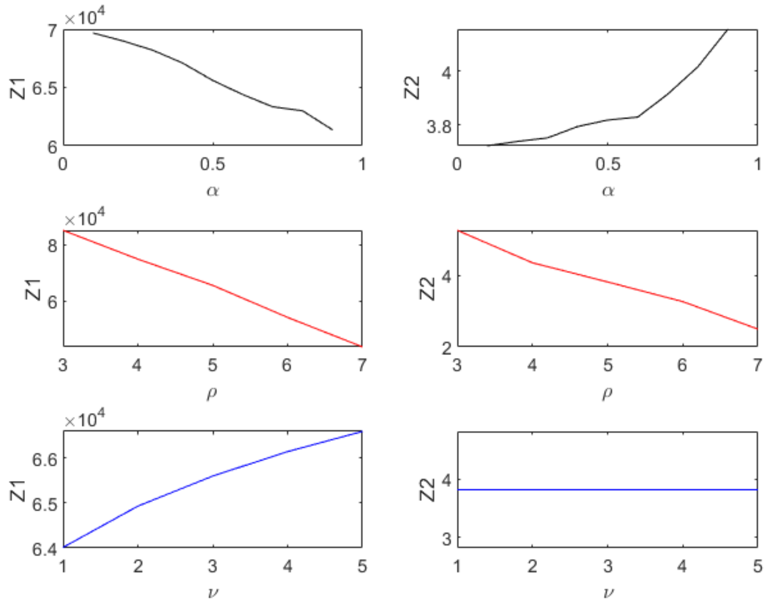


Fig 4. The process of changing the values of the objective functions of the problem by changing different parameters

To solve numerical examples in larger sizes, the use of two meta-innovative algorithms, MOPSO and NSGA II, has been proposed. Therefore, first, the parameter of meta-heuristic algorithms is regulated by Taguchi method and the small numerical example designed in the previous section is compared with the two proposed algorithms and the solutions obtained by the epsilon constraint method. Given the two objective functions of the proposed model, the value of each experiment must first be calculated from equation (48). In this regard, in case of subtraction of the indicators used in comparison of meta-heuristic algorithms including (multiple efficient answers, maximum expansion index, metric distance index and computational time) has been used. After determining the value of each experiment, the scaled value of each experiment (RPD) is calculated from equation (49) to analyze the design of the Taguchi experiment.

$$S_i = \left|\frac{NPS + MSI + SM + CPU\_time}{4}\right| \tag{48}$$

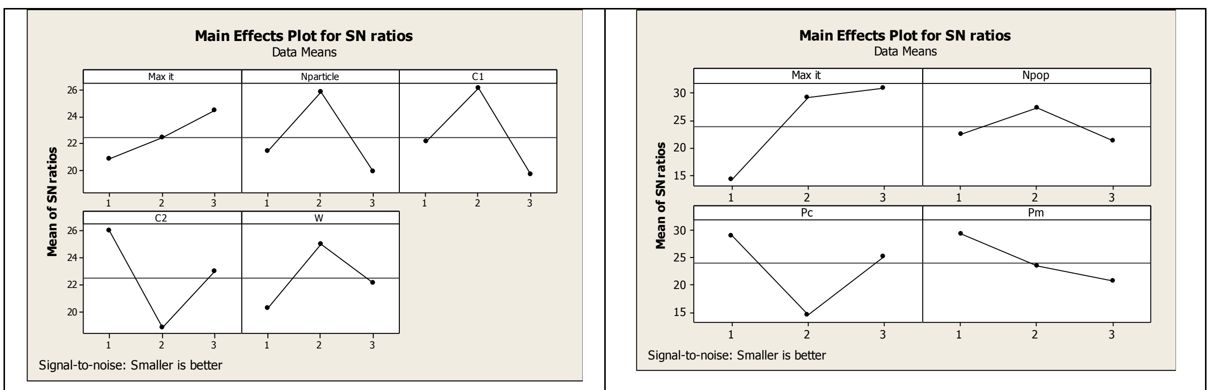
$$RPD = \frac{S_i - S_i^*}{S_i^*} \tag{49}$$

Table (7) shows the proposed parameter levels of the meta-heuristic algorithms of the problem.

