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Smart multi-commodity location-routing model for perishable goods with an emphasis on big data under uncertainty and congestion

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ABSTRACT

In recent decades, the integrated optimization approach of information-based logistics systems has been one of the most important aspects of optimization in supply chain management. This approach deals with the simultaneous investigation of dependencies between facility location, allocation of suppliers/customers to facilities, the structure of transportation routes, planning, and inventory control. One of the most critical issues related to logistics is location routing. Therefore, in this research, a multi-objective mathematical model for locating and routing multiple perishable goods is presented, considering the objectives of minimizing logistics costs and transportation costs, minimizing product distribution time among customers, and maximizing customer service. Among the most critical limitations considered are the capacities of suppliers, vehicles, and producers and the soft time window of product distribution. Due to the uncertainty in the number of customers' orders for product delivery in the supply chain and the large volume of big data, the queue model based on M/M/C/K was introduced in the fuzzy conditions of customer demand. Finally, the mathematical model was optimized and analyzed with MOSA and MOKA. The analysis results of two meta-heuristic algorithms in the studied problem showed that the MOSA has better efficiency.

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1. Introduction

Today, the competitiveness of markets and the development of management concepts have forced companies to design and manage supply chains better (Ghahremani-Nahr et al., 2023). Supply chain management emphasizes the integration of chain members. Because to increase the efficiency of a supply chain, its decisions cannot be considered separately and optimized (Sahebjamnia et al., 2018). Recently, the rapid growth of the population has led to a significant increase in people's demand for food, which is why the food industry is considered one of the most critical industries. So, to manage the high demand for food, food supply chain management plays a crucial role (Chernonog, 2020; Ghahremani-Nahr et al. 2023). Based on this, the activities of raw material procurement, production, storage, and warehousing of goods, inventory control, distribution, delivery, and customer service, which were previously carried out at the company level, have now been transferred to the supply chain level (Biuki et al., 2020). Therefore, supply chain management has become more critical in the food industry. On the other hand, logistics and transportation in the supply chain require special planning due to the amount of pollution (Yavari et al., 2020). For a food supply chain network to be effective, it is necessary to make strategic and tactical decisions about the location and allocation of relevant facilities in the network, as well as the optimal amounts of product transfer and storage (Mohebalizadehgashti et al., 2020; Kumar et al., 2023). Perishable products need special measures because, besides the known economic aspects, they have social and environmental effects (Jouzdani & Govindan, 2020).

Shortening the transportation cycle, controlling inventory transportation costs, and delivering orders on time have become the main concerns of all organizations in the body of supply chains to gain more market share in this competitive environment. Supply chain managementcan, as an integrated approach for proper management of material and goods flow, information, and financial flow, has the ability to respond to these conditions (Tavakkoli-Moghaddam et al., 2022). Supply chain management coordinates all these activities so that customers can get quality products and reliable services at minimum cost. Storing the manufactured goods of the factories near the consumption markets in order to distribute them in a timely and appropriate manner to meet the needs of the customers is one of the important issues in every supply chain; Because not making appropriate decisions in this regard usually the supply chain to incur huge costs (Zheng, 2019; Ghahremani-Nahe et al. 2022). In today's industrial world, in addition to leaving behind their commercial competitors in the field of sales, manufacturing units are trying to reduce their costs by having proper storage of goods demanded by customers and also routing vehicles to transport manufactured goods to these warehouses or customers (Gómez & Martinez, 2023). The routing problem consists of two sub-problems: locating depots and routing vehicles. These two issues are considered new issues in the supply chain. This problem tries to optimize the total cost of logistics activities of a broadcasting system by optimizing two sub-problems simultaneously. At the same time, this issue, which determines the optimal points for creating and building a warehouse, also optimizes how to distribute warehouse goods. Considering the approach that this problem has and the dependence between the location of warehouses and the details of product distribution tours, the location routing problem takes two interdependent decisions simultaneously. This problem was proposed and solved for the first time in the late eighties by researchers in the field of optimization and research in operations (Schneider, 2017).

The usual situation of the LRP problem is that the candidate places for establishing depots (or warehouses) are specific. Several customers are also stationed at specific points and are ready to receive service (receiving goods) from the depots. The work of providing customer service is done by vehicles that are required to start their tour from the depot and return to the same depot after delivering goods or providing services to customers (Govindan et al., 2021). Determining the number of necessary depots and placing them in suitable places, assigning customers to the opened depots and forming a vehicle tour between the depot and the customers, is part of the objectives of the vehicle routing problem (Khan et al., 2023). The establishment of depots and vehicle tours causes costs in the transportation system, including the fixed cost of the depot and the cost of transporting the vehicle. The evaluation criterion is the sum of these two costs, which should be minimized.

Considering the development of food supply chain production, the need for systems that can carry out transportation operations as efficiently as possible has been noticed by organizations more than in the past. In addition, due to the reduction of fuel reserves in the world and the increasing need to optimize energy consumption in all organizations, transportation planning is essential to reduce energy consumption and costs and pollution. Therefore, in this research, we are looking at the design of the perishable food supply chain, taking into account goals such as minimizing transportation costs ,locating warehouses, and maximizing the level of customer service (minimizing the average number of customers in the queue to receive the requested products) (Aliahmadi et al., 2023) and on the other hand, the supply chain of perishable food products is highly important. Accuracy in evaluating the optimal solutions of the supply chain is doubly important because an inappropriate assessment of the space of Pareto optimal solutions of the problem causes irreparable losses in the operational area of the supply chain in question. One of the innovations considered in this research is the use of concepts related to queuing theory when delivering products to customers and crowd management in product delivery, due to which a new model has been presented in the perishable food supply chain field. On the other hand, because the supply chain problem in the real world has uncertainty in decision-making, this uncertainty in decision-making creates whiplash effects in the chain. Therefore, the development of concepts of uncertainty in the supply chain causes resilience to be made in the supply, production, and distribution system. Considering that in the studied problem, organizational managers can have an optimistic, pessimistic, and average estimate of customer demand, fuzzy uncertainty theory has been used in of evaluating and analyzing customer demand, which is used as a chance limit in fuzzy analysis.

