Journal of Optimization in Industrial Engineering
Vol.17, Issue 1, Winter & Spring 2024, 55-76
DOI: 10.22094/QJIE.2024.951323

Research Article

Providing a Multi-Objective Sustainable Distribution Network of Agricultural Items Considering Uncertainty and Time Window Using Meta-Heuristic Algorithms

Abbas Toloie Eshlaghya [a], Amir Daneshvar [b,*], Adel Pourghader Chobar [c], Fariba Salahi [d]
[a] *Department of Industrial Management, Science and Research Branch, Islamic Azad University, Tehran, Iran*
[b] *Department of Information Technology Management, Electronic Branch, Islamic Azad University, Tehran, Iran*
[c] *Department of Industrial Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran*
[d] *Department of Industrial Management, South Tehran Branch, Islamic Azad University, Tehran, Iran*
Received: 06 January 2024; Revised: 15 June 2024; Accepted: 30 June 2024

Abstract

In this article, a sustainable network of distribution of agricultural items with suppliers, distribution centers, and retailers is considered. The main purpose of presenting the mathematical model in this article is to determine the optimal number and location of suppliers, assigning suppliers to distribution centers and optimal routing for the distribution of agricultural items to retailers in a predefined time window. Also, determining the optimal amount of inventory and the reorder point in retailers and distribution centers is another problem decision. To model the problem, some parameters of the model were considered non-deterministic and were controlled by the probabilistic fuzzy method. The results of solving numerical examples in different sizes showed that with the increase of the total costs of the distribution network of agricultural items, the amount of greenhouse gas emissions decreases, and the employment rate increases. Also, with the increase of the uncertainty rate, due to the increase of the real demand and the change in the optimal amount of production, distribution, storage and reorder point, the values of all the objective functions also increase. It was also observed by solving different numerical examples with NSGA II and MOGWO algorithms, these algorithms have been able to solve the problem in a much shorter period than the epsilon constraint method, and comparison indicators such as NPF, MSI, SM, and computing time show These algorithms have a high efficiency in solving numerical examples of the problem of the distribution network of agricultural items.

Keywords: Stable network; Agricultural items; uncertainty; Meta-heuristic algorithm; Jimenez fuzzy; Time window

1. Introduction

Researchers and practitioners often classify supply chain decisions into strategic, tactical, and operational based on the time horizon of impact. Strategic decisions have a longer time horizon of impact, which can even take years, because they deal with decisions that cannot be easily changed, such as the location of facilities. Tactical decisions have a time horizon of several months and include planning aspects related to inventory management (Gruler et al., 2018). Finally, operational decisions are made daily, with almost immediate effect, and include distribution decisions. Historically, these decisions are reviewed separately. Each entity in the supply chain tries to minimize the costs incurred in the same facility without considering the consequences of these actions on the upstream or downstream units of the supply chain. While this approach ensures that cost is minimized for each level, the sum of all costs throughout the supply chain may not be minimal. A situation in which each level tries to maximize its benefits regardless of other levels leads to local optimization and sometimes suboptimal systems and excessive costs (Saragih et al., 2019).

Recently, supply chain managers and researchers have realized the importance of integrating supply chain decisions. Many researchers have shown significant savings by considering a combination of the above decisions in a single model. Many models presented in the literature combine two supply chain decisions into a single model. These models are location inventory models, location routing, and inventory routing models (Tavana et al., 2021). However, few models integrate all three decisions and solve them simultaneously. In other words, positioning-inventory-routing models have not been widely studied (Zarean Dowlat Abadi et al., 2022).

Due to the increasing trend in supply chain management issues, the combination of location, routing, and inventory of perishable products has become very important in the field of agriculture. Perishable products, due to the limited time allowed for storage, bring more challenges to the supply chain. In general, a perishable product is a product that loses its value over time, such as fruits, vegetables, etc. (Mini et al., 2020). Deterioration of goods, in addition to causing economic losses to companies, also causes an increase in waste from an environmental point of view, resulting in more pollution of the environment. In this situation, the manufacturer can return the expired products and properly manage them for disposal or recycling by creating a suitable collaboration process with retailers and sharing information related to demand and inventory. And in this way, it provided the basis for saving costs, reducing environmental pollution, and using fewer natural resources (Mahjoob et al., 2022).