Table 7. Levels of proposed parameters for parameterization of meta-heuristic algorithms by Taguchi method

Algorithm	Parameter	symbol	Level 1	Level 2	Level 3
NSGA II	Maximum number of repetitions	Max it	100	200	400
	Number of population	Npop	50	100	200
	Combination rate	Pc	0.7	0.8	0.9
	Mutation rate	Pm	0.02	0.03	0.04
MOPSO	Maximum number of repetitions	Max it	100	200	400
	Number of particles	N particle	50	100	200
	Individual learning coefficient	C1	1	1.5	2
	Collective learning coefficient	C2	1	1.5	2
	Gravity coefficient	w	0.7	0.8	1

After calculating the value of each experiment and also scaling the values of each experiment for each algorithm, the data are entered for analysis in Minitab 16 software. In this method, the maximum value of SN criterion is the criterion for selecting the values of the parameters. Figure (5) shows the mean SN ratio diagram for the NSGA II and MOPSO algorithms.



MOPSO	NSGA II

Fig 5. Mean SN ratio diagram for meta-heuristic algorithms

According to figure (5) and also the criterion for selecting the highest level of SN diagram for each parameter, the most optimal level and parameter value of meta-heuristic algorithms is described in table (8).

Table 8. Optimal parameter levels for parameterization of meta-heuristic algorithms by Taguchi method

Algorithm	Parameter	Symbol	Optimal level	Optimal amount
NSGA II	Maximum number of repetitions	Max it	3	400
	Number of population	Npop	2	100
	Combination rate	Pc	1	0.7
	Mutation rate	Pm	1	0.02
MOPSO	Maximum number of repetitions	Max it	3	400
	Number of particles	N particle	2	100
	Individual learning coefficient	C1	2	1.5
	Collective learning coefficient	C2	1	1
	Gravity coefficient	w	2	0.8

After setting the parameter of the meta-heuristic algorithms, in order to evaluate the effectiveness of the proposed initial solution (primary chromosome), a small size numerical example with the metaheuristic algorithms and Pareto front obtained from them is compared with the Pareto front of the problem solving by epsilon constraint method. Therefore, table (9) and figure (6) show the efficient and Pareto front solutions obtained from different solution methods in a small numerical example, respectively.

Table 9. A set of efficient solutions to a small sample problem with different solution methods

Efficient solution	Epsilon constraint		NSGA II		MOPSO	
	Z1	Z2	Z1	Z2	Z1	Z2
1	69658.572	5.580	69812.99	5.52	69883.02	5.57
2	69654.694	5.288	69649.91	5.30	69801.79	5.03
3	69601.845	4.983	69617.73	5.21	69672.57	4.69
4	69594.997	4.894	69562.78	5.08	69389.69	4.47
5	69590.796	4.736	69546.67	5.06	68950.93	4.43
6	69477.658	4.503	69536.60	4.97	68875.75	4.31
7	69372.849	4.389	69516.04	4.82	68852.72	4.26
8	68579.576	4.098	69446.98	4.59	68823.79	4.26
9	-	-	69312.71	4.44	68711.86	4.22
10	-	-	69209.47	4.28	68385.15	4.11
11	-	-	68818.74	4.27	-	-
12	-	-	68444.66	4.25	-	-
13	-	-	68422.22	4.21	-	-
14	-	-	68365.70	4.16	-	-

According to the table above, NSGA II algorithm has 14 efficient answers and MOPSO algorithm has obtained only 10 efficient answers, which is more limited than the number of efficient answers obtained by epsilon constraint method.

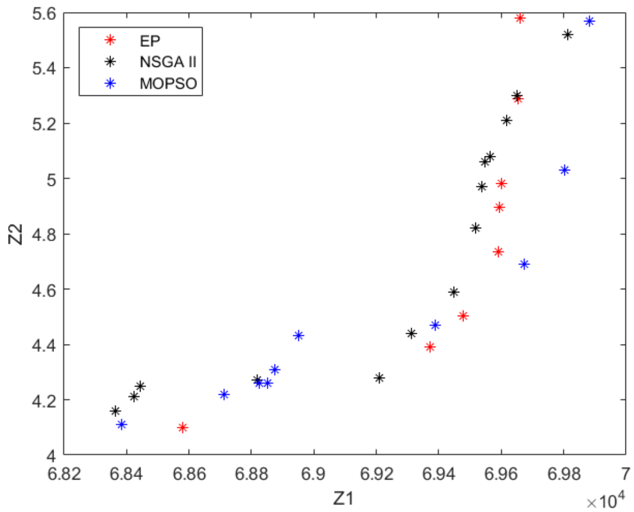


Fig 6. Comparison of the Pareto front obtained from solving a small size numerical example with different solving methods

Since the number of efficient solutions obtained from different solution methods are different from each other, so continue to compare efficient solutions according to the expressed criteria such as (average objective functions, number of efficient answers, maximum expansion, metric distance and computational time) Been paid.