The importance of perishable goods supply chain management has led to the modeling of a perishable goods supply chain location-routing problem in this article. The difference between the model presented in this article and previous models is related to the use of M/M/c/K queuing theory in the distribution of products under fuzzy conditions. The integration of these two issues has led to the closeness of the mathematical model to the real world. Also, the control of non-deterministic parameters and big data and the use of multi-objective simulated annealing (MOSA) and multi-objective keshtel algorithm (MOKA) for complex mathematical models are other unique features of this article. In this model, strategic and tactical decisions such as facility location and vehicle routing are taken simultaneously.

2. Literature Review

Wang & Lim (2018) presented an integrated model of location-routing problem and inventory problem (ILRIP) with the selection of warehouse locations and product inventory. Therefore, a two-stage optimization problem is designed and two main objective functions are evaluated to minimize the total expected cost for inventory and location selection and distribution costs with a time window. Due to several limitations, a multi-objective optimization problem has been designed. Rafie-Majd et al (2018) presented a three-level supply chain, consisting of a supplier, a number of distribution centers (DC), and a number of retailers (customers) in the form of an Integrated Routing-Placement Problem (ILRP). The way perishable products are delivered to customers in a limited time horizon consists of several time periods. Saif-Eddine et al. (2019) developed the Inventory Locating-Routing Problem (ILRP), considering the vendor's inventory management (VMI) strategy to minimize the total supply chain cost in the form of an NP-hard mathematical model. Therefore, an improved genetic algorithm (IGA) has been designed and used to solve the problem. Zheng . (2019) investigated the integrated optimization of inventory location routing in the supply chain network (SCDN). The constraints in the real world, including capacity and routing constraints, were introduced in the integrated model to describe the model more precisely. to optimize the mathematical model, they proposed the exact algorithm of Generalized Boundary Decomposition (GBD) to solve the model. Rohmer et al. (2019) presented a two-stage inventory routing problem for perishable products. The studied network sends products from a supplier to an intermediate warehouse, where storage may take place, and from there, they are delivered to customer locations by smaller vehicles. Liu et al. (2019) presented stochastic routing with alternative displacement components and limited capital budget under partial distribution information (i.e., mean and covariance matrix of customer demands). The goal of the model was to maximize the service level. Meidute-Kavaliauskiene et al. (2022) presented a multi-stage, multi-layered perishable supply chain about procurement time, cycle cost, and customer satisfaction. This study presented a new form of location routing in the supply chain network for perishable products, considering environmental considerations, cost, lead time and customer satisfaction. So that the total costs, delivery time and release of pollutants in the network were minimized while customer satisfaction was maximized.

Wu et al (2022) propose an integrated approach for the simultaneous optimization of decisions involved in the supply chain. including location, inventory and routing strategy. The optimized results show that considering direct supplier-to-retailer shipping reduces overall supply chain costs by 31% with a 43% reduction in shipping costs, a 69.4% reduction in shipping losses, a 99.4% increase in Useful in inventory costs. With the development of e-retailing for perishable products, the ability to ship directly from the supplier to the retailer will bring more benefits in the future. Rahbari et al (2022) proposed a new multi-period location-inventory routing problem for a red meat supply chain in an emerging economy with heterogeneous vehicle fleets and logistics decisions. The proposed model is presented in two stages and four stages including carcass suppliers, packaging facilities, cold stores, and retailers. In this research, the number of transported products at each level, the number of stored products, the amount of red meat produced, the required cold storage facilities, and the required vehicles were determined optimally. Alamatsaz et al (2022) presented a multi-objective model for location routing problems with green capacity considering driver satisfaction and time window with uncertain demand. The main innovation of this study is the combination of the mentioned features and the consideration of the problem to be used in the real world. A mixed integer programming model has been developed and the scenario generation method has been used to solve this stochastic model.