The supply chain of food and agricultural products has recently received a lot of attention due to public health issues. What has become more tangible is that, shortly,

Corresponding Author Email Address: a_daneshvar@iauec.ac.ir

the design and operation of the agricultural supply chain will be heavily regulated and monitored, especially for products intended for human consumption. This means that traditional supply chain operations may be subject to change. The planning of activities carried out along the supply chain of agricultural products is one of the aspects that may be a thoughtful subject of detailed investigations (Iraj et al, 2024). Recently, timely and accurate access to products and supply chain activities has become a new factor in nutrition. Consumers in many parts of the world are constantly demanding reliable evidence as an important measure of quality and health. This trend is caused by several factors, including the increase in global demand for food products from diverse sourzces, the emergence of food-related health risks, and increasing concern about the effects of genetically modified organisms in the human food chain and the environment in the market. To meet consumers' needs for a consistent supply of high-quality, healthy, and nutritious foods, as well as to restore public trust in the food chain, the design and implementation of complete supply chains from farm to end user becomes an important part of the food quality assurance system (Kresnanto et al., 2021). Farmers, marketers, research professionals, and policymakers need a useful understanding of supply chain traceability concepts to help develop and implement appropriate technology to meet consumer demand for a traceable agricultural supply chain (Mahdavimanshadi et al., 2024).

The number of officials in the food chain varies greatly at each level. In the European Union, about 11 million farms produce agricultural products for processing by about 300,000 companies in the food and beverage industry. Food manufacturers sell their products through 2.8 million outlets Companies within the food distribution and food service industry deliver food to 500 million consumers in the European Union. Primary agriculture still employs twenty-two million people (full-time and part-time). In addition, together with food production, food retailing, and food services, it constitutes the agricultural sector and provides approximately 44 million jobs in the EU. The majority of the more than 15 million holdings/companies in food chains are small or medium (Shirzadi et al., 2021). In 2010, for agriculture, 70% of all farms in the EU were less than 5 hectares and only 2.7% were more than 100 hectares. But if small businesses or companies define all stages of the food chain, the concentration in the food manufacturing and retail sectors will be much higher than in the agricultural sector. The market share of the top five companies (or C5 concentration ratio) in the EU food industry averaged 56% in 2012 across the 14 EU member states. At the same time, in 13 member countries, the share of the top five retailers is more than 60%. As a geological function, agriculture is facing physical, logistical, economic, and regulatory constraints. At the European Union level, the proportion of C5 concentration in agriculture in 2010 was 0.19%. At the member country level, this ratio has been classified from 0.4% in Germany to about 4% in Estonia. Concentration helps achieve an economic equilibrium, but also reduces the number of downstream players in the food chain, and uses them when purchasing. Buying more is not a problem in itself, but abuse is at the heart of unfair trade in the food chain.

The supply chain of agricultural products is vital for human survival on this planet. It doesn't matter if these chains are local or international, the availability of food at the right time, of the right quality, and in the right quantities is very important. A recent United Nations report on the consequences of global population projects that the world's population will be 9.6 billion by 2050, and one of humanity's biggest challenges is to feed this growing population (Soysal et al., 2018). Another think tank insists that although it is a big challenge and food production needs to increase, we already produce enough to sustain the population. If this trend continues, there will be enough products for the future. If this is the case, why does half of the world's population go hungry every day or have only one meal a day? Food poverty is common in developing countries, and this is not only a cover for fraud in the food supply chain but also a change in the social environment where people resort to crime to get enough food (Li et al., 2016) International organizations such as the United Nations and the World Health Organization promote programs to combat child poverty. These programs focus not only on the availability of food but also on the quality and nutritional aspects of food. History has shown that they have won or lost by controlling the food supply chain. Studying food supply chains from an operational perspective is essential because they affect not only daily life but also business and livelihoods. Therefore, applying the concepts and principles of logistics and supply chain for various organizations, especially the industries related to perishable agricultural items, seems to be necessary, which has attracted the attention of many researchers. In addition to the need for supply chain design, the integration of decision-making in the supply chain has become one of the most important aspects of the supply chain management system. This concept examines the dependence between the location of the facilities, the allocation of suppliers and customers to the facilities, the structure of the transportation system and their routing, and the inventory control system.

Based on the material presented in this article, a sustainable distribution network model for agricultural items is presented in conditions of uncertainty with high perishability, in which there are issues such as facility location, vehicle routing, and inventory. Also, the sustainability of the supply chain network, including economic, social, and environmental, is taken into account. Various objectives of sustainability issues such as minimizing total costs, minimizing the amount of greenhouse gas emissions, and maximizing the employment rate have been considered. Also, the lack of precise determination of demand parameters, and transmission and maintenance costs, these three parameters are assumed to be non-deterministic in the model, which has been controlled using the probabilistic fuzzy method.