Table 10. Indicators obtained from solving small size numerical examples with different solution methods

Indicator	Epsilon constraint	NSGA II	MOPSO
Average Z1	69441.37	69233.08	69134.72
Average Z2	4.808	4.725	4.535
NPS	8	14	10
MSI	1078.99	1447.29	1497.87
SM	0.739	0.912	0.542
CPU_time	489.34	34.29	26.47

Based on the obtained indicators, it can be stated that the epsilon constraint method was the best solution to obtain the mean of the first objective function (total profit). The NSGA II algorithm has performed better than other solving methods in terms of efficiency in obtaining the number of efficient answers. The MOPSO algorithm, on the other hand, is the best algorithm in terms of obtaining the mean of the second objective function, maximum expansion, metric distance, and computational time. Also, by examining the means of the first and second objective functions, the percentage of error obtained by meta-heuristic algorithms is less than 1%. Therefore, this method can be used to solve larger size numerical examples.

4-2- Analysis of larger size numerical examples

Considering the efficiency of meta-heuristic algorithms in solving small size numerical examples, the following is the analysis of larger size numerical examples. Therefore, 15 sample problems in different sizes are designed according to table (11).

Table 11. Size of sample problems in larger sizes

Sample problem	C	D	P	N
1	12	10	4	8
2	15	10	4	8
3	18	10	4	8
4	20	10	5	8
5	25	15	5	10
6	28	15	5	10
7	30	15	6	10
8	34	20	6	10
9	38	20	6	12
10	42	20	7	12
11	45	25	7	12
12	50	25	7	12
13	55	25	8	15
14	60	30	8	15
15	65	30	10	15

In order to prevent the occurrence of random outliers, each sample problem is solved three times by each meta-heuristic algorithm and the mean of the indicators and objective functions are shown in table (12).

Table 12. Mean object functions and comparison indicators in large sample problems with trans-innovative algorithms

Sample problem	NSGA II						MOPSO					
	Z1	Z2	NPS	MSI	SM	CPU_time	Z1	Z2	NPS	MSI	SM	CPU_time
1	236955.76	6.66	53	2578.79	0.63	36.46	240951.33	6.77	46	4827.16	0.85	22.46
2	250089.06	7.12	55	3988.41	0.88	108.00	250524.45	7.02	57	5136.11	0.62	25.98
3	341647.41	7.86	64	3594.52	0.59	170.30	342604.73	7.91	62	4519.05	0.56	33.76
4	430193.60	8.38	63	3065.20	0.64	242.54	424889.32	8.27	69	5549.95	0.80	62.86
5	486002.34	9.98	44	3125.68	0.55	375.50	494874.84	10.05	69	5295.90	0.73	86.90
6	504059.01	10.12	63	3980.10	0.79	534.40	504258.52	10.11	44	5921.62	0.73	183.76
7	854021.84	12.75	44	2829.80	0.84	685.78	843417.02	12.56	59	4828.34	0.83	237.42
8	888792.63	16.78	50	4594.83	0.77	869.08	886746.93	16.52	66	4312.86	0.89	330.24
9	1031985.09	19.64	55	4148.24	0.71	1039.60	1034018.62	19.98	55	3764.07	0.68	482.88
10	1260856.63	21.26	47	4935.82	0.82	1259.68	1279299.45	21.53	56	5027.40	0.83	651.76
11	1356984.54	23.53	53	4949.61	0.82	1520.14	1352237.96	23.92	44	5447.01	0.71	885.32
12	1469846.64	27.21	58	4734.86	0.84	1825.94	1493183.97	27.20	58	4558.63	0.92	1237.56
13	1554908.46	27.64	53	2617.61	0.82	2221.36	1529911.76	27.44	48	3727.06	0.92	1549.12
14	1695464.84	33.06	67	2740.82	0.97	2810.36	1704531.60	33.02	70	4166.18	0.63	1986.90
15	1756469.96	33.45	40	3618.60	0.60	3676.34	1786213.81	33.51	65	3884.14	0.81	2668.90
average	941218.52	17.70	53.93	3700.19	0.75	1158.37	944510.95	17.72	57.87	4731.03	0.77	696.39

In order to evaluate the results obtained, each of the indicators was evaluated using T-Test at 95% confidence level and the significance of the mean differences between the two algorithms was investigated.