Ghasemkhani et al (2022) presented an integrated production-inventory routing problem for perishable products under uncertainty by meta-heuristic algorithms. The goal of the proposed model is to maximize total profit, which is equivalent to sales revenue from the sum of maintenance, production, transportation, and priority costs. At the production level, a multi-period production system with limited production capacity is considered, where the inventory at each stage of production is planned to calculate the related maintenance costs and more appropriate planning. Chen et al (2023) presented a mixed multi-layer location-routing problem with distinct intermediate warehouses. which includes a multi-layer mixed urban logistics network to handle parcels distributed in the region. The network consists of limited urban distribution centers, many distinct intermediate warehouses, and a large number of terminals. It is modeled in the form of mixed integer linear programming and optimized by a hybrid heuristic algorithm based on local search. Mohamed et al (2023) presented a two-level stochastic multi-period limited capacity location-routing problem. In this article, the problem of distribution network design under uncertainty at the strategic level has been investigated. It considers a network divided into two levels of limited capacity distribution: each level includes a specific location-allocation-transport scheme that must deal with future demand. Its purpose is to decide the number and location of warehouse/storage platforms and distribution/fulfillment platforms and the allocated capacity from first-floor platforms to second-floor platforms. This problem has been solved through a two-stage integer random program modeled with Bander's decomposition approach. Basso et al. (2021) optimized the electric vehicle routing problem by considering the time window. In this study, routing is done on two levels. In the first level, the best routes are identified and in the second part, taking into account the time windows, the best order of visits is determined. Haghi et al (2023) addressed the location-routing problem with partial coverage. This paper studies a generalized routing location problem considering the partial coverage of users according to the distance coverage function. There is a set of candidate locations to open a warehouse and a set of locations with a certain number of users to be covered by open centers. If users are within its coverage area, they may travel directly to an open center or may be transported to the centers by capacity vehicles. A distance reduction function is considered for facility coverage,, and cars can partially cover co-located users. Calculation results show that considering the partial coverage of users reduces the number of people without coverage by lowering the car capacity.

Oscar et al. (2023) addressed the approximation of two factors for location routing by considering the capacity for vehicles and distribution centers. Strategic decisions regarding the deployment of equipment (warehouses, distribution centers, etc.) are made based on accurate estimates of operational routing costs. It has been shown that this problem can be cost-optimized with a two-factor approximation algorithm that may slightly exceed facility capacities with an arbitrarily small adjustable fraction of vehicle capacity. Maghfiroh concerningthis al. (2023) proposed a location routing problem concerning time window and its solution by a meta-heuristic approach; this research addresses the location routing problem with time window constraints, including working hours as well as time constraints per customer. Partovi et al. (2023) proposed a bi-level programming formulation for the location-inventory-routing problem in a two-story supply chain, including several central warehouses on the first floor and retailers on the second floor with perishable products under uncertain demand. Total operating costs in both levels are minimized due to capacity limitations.

Most of the researches have worked on vehicle routing at different levels of the supply chain and examined its different situations. However, in this research, the integration of the queuing theory problem in the problem of routing and locating perishable food products is considered. MINLP mathematical model is used in this research. To optimize the mathematical model, two traditional meta-heuristic algorithms (MOSA) and new (MOKA) have been developed.

3. Problem modeling

In today's era, many companies have taken various measures to improve the supply chain performance of perishable products. These measures were focused on three areas: increasing income (including more variety of products, increasing the speed of introducing new products and broader sales markets), andreducing costs (including meeting needs with the approach of reducing costs). Judy, just-in-time sourcing and vendor inventory management) and reduction of assets (including outsourcing of production activities, information technology, and logistics). These actions in a stable environment will have good results, but today's business environment is constantly changing. Recent changes in supply chains due to the globalization of trade and the increase in the number of chain partners have created a long network with more dispersion and complexity. This has resulted in the reduction of direct and indirect control and supervision of companies on the current activities (Saif-Eddine et al, 2019). On the one hand, long and complicated supply chains usually respond slowly to changes and will have vulnerable points as well as multiple challenges. In addition to the financial effects, supply chain challenges are also effective on other aspects of production. Based on the breakdown and analysis done in the manufacturing companies that took place for 10 years, they found out that the inventory of the companies decreases between 40%-33% in three years. Therefore, the current research aims to provide a mathematical model for locating and routing for the distribution of food products.

- **Assumptions of the proposed model**
  1. Vehicles have limited capacity.
  2. The number of vehicles is limited.
  3. Vehicles have the ability to carry one or more types of special goods.
  4. All vehicles are placed in transit warehouses (distribution centers) that belong to them.
  5. The beginning and end of each transit warehouse route (distribution center) are the same.
  6. The total amount of withdrawals at suppliers is equal to the total amount to be delivered to customers.
  7. Incoming vehicles must arrive at transit warehouses (distribution centers) at the beginning of the day, and outgoing vehicles must distribute cargo during the day.
  8. The demand of the studied problem has fuzzy uncertainty.

Sets

i : supplier set
j: distributor set
p: collection of products
k: set of customers
t: set of time periods
V: Collection of vehicles (owned and leased)

Parameters

cap_i	The capacity of the supplier i
cap_j	The capacity of the distributor j
cav_v	Capacity of the vehicle v
c_{ij}	Transportation cost from supplier i to distribution center j
cD_{jk}	Shipping cost from distribution center j to customer k

cc_{jm}	Transportation cost from distribution center j to recycling m
$cost_p$	Penalty for late and early delivery of product p to customers, delivery time window to customers
cv_v	The fixed cost of using a car v
ef_{vij}	The cost (rental or salary) of car v from i to j
ef_{vjk}	The cost (rental or salary) of car v from j to k
fx_j	The fixed cost of locating the distribution center j
λ_{vkt}	Visit rate of car v to customer k in time interval t
μ_k	Customer service rate k
Ct_{tv}	The maximum number of vehicles v that are active during period t
D_{kpt}	Customer demand k in period t of product p (uncertainty)
v_p	Weighing the volume of the product
DD	The deadline for distributing products to customers
sh_{kp}	Deficit cost of product p with customer k (lost sales)
h_{jp}	The cost of keeping product p at the distribution center j
tt_{ij}	The duration of transportation from i to j
ts_i	Duration of loading in i
tf_j	Discharge duration j
tt_{jk}	The duration of transportation from j to k
$tmax$	The maximum duration of the soft time window

Decision variables

The decision variables used in this model are mixed. The variable amount of goods sent from each product is also continuous and approximate, which in reality and in most cases, this amount is considered as an integer. The approximations of the amount of goods sent will have a small effect on the results as long as the capacity of the transport vehicle is greater than the volume of one unit of goods.