The structure of the article is as follows, in the second part, the research literature review and the research gap are discussed. In the first third part, a non-deterministic system of a sustainable model for agricultural items has been presented and the control of non-deterministic projects has been discussed using the probabilistic fuzzy planning method. In the fourth part, problem-solving methods such as definition epsilon, NSGA II algorithm, and MOGWO are described. In this initial answer, the use in obtaining effective answers is also stated. In the fifth part, the numerical and computational results of the analysis and analysis of the research on important topics are discussed. Finally, in the sixth section, the conclusions and suggestions of the research have been discussed.

2. Literature Review

In this section, the research conducted in the field of the distribution of agricultural items in the supply network has been investigated. Ghezavati et al. (2017) presented a periodic scheduling mathematical model for the production of fresh agricultural products (tomatoes). The main purpose of presenting this model is to maximize the profit of the distributor, who has relative control over the logistics decisions related to the production of fresh products in the agri-food supply. To solve the problem, their analysis method is used and they checked their model for a domestic distributor of fresh tomatoes in Iran. Ong et al. (2019) considered an agricultural supply chain with a fresh food supplier and several retailers. In this article, the supplier's availability and routing decisions for the transportation and receipt of available food, food waste, and costs are discussed using random customer and perishable products that must be delivered to each retail outlet. can be carried. They used a Monte Carlo simulation algorithm to solve the problem. Keyvan et al. (2019) consider the horizontal survey of customers in the optimization of vehicle routing and control and show that it significantly reduces the market in total costs. The routing-inventory-location theme optimizes the combination of location, vehicle routing, and inventory control. In their research, Imran et al. (2020) investigated the routing problem in the collection of perishable products without uncertainty. This research consists of three stages. In the first step, a mixed multi-objective mathematical model is formulated considering cost uncertainty. The second stage includes the development of the solution methodology. In this step, solving the mathematical model, a modified multi-objective fuzzy programming is used to make decisions to satisfy their experiences. Finally, in the third phase, a case of surgical instruments is presented as an example. In their research, Ji et al. (2020) presented a mixed integer linear programming (MILP) model to minimize the total costs to solve the routing problem of perishable products with time window constraints. Due to the uncertainty in the market, the MILP model is transformed into a robust mixed integer programming (MIRP) model by introducing uncertain sets (box, ellipse, and facet). Experiments with real data show that, when used with increasing uncertainty, MIRP models pay higher costs, but can achieve better.