Table 13. T-test results in the mean difference of the indicators between the two algorithms

Algorithm	Indicator	Average	Standard deviation	average difference	95% confidence interval		Statistics of T	Statistics of P
					Lower bound	upper bound		
NSGA II MOPSO	Z1	941219 944511	546143 549976	3292	-407329	413914	0.02	0.987
NSGA II MOPSO	Z2	17.70 17.72	9.58 9.60	0.02	-7.16	7.21	0.01	0.994
NSGA II MOPSO	NPF	53.93 57.87	8.08 9.13	3.93	-2.52	10.39	1.25	0.222
NSGA II MOPSO	MSI	3700 4731	853 677	1031	453	1609	1.27	0.211
NSGA II MOPSO	SM	0.751 0.767	0.124 0.112	0.0160	-0.0725	0.1045	0.37	0.714
NSGA II MOPSO	CPU-time	1158 696	1079 819	462	-257	1181	1.32	0.198

According to table (13), due to the fact that the value of P statistic is greater than 0.05, there is no significant difference between the means of the problem indices between the meta-heuristic algorithms. Figure (7) also shows the average of the indicators obtained in each of the sample problems.

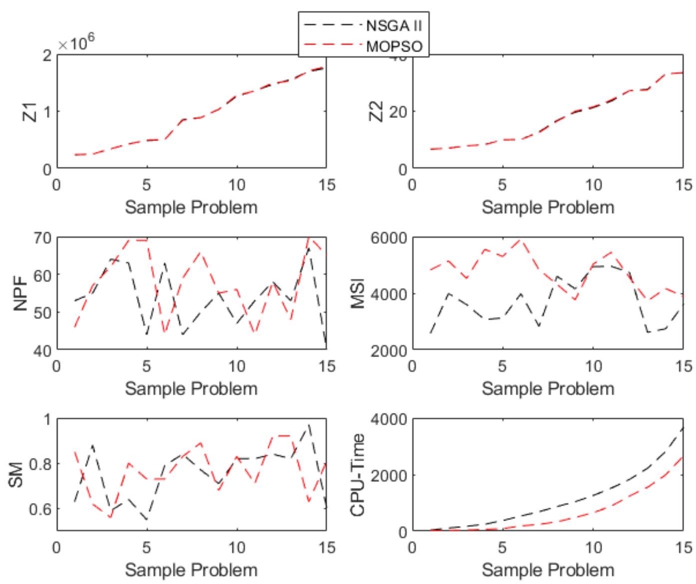


Fig 7. Averages of indices obtained in large size sample problems

Based on the analysis of the results, it was observed that MOPSO and NSGA II algorithms do not have significant differences in any of the indicators. Therefore, in order to select the best solution method, the

TOPSIS multi-criteria decision making method has been used. In this method, all index weights are considered the same. Table (14) summarizes the results obtained from the means of the indicators and the weight of the utility obtained from the TOPSIS method.

Table 14. Averages of Comparison Indicators in Large Size Sample Problems

Algorithm	Z1	Z2	NPS	MSI	SM	CPU_time	Weight of utility
NSGA II	941218.52	17.70	53.93	3700.19	0.75	1158.37	0.0259
MOPSO	944510.95	17.72	57.87	4731.03	0.77	696.39	0.9744

Based on the weight of utility index, MOPSO algorithm is the most efficient algorithm in solving the problem of locating distribution centers of electronic stores.

5- Conclusion

Due to the importance of locating distribution centers, in this article, an issue of locating distribution centers of e-shops in conditions of uncertainty was developed. The unique feature of this paper was the consideration of the queuing system in registering online orders by selected distribution centers and the use of fuzzy stable optimization method to control non-deterministic parameters of the problem. The objective functions considered for the article include profit maximization and minimization of the total transfer time of electronic products between distribution centers and customer clusters. Therefore, three different problem solving methods were considered, including epsilon constraint method, NSGA II algorithm and MOPSO. The results obtained from the analysis of the sample problem in small size showed that the NSGA II algorithm obtained 14 efficient answers, the MOPSO algorithm obtained 10 efficient answers and the epsilon method obtained a limit of 8 efficient answers. However, by comparing the efficient response indices, the relative difference between the results of the mean of the first and second objective functions between the meta-innovative method and the exact method was less than 1%.Examining the changes of different parameters of the problem on the objective functions was also observed, with increasing uncertainty rate, due to increasing the amount of electronic products transferred and also increasing the queue length of customer orders, shipping costs and waiting for orders increased and thus the amount The profit of the whole network has decreased. Also, with the increase of network uncertainty rate due to more use of vehicles to transfer electronic products, the total transfer time of electronic products in the network has increased. Also, with the increase in the number of distribution centers built, due to the proximity of the distance of e-shops to customer clusters, transfer costs have decreased and in return, the costs associated with the construction of centers have increased. This has led to a reduction in total profits. On the other hand, by reducing the distance between distribution centers and customer clusters, the total transfer time of electronic products has decreased.

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