Q_{vpijt}	The amount of product p sent by vehicle v from i to j in period t.
Q^1_{vpjkt}	The amount of product p sent by vehicle v from j to k in period t.
Q^2_{vpkjt}	The amount of product p sent by vehicle v from k to j in period t.
B_{kpt}	The amount of inventory deficit p in period t in k
HH_{jpt}	Inventory amount of product p in center j in period t
X_{vpijt}	binary variable when a product p is sent by vehicle v from i to j in period t, the value is 1, otherwise 0
XX_{vpjkt}	binary variable when a product p is sent by vehicle v from j to k in period t, the value is 1, otherwise 0
y_{jt}	Binary variable 1 when warehouse j is open in period t, otherwise 0
ctv_{tv}	The value is 1, if the vehicle v is active in the time interval t, otherwise 0

Mathematical model

$$\begin{aligned}\min c1 = &\sum_v\sum_i\sum_j\sum_t\sum_p x_{vpijt} * c_{ij} * ef_{vij} + \sum_v\sum_j\sum_k\sum_t\sum_p xx_{vpjkt} * c_{jk} * ef_{vjk} \\ &+ \sum_v\sum_i\sum_j\sum_t\sum_p ctv_{tv} * \left(x_{vpijt} + x_{vpjkt}\right) + cost_p * max\left\{\left(tmax - dd\right), 0\right\} + \\ &\sum_j\sum_t fx_j * y_{jt} + \sum_j\sum_t\sum_p HH_{jpt} * h_{jp} + \sum_k\sum_t\sum_p B_{kpt} * sh_{kp}\end{aligned} \tag{1}$$

$$\begin{aligned}&\text{Min}: \sum_v\sum_k\sum_{t=1}^{n}\left[\left(1 + \sum_{n=1}^{c_{tv}-1}\left(\lambda_{\text{vkt}}/\mu\right)^n \left(1/n!\right) + \left(\lambda_{\text{vkt}}/\mu\right)^{c_{tk}} \left(1/ct_{tv}!\right)\sum_{n=c_{tk}}^{\infty}\left(\lambda_{\text{vkt}}/c_{tv}\mu\right)^{n-ct_{tv}}\right)^{-1}\right] \\ &\left[\left(\lambda_t/\mu\right)^{c_{tv}} \sum_{n=c_{tv}}\left(n - ct_{tv}\right)\left(\lambda_{\text{vkt}}/ct_{tv}\mu\right)^{n-ct_{tv}}\right]\end{aligned} \tag{2}$$

$$\sum_v\sum_j\sum_p q_{vpijt} * v_p \le ca_i \quad \forall i,t \tag{3}$$

$$\sum_v\sum_i\sum_p q_{vpijt} * v_p \le cap_j \qquad \forall j,t \tag{4}$$

$$\sum_i \sum_p \sum_k q_{vpjkt} * v_p \leq cav_v \qquad \forall v, t, j \tag{5}$$

$$\sum_k \sum_p q_{vpjky} * v_p \leq qv_v \qquad \forall v, j, t \tag{6}$$

$$\sum_i \sum_v q_{vpijt} + HH_{jpt-1} = \sum_k \sum_v q_{vpjkt} + HH_{jpt} \qquad \forall j, p, t \tag{7}$$

$$d_{kpt} - B_{kpt} = \sum_v \sum_j q_{vpjkt} \qquad \forall k, p, t \tag{8}$$

$$\sum_v \sum_i \sum_p q_{vpijt} \leq big * y_{jt} \qquad \forall j, t \tag{9}$$

$$q_{vpijt} \leq big * x_{vpijt} \qquad \forall v, p, i, j, t \tag{10}$$

$$q_{vpjkt} \leq big * xx_{vpjkt} \qquad \forall v, p, j, k, t \tag{11}$$

$$\sum_j \sum_p x_{vpijt} \leq 1 \qquad \forall i, v, t \tag{12}$$

$$\sum_v \sum_i \sum_p x_{vpijt} \leq 1 \qquad \forall j, t \tag{13}$$

$$x_{vpijt} - x_{vpjit} = 0 \qquad \forall v, p, i, j, t \tag{14}$$

$$\sum_v \sum_i x_{vpijt} = \sum_v \sum_k xx_{vpjkt} \qquad \forall j, p, t \tag{15}$$

$$\sum_j \sum_p xx_{vpjkt} \leq 1 \qquad \forall k, v, t \tag{16}$$

$$\sum_i \sum_j \sum_v (tt_{ij} + ts_i + tf_j) * x_{vpijt} + \sum_j \sum_v xx_{vpjkt} * tt_{jk} \leq tmax \qquad \forall k, p, t \tag{17}$$

Explanation of the mathematical model

The first objective function (1) is to minimize costs related to logistics. This cost includes the following items.