Violi et al. (2020) proposed a dynamic and stochastic approach to an inventory routing problem where highly perishable products must be delivered from a supplier to a set of customers. Also, in this article, demand is considered a non-deterministic parameter. They performed their numerical calculations on real data from an agri-food company in southern Italy. Giallanza and Puma (2020) presented a mathematical model for the green vehicle routing problem in the agri-food supply chain. In this model, they considered heterogeneous vehicles with different capacities. In this model, the main goal was to minimize total costs and greenhouse gas emissions. NSGA II algorithm was used to solve the model. Finally, using the model for a case study of the Sicilian agro-food field confirmed the strength of the model. Li et al. (2020) optimized a fresh and green food logistics distribution problem with heterogeneous vehicles. They used a developed genetic algorithm and a refrigeration simulation algorithm. The main goal was to minimize the total cost of distribution of items and to minimize the amount of greenhouse gas emissions. In their research, Biuki et al. (2020) introduced an integrated model of location, routing, and inventory problem as three key problems in optimizing a logistics system, and since finding the optimal solution for this problem is an NP-hard problem, They have used two hybrid meta-heuristics as parallel and series combinations of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to solve the problem. Navazi et al. (2021) modeled a stable closed-loop location-routing-inventory problem for perishable products and developed two evolutionary algorithms, including the Non-Dominated Sorting Genetic Algorithm (NSGA) and a new hybrid algorithm to solve cases with They have developed a lot. The results indicate the importance of closing the network loop for perishable products. Taşkıner and Bilgen (2021) provided a comprehensive review of research conducted on optimization models in planning the harvest and production of agricultural products. They used a new taxonomy to categorize articles systematically. Their classification was based on the scope of the problem, model features, and modeling approach. Shirzadi et al. (2021) developed a new periodic mixed integer mathematical model in the field of the distribution of agricultural and fresh food products. In this article, concepts such as routing and inventory for perishable products are considered. The main goal of this research was to minimize total costs and minimize greenhouse gas emissions. They stated that the use of vehicles with fewer emissions and the increase in the delivery level of the factory to achieve a green environment and a higher level of profit should be mentioned. Esteso et al. (2021) proposed a mixed-integer linear programming model for the design of an entire multi-product agricultural commodity distribution network that considers capacity, planting, harvesting, transportation, and perishability constraints for a multi-period horizon. The results show that when designing the network, the economic performance is improved when the perishability of the product is considered. Gupta et al. (2021) designed a flexible and efficient agri-food supply chain network for optimal multi-layer storage and distribution to reduce food loss and quality degradation. They used a fuzzy multi-objective linear programming model. The objective functions of the problem were to minimize food losses and maximize flexibility. They tested their model in an Indian food company. Tirkolaee et al. (2021) selected the supply of pesticides in a supply chain network of agricultural products by considering environmental criteria. They used the process of hierarchical analysis and fuzzy technique for prioritization and the TOPSIS method to evaluate the ranking of suppliers. Wu et al. (2021) presented a multi-period routing-inventory-location problem with time windows and fuel consumption. The proposed problem simultaneously optimizes locating, finding, and inventory decisions for shopping malls in a multi-layer route. Alvarez et al. (2022) investigated the issue of routing perishable products with fixed shelf life and terminal decay. They examine vulnerability in the form of useful life and decay of the product and are more effective. In their research, Barma et al. (2022) proposed a multi-objective model of the capacity vehicle routing problem to predict the delivery of perishable items. The main principle of this model is to minimize the quality of perishable items for delivery and delivery cost. The proposed model is solved using a non-dominant ordered genetic algorithm and a Strength Pareto structural algorithm. Ada (2022) addressed the selection of sustainable suppliers in the management of highly perishable food-agriculture supply chains. Harahap and Rahim (202) investigated the capabilities of the production of the perishable product process from the delivery center to a set of facilities to minimize total operating costs.

In this paper, they aimed to achieve the optimal route of perishable items and optimal inventory in a single period problem. Song and Wu (2022) proposed an integrated approach to simultaneously optimize the decisions involved in the supply chain for location, inventory, and routing strategy decisions. Their proposed network consisted of a set of suppliers, distribution centers, and retailers. They used the Cplex method to solve the problem and showed that considering direct shipping from supplier to retailer reduced total supply chain costs by 31%, 43% reduction in transportation costs, and 69.4% reduction in losses. Shipping is a 99.4% increase in useful inventory costs. Ghasemkhani et al. (2022) presented an integrated production-inventory-routing problem with a mixed integer linear programming model, specifying a multi-perishable, multi-period product and heterogeneous fleet with time windows in a distribution network. In this article, the goal of the proposed model is to maximize the total profit, which is equivalent to the sales revenue from the total costs of maintenance, production, transportation, and priority. They used a hybrid colonial competition algorithm and self-adaptive differential evolution to solve the problem. Pratap et al. (2022) considered an integrated production-inventory-routing problem for perishable food products, where the concepts of capacity, timescale, and carbon emission reduction were addressed. Due to the NP-Hardness of the problem, a pollination algorithm and cuckoo search were used to solve the problem. By examining 10 numerical examples, they showed that the pollination algorithm has a better performance than the cuckoo search algorithm. By examining the background of the research, it can be seen that there is no comprehensive model of the distribution network of agricultural products in which the sustainability of the network (economic, social, and environmental) is considered. Also, in most of the models, the parameters of the problem are taken into account in a definite way, which in the real world, considering the issue of uncertainty is one of the necessities of every research. Therefore, taking into account the uncertainty in the demand parameter and maintenance cost; the Fuzzy-probabilistic method has been used to control non-deterministic parameters and problem modeling.

3. Defining the problem and presenting the mathematical model

In this section, the problem of the sustainable distribution network of agricultural items with high perishability has been modeled. The mathematical model presented in this article corresponds to Figure (1) in which there are a set of potential suppliers, distribution centers, and retailers. In this network, suppliers send raw materials needed to produce products to distribution centers. Distribution centers supply products based on the reorder point and ordering time and send them to retailers in the form of routing. In this issue, the distribution of agricultural products to retailers and distributors must be done in a predetermined time window. Considering sustainability in the distribution chain network of agricultural items, three aspects are considered: economic (minimization of total costs), environmental (minimization of greenhouse gas emissions), and social (maximization of employment rate).