- Minimization of transportation costs and car fuel consumption from the supplier to the distribution center (transportation costs are considered separately in two forms: car cost (c) and driver's wage and rental cost (ef) Is)
- Transportation costs and fuel consumption from the distribution center to customers
- Fixed cost of using the car
- Soft time window delay penalty fee
- The fixed cost of locating distribution centers
- The cost of maintaining inventory in distribution centers
- Deficit cost or lost customer sales

The second objective function (2) is to maximize the level of service to customers (minimizing the average number of customers in the queue to receive perishable products in demand) considering that the queue created in the delivery of products is a serial queue. The series queuing chain is used to model the second objective function. Constraint (3) guarantees that the products supplied from the supplier do not exceed the capacity of the supplier. Constraint (4) guarantees that the transferred product does not exceed the capacity of the distribution center. Constraint (5) guarantees that the amount of transported product does not exceed the capacity of the vehicles. Constraint (6) guarantees that the amount of product transferred from the distribution center to the customers does not exceed the capacity of the vehicle. Constraint (7) guarantees that the inventory balance is created in the distribution warehouse and the inventory of the previous period and the amount of the new product received is equal to the amount of the inventory at the end of the period along with the product sent to the customer. Constraint (8) guarantees that for customers either full demand is delivered or lost sales occur. Constraint (9) ensures that if the product is transferred between the supplier and the distribution center, then the distribution warehouse will be reopened and located. Limitation (10) is the routing between the supplier and the distribution center. Limitation (11) is routing between the distribution center and customers. Constraint (12) guarantees that the number of times the car can leave the supplier is limited. Constraint (13) ensures that the number of times a vehicle can enter the supplier is limited. Constraint (14) guarantees that sub-touring does not occur. Constraint (15) ensures that the number of cars entering and exiting the distribution warehouse is equal. Constraint (16) ensures that the number of vehicle exits from the distribution center is limited. Constraint (17) guarantees that the time window of distribution (soft window) is observed in the distribution of products.

On the other hand, due to the nonlinearity of the first objective function, we convert the mathematical model into a linear state by using the heuristic Eq. (18):

$$\begin{aligned} &\max\{x1, x2, x3, \ldots.., xn\} \quad \rightarrow y \\ &y \geq x_i \quad \forall i = 1\ldots\ldots n \\ &y \leq x_i + m * z_i \quad \forall i = 1\ldots\ldots n \\ &\sum_{i=1} z_i \leq n-1 \end{aligned} \tag{18}$$

In the above model, z_i will be a binary decision variable. Also, the variable isalso a positive integer variable.

Considering the uncertainty in the demand parameter

As we know, the assessment of uncertainty in the components of the supply chain occurs in optimistic, moderate, and pessimistic states to evaluate and analyze the natural environmental conditions in the supply chain by evaluating the opinions of experts. Since the theoretical dimensions of the subject of the mathematical model demand approach towards fuzzy values have been a problem, hence the environmental conditions of the fuzzy values algorithm with limited chance will be used. According to Dicker, due to the accuracy of evaluating opinions in the trapezoidal phase compared to the triangular phase, this theory has been used. In this part, in order to deal with the uncertainty in the demand parameter, a fuzzy programming model with limited chance is presented for the research problem. Fuzzy programming used in this research is a conventional method that relies on mathematical concepts such as the expected value of an undefined number and probability measures (POS) and necessity (NEC) and allows the decision maker to control the conservatism level satisfying the constraints. Gives for further introduction, for simplification, first, consider the following mathematical programming problem:

$$\begin{aligned} &Min\, Z = f.y + \tilde{c}.x \\ &A.x \geq \tilde{d} \\ &B.x = 0 \\ &s.x \leq N.y \end{aligned} \tag{19}$$

Let f be the vector of deterministic parameters and c be the vector of non-deterministic parameters of the problem. Also, x is a vector of continuous variables and y is a vector of zero and one variables. Also, d are the numbers on the right side of the problem. Assuming the non-deterministic parameters (d), considering that in this research the customer demand is considered non-deterministic, the above model can be written as follows:

$$\begin{aligned} &Min\, E[Z] \\ &Pos\{A.x \geq \tilde{d}\} \geq \alpha_m \\ &B.x = 0 \\ &s.x \leq N.y \\ &0.5 \leq \alpha_m \leq 1 \\ &x \geq 0 \\ &y \in \{0,1\} \end{aligned} \tag{20}$$

The above model can be written as follows:

$$\begin{aligned}
&Min\,Z = f.y + \left(\frac{c_{(1)}+c_{(2)}+c_{(3)}+c_{(4)}}{4}\right).xA.x \geq (1-\alpha_m).d_{(1)} + \alpha_m.d_{(2)} \\
&B.x = 0 \\
&s.x \leq N.y \\
&0.5 \leq \alpha_m \leq 1 \\
&x \geq 0 \\
&y \in \{0,1\}
\end{aligned} \tag{21}$$

Therefore, (8) is modified as follows.

$$\begin{aligned}
&(1-\alpha)d^1{}_{kpt} + \alpha d^2{}_{kpt} - b_{kpt} \leq \sum_v \sum_j q_{vpjkt}\ \forall k,p,t \\
&(1-\alpha)d^4{}_{kpt} + \alpha d^3{}_{kpt} - b_{kpt} \geq \sum_v \sum_j q_{vpjkt}\ \forall k,p,t
\end{aligned} \tag{22}$$

4. The findings

In this section, according to the presentation of the multi-objective mathematical model, then the evaluation and validation of the presented model was done using two meta-heuristic algorithms. Therefore, the most important parameters of the evaluated mathematical model inputs are considered as follows.