To model the proposed problem, the following assumptions are presented:

The presented model is single-period and multi-product.

Each product has different perishability rates.

- Demand for perishable products in retailers and transportation costs are uncertain.
- Warehouses of distribution centers and retailers have safety stock.
- The reorder points of distribution centers and retailers are different from each other.
- There are a different number of heterogeneous vehicles.

According to the above assumptions, the mathematical model presented in this section aims to select suppliers of agricultural products, optimal allocation of suppliers to distribution centers, optimal routing of distribution of agricultural products to retailers, optimal determination of the order quantity of agricultural products with a high perishability rate and Determining the best transportation options.

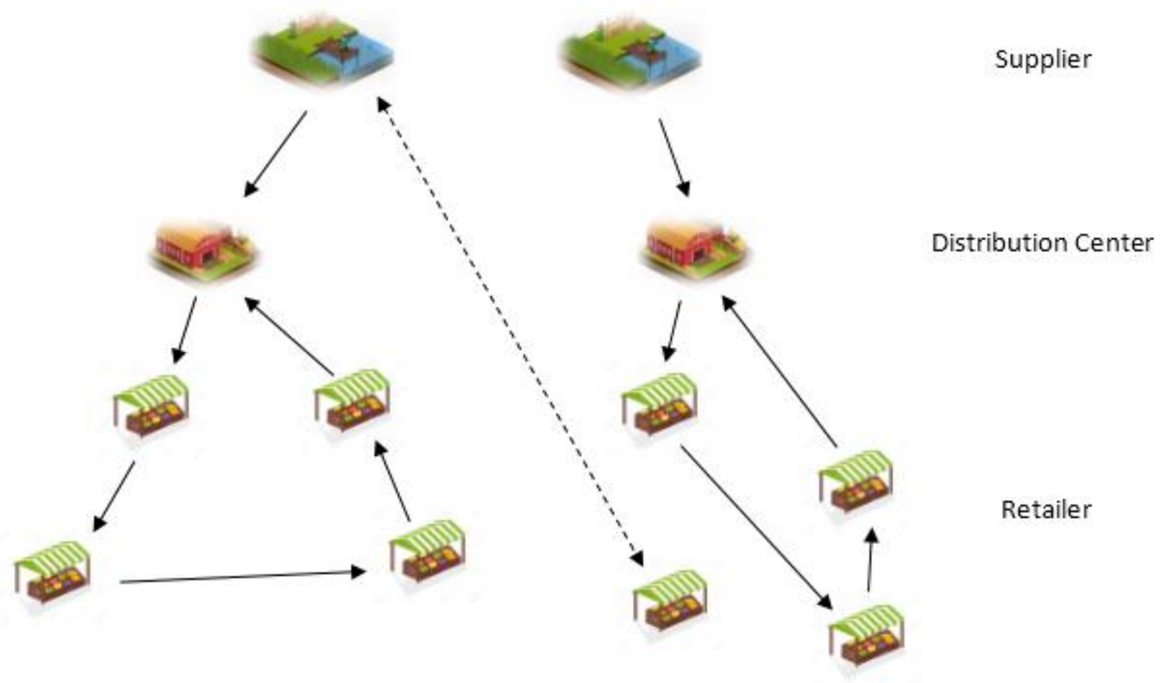

Fig.1. Sustainable distribution chain network of agricultural items

The symbols used in problem modeling are as follows:

Sets

N Retailers $n, l \in N$
M Distribution centers $m \in M$
B Suppliers $b \in B$
F Products $f \in F$
V Shipping options $v \in V$