Table 2. The most important parameters of the mathematical model

Parameter	Amount	Currency
c_{ij}	Uniform ~ [110000, 180000]	IRR
cD_{jk}	Uniform ~ [14000, 22000]	IRR
cc_{jm}	Uniform ~ [120000, 210000]	IRR
ef_{vij}	Uniform ~ [70000, 90000]	IRR
ef_{vjk} و cf_{vjm}	Uniform ~ [4000, 5000]	IRR

Taguchi experiments

In the late 1940s, Taguchi proposed new statistical concepts and later it was proved that these concepts are valuable tools in the category of quality control and improvement. Since then, many Japanese craftsmen use this method to improve the quality of products and process. Increasing the quality of cars made in this country is strongly related to the widespread use of this method. Taguchi's method is in the field of quality control in manufacturing industries and is based on three main and simple concepts:

- Quality should be designed during production, not checked during the manufacturing process of the product.
- The product must be designed to be safe against uncontrollable environmental factors.
- The cost of quality should be measured as a function of deviation from the standard state and the losses should be measured across the system.

Designing an experiment includes choosing the most suitable orthogonal array, determining the factors with suitable columns and finally the location of the experiments (experiment conditions). In this research, we have used the smaller the better equation of the Taguchi method.

$$SN_s = -10log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{23}$$

Since the mathematical model of this research is two-objective, an equation using standard multi-objective indicators is used as a response in the Taguchi method; This equation is as follows.

$$MCOV = \frac{MID}{MS} \tag{24}$$

Number of Pareto Solutions

This criterion is equal to the number of output answers each time the algorithm is executed. In the comparison between several algorithms, this criterion is defined as the number of output solutions resulting from the execution of each algorithm. Obviously, the more Pareto solutions of a method, the more desirable that method is.

The mean distance from the ideal solution (MID)

This criterion is used to calculate the average distance of Pareto solutions from the coordinate origin. In the following equation, it is clear that the lower this criterion is, the more efficient the algorithm will be.

$$MID = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f1_i - f1_{best}}{f1_{total}^{max} - f1_{total}^{min}} \right)^2 + \left(\frac{f2_i - f2_{best}}{f2_{total}^{max} - f2_{total}^{min}} \right)^2}}{n} \quad (25)$$

Algorithm execution time criterion (CPU time)

In big problems, one of the important criteria is their execution time, and for this reason, algorithm execution time is considered as a quality evaluation criterion.

Maximum Scattering (MS) criterion

The distance index is defined as follows:

$$MS = \sqrt{\sum_{i=1}^{n} \left(minf\left(i\right) - maxf\left(i\right) \right)^2} \quad (26)$$

The dispersion measurement index of non-defeated answers (SNS)

This index is presented to identify the dispersion and diversity of the obtained Pareto solutions.

$$SNS = \sqrt{\frac{\sum_{i=1}^{n} \left(MID - C_i \right)^2}{n-1}} \qquad C_i = \sqrt{f1_i^2 + f2_i^2} \quad (27)$$

5. Results of design experiments

After designing the current problem, it is time to design the experiment using the Taguchi method. As explained, the Taguchi method reduces the parameter setting time by reducing the number of trials. First, we specify the parameters we want to adjust in each algorithm. Using the minitab software, we obtain the levels of parameters and orthogonal arrays for the tests, and after determining the number of tests for each algorithm, we tested the algorithms with the same specified levels and ran them ten times and averaged the results obtained from these ten tests. Then we deweighted them and obtained S/N plots and obtained better parameters. First, it is necessary to obtain and mention the levels of each algorithm. For this purpose, related articles were studied and candidate levels were identified from among them, which is according to table (3).

Introduction of MOSA: One of the most successful single solution algorithms can be called simulated refrigeration algorithm. This algorithm uses mathematical logic and at the same time simple to search. The efficiency of this algorithm has been praised many times in various research problems in operations and engineering sciences. This algorithm uses the logic of cooling crystallized metal at high temperatures. This algorithm was first introduced in 1983. This algorithm starts searching with a random high-temperature solution. In each step of the algorithm, a neighborhood is created for the answer of the previous step. If the mentioned answer is improved, the new answer will be accepted. Otherwise, we will probably accept the mentioned answer; This probability is controlled according to the current temperature and using the Boltzmann function. This logic helps the algorithm accept bad answers with a high probability first and then with a lower probability and escape from the local optimum.

Introduction of MOKA: One of the most efficient optimization algorithms in recent years has been Keshtel's algorithm. This method, which has shown its effectiveness in solving various engineering and research problems in operation, was inspired by the greedy behavior of a group of ducks in the Keshtal region of Mazandaran province. Like other meta-heuristic algorithms, this algorithm uses an initial population to start the algorithm. The primary population is divided into three different types. The first type, which they call lucky kestrels, hang around next to their nearest neighbor to get better.

The second sex is among the lucky kestrels to properly search their neighborhood. The third group is the Keshtels, who got tired and flew away, and another group sits next to them again. In this algorithm, it is important to meta-heuristics phases and allows the user to choose one or two of the three algorithm search operators among them. In this algorithm, the population of lucky hits regulates the focus of the algorithm and two other operators for the search phase, and the variety of answers is included in the algorithm engine.

Finally, experiments were designed with the help of minitab16 software and L9 orthogonal arrays were selected for MOSA. But for the MOKA, L27 orthogonal arrays were considered. After running the algorithms for each of the mentioned tests, the response values for the Taguchi method were obtained. TablesTables (4) and (5) present these values and orthogonal arrays.

Table 3. Different levels for parameters of each algorithm

Algorithms	**parameters**	**Parameter level**		
		Level 1	**Level 2**	**Level 3**
MOSA	T_0	40	50	60
	α	0.99	0.9	0.88
	Max-iteration	4*(i+j+k+l+o)	8*(i+j+k+l+o)	12*(i+j+k+l+o)
MOKA	M_1	10%	15%	20%
	M_2	25%	30%	35%
	S_{max}	20	25	30
	N-Keshtel	150	200	250
	Max-iteration	2*(i+j+k+l+o)	3*(i+j+k+l+o)	4*(i+j+k+l+o)

Table 4. L27 orthogonal array and calculation results for MOKA

Experiment	M_1	M_2	S_{max}	**N-Keshtel**	**Max-iteration**	**MOKA Response**
1	1	1	1	1	1	0.8434992
2	1	1	1	1	۲	0.592161
3	1	1	1	1	3	0.7415502
4	1	2	2	2	1	0.6823188
5	1	2	2	2	2	0.5154978
6	1	2	2	2	3	0.884799
7	1	3	3	3	1	0.5106732
8	1	3	3	3	2	0.792336
9	1	3	3	3	3	0.2934744
10	2	1	2	3	1	0.4573068
11	2	1	2	3	2	1.25358
12	2	1	2	3	3	0.586398
13	2	2	3	1	1	0.5756574
14	2	2	3	1	2	2.57142
15	2	2	3	1	3	0.6287076
16	2	3	1	2	1	0.7478028
17	2	3	1	2	2	0.686715
18	2	3	1	2	3	0.318546
19	3	1	3	2	1	0.438345
20	3	1	3	2	2	1.245114
21	3	1	3	2	3	0.3648336
22	3	2	1	3	1	1.084158
23	3	2	1	3	2	0.306102
24	3	2	1	3	3	1.75083
25	3	3	2	1	1	2.790924
26	3	3	2	1	2	0.7442634
27	3	3	2	1	3	0.8737422

Finally, after drawing the signal-noise diagrams of each algorithm, the best values of the parameters can be identified. These values are presented in graphs (1) and (2).

Table 5. L9 orthogonal array and calculation results for MOSA

Experiment	T_0	α	Max-iteration	MOSA Response
1	1	1	1	1.412292
2	1	2	2	1.012829
3	1	3	3	1.364352
4	2	1	2	0.995285
5	2	2	3	1.584672
6	2	3	1	1.732878
7	3	1	3	0.552442
8	3	2	1	1.210944
9	3	3	2	0.913012

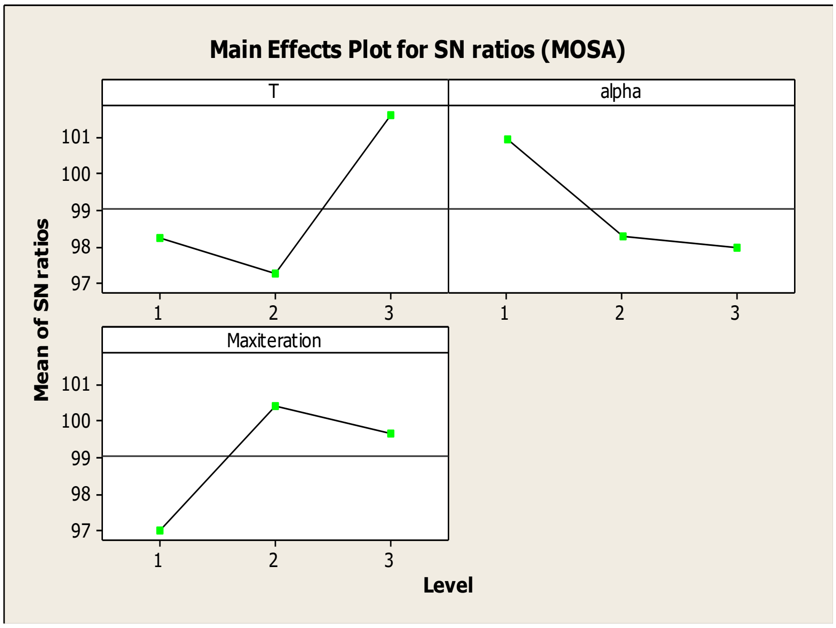

Fig. 1. Signal-to-noise diagram of MOSA

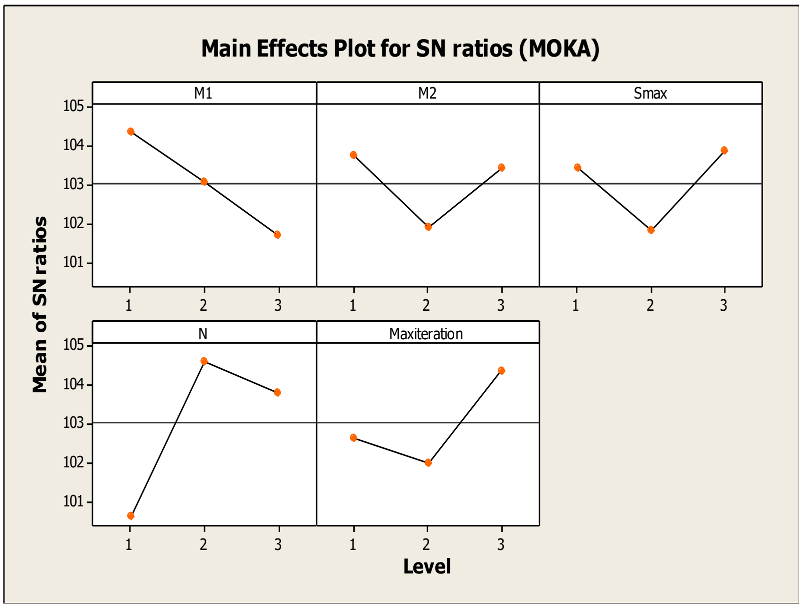

Fig. 2. Signal-noise diagram of MOKA

After solving the proposed mathematical model using the mentioned methods, finally, based on the dimensions of the sample problem in Table (6), table (7) shows the results for the problem.

Table 6. Different dimensions of the problem

Problem number	*I*	*J*	*p*	*k*
1	3	4	3	4
2	5	7	5	7
3	7	10	7	10
4	9	13	9	10
5	15	22	15	13
6	17	25	17	22
7	19	28	19	25
8	25	37	25	28
9	35	52	35	37
10	37	55	37	52
11	39	58	39	55
12	41	61	41	58

Table 7. Computational results of algorithms for 12 sub-problems

Problem	NPS		CPU Time		MID		MS		SNS	
number	MOSA	MOKA	MOSA	MOKA	MOSA	MOKA	MOSA	MOKA	MOSA	MOKA
1	6	12	21.1834	132.2293	5.87049	2.510198	329286	601828.2	661202.8	389473.6
2	9	11	26.00746	260.5447	3.078883	1.191484	701826.1	1218659	1285026	682065.2
3	8	10	32.36283	596.912	2.352114	2.920867	563728.5	1041369	1281900	1215255
4	4	14	50.6234	712.5168	9.949745	4.378978	820655.9	883799.3	2979866	1494606
5	8	12	49.65863	3111.587	3.387842	6.159697	1702567	1070950	2844734	3691123
6	8	11	67.78848	2478.924	8.1863	3.983655	1430007	2812801	2873859	5069426
7	8	14	58.08107	4043.673	5.90531	6.513643	1279556	1196453	5411036	2969448
8	6	12	135.3342	7913.826	9.457389	7.27548	1337295	1620368	4680322	6662891
9	8	12	132.5492	13854.84	8.731648	11.34515	2586521	1504772	8224257	5709284
10	11	9	176.3517	18167.14	8.212444	19.82508	1524766	1956791	11735598	9700917
11	11	14	160.5797	26164.37	15.97272	8.491642	1141240	3527042	6988162	6887722
12	9	12	154.4991	26537.09	15.01994	10.56788	2931624	2705478	8694685	7282089

6. Discussion and conclusion

Intense competition, rapid changes in markets and customer priorities, and the rapid development of technology and globalization have forced organizations to work as members of a supply chain instead of working individually. In today's competitive market, economic and production enterprises, in addition to dealing with their organization and internal issues, also pay a lot of attention to managing and monitoring related resources and elements outside the organization. It is common knowledge that organizations cannot compete as isolated entities, and it is clear that working together in a network can be more accessible. The reason for this is to achieve a competitive market advantage or advantages and finally to gain more market share. In recent years, many researchers have addressed the issue of supply chain.

The importance of the food supply chain and its management led to modeling a perishable material supply chain network problem to make simultaneous location-routing decisions under uncertainty. This article used queuing theory to distribute food products in fuzzy conditions and MOSA and MOKA were used to solve the problem. The results of solving the model showed that with the increase in customer satisfaction, the supply chain network design costs increase. As the waiting time for delivery of food products to customers in the queue system decreases, the costs associated with the number of servers in each distribution center and transportation costs increase. Also, based on the analysis, if the maximum delivery time of products to customers decreases, the service level drops and the transportation costs increase.

On the other hand, with the analysis, it is observed that tomore significantof to increase the level of service to the customers, a more significant number of vehicles can be used, which has led to an increase in the costs associated with using vehicles in the supply chain network. By analyzing the uncertainty rate, it was also observed that with the rise of this coefficient, the amount of demand in the distribution system has increased. The increase in demand in the supply chain network has led to a decrease in the level of service due to the limited capacity of vehicles and distribution centers. Hence, the costs associated with the network have increased. Due to the NP-Hard nature of the presented model, MOSA and MOKA were used to solve the model in larger sizes. Solving 12 numerical examples in larger sizes showed that MOKA obtained the highest NPS and the lowest MID. Compared to MOKA, MOSA has received the most SNS and the least MS, and in addition, it has been able to solve various numerical examples in a much shorter period. Examining these results shows that MOSA is more efficient for solving the presented model. According to the features of the proposed model and the closeness of this model to the real world, several management insights can be provided. Managers should be informed of the results of this article to determine the limits of the level of service to customers and the minimum-maximum costs incurred on the food supply chain network.

Also, the queue system in this network helps the managers make the necessary decisions regarding the more appropriate food distribution. In this article, location and routing decisions have been taken together, and managers can choose the most suitable place among the many options for establishing their distribution centers according to the available budget and the desired service level of their company.

This research's results align with the results of various researchers such as (Ghahremani-Nahr et al., 2023, and AliAhmadi et al., 2023). In this research, as in previous studies, the conflict between the objective functions at the level of service and the costs related to the network can be seen.

The existence of multiple possibilities in the real world with the possibility of different events can be one of the primary challenges in providing mathematical models that have been ignored in this research. Also, for the better distribution of food due to its high perishability, the use of Internet of Things tools can greatly help managers. These tools reduce costs associated with data collection and food distribution. Therefore, it is suggested that a conceptual model for this issue be proposed in future research. Also, using accurate methods such as branch-price can help the researcher provide more accurate results.

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