Parameters

f_v *Fixed cost of using the shipping option* $v \in V$
A_{fm} *Cost of ordering product* $f \in F$ *from distribution center* $m \in M$
H_{fm} *Cost of keeping product* $f \in F$ *in distribution center* $m \in M$
h_{fn} *Cost of keeping product* $f \in F$ *at retailer* $n \in N$
a_{fn} *Cost of ordering product* $f \in F$ *from retailer* $n \in N$
μ_{fn} *Daily demand of product* $f \in F$ *from retailer* $f \in F$
σ_{fn} *standard deviation* μ_{fn}
θ_f *Perishability rate of the product* $f \in F$
ρ_{nl} *The correlation coefficient of demand of retailer* $n \in N$ *and retailer* $l \in N$
l_{fmb} *A lead time of product* $f \in F$ *distribution center* $m \in M$ *from supplier* $b \in B$
l_{fnm} *A lead time of product* $f \in F$ *retail seller* $n \in N$ *From the distribution center* $m \in M$
l_{fnb} *A lead time of product* $f \in F$ *retail seller* $n \in N$ *from supplier* $b \in B$
cap_{fm} Product inventory capacity $f \in F$ from distribution center $m \in M$
cap_v The capacity of transport option $v \in V$
p_b The fixed cost of selecting and creating a supplier $b \in B$
q_{mb} The fixed cost of building the route between the distribution center $m \in M$ and the supplier $b \in B$
t_{fmb} Cost of moving product $f \in F$ between distribution center $m \in M$ and supplier $b \in B$
t_{fnm} Cost of moving product $f \in F$ between retailers $n \in N$ distribution center $m \in M$
t_{fnb} Cost of moving product $f \in F$ between retailers $n \in N$ distribution center $b \in B$
c_{fmb} The amount of greenhouse gas emissions in the transportation of product $f \in F$ between the distribution center $m \in M$ and the supplier $b \in B$
c_{fnm} The amount of greenhouse gas emissions in the transportation of product $f \in F$ between the *retailer* $n \in N$ and the distribution center $m \in M$
c_{fnb} The amount of greenhouse gas emissions in the transportation of product $f \in F$ between the *retailer* $m \in M$ and the supplier $b \in B$
co_{fm} The amount of greenhouse gas emissions in product warehouse $f \in F$ in distribution center $m \in M$
co_{fn} The amount of greenhouse gas emissions in keeping the product $f \in F$ in the retailer $n \in N$
λ Number of working days in a year
o_f Product failure cost $f \in F$
Z_α The cumulative probability distribution function
g_b The number of jobs created due to the establishment of the supplier $b \in B$
$[a_n, b_n]$ The time window for delivering the products to the retailer $n \in N$
$[c_n, d_n]$ The time window for delivery of products to the distribution center $m \in M$

Decision variables

X_{nm} It takes the value 1 if the retailer n ∈ N has received service from the distribution center m ∈ M
Y_{mb} It takes the value 1 if the distribution center m ∈ M has received services from supplier b ∈ B
Z_{nb} It takes the value 1 if retailer n ∈ N has received services from supplier b ∈ B
W_b It takes the value 1 if supplier b ∈ B is selected.
D_{fm} Actual daily demand of product f ∈ F from distribution center m ∈ M
U_{fm} Variance D_{fm}
SS_{fm} Confidence inventory of product f ∈ F from distribution center m ∈ M
SS_{fn} Confidence inventory of product f ∈ F from retailer n ∈ N
R_{fm} Reorder point of product f ∈ F from distribution center m ∈ M
R_{fn} Reorder point of product f ∈ F from retailer n ∈ N
INV_{fm} Total inventory of product f ∈ F from distribution center m ∈ M
INV_{fn} Total inventory of product f ∈ F from retailer n ∈ N
Q_{fm} Optimal order point of product f ∈ F from distribution center m ∈ M
Q_{fn} Optimal order point of product f ∈ F from retailer n ∈ N
U_v The number of transport options used is v ∈ V

After presenting the symbols used in the modeling, the mathematical model of the sustainable distribution network of agricultural items is as follows:

$$\begin{aligned}\text{Min OBF}_1 &= \sum_{b\in B} p_b.W_b + \sum_{m\in M}\sum_{b\in B} q_{mb}.Y_{mb} + \sum_{m\in M}\sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda\mu_{fn}.X_{nm}.t_{fmb}.Y_{mb}}{(1-\theta_f)^2} + \sum_{m\in M}\sum_{n\in N}\sum_{f\in F}\frac{\lambda\mu_{fn}.X_{nm}.t_{fnm}}{(1-\theta_f)} \\ &+ \sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda\mu_{fn}.Z_{nb}.t_{fnb}}{(1-\theta_f)} + \sum_{v\in V} f_v.U_v + \sum_{m\in M}\sum_{f\in F} H_{fm}.INV_{fm} + \sum_{n\in N}\sum_{f\in F} h_{fn}.INV_{fn} \\ &+ \sum_{m\in M}\sum_{f\in F}\frac{\lambda.A_{fm}.D_{fm}}{Q_{fm}} + \sum_{n\in N}\sum_{f\in F}\frac{\lambda.a_{fn}.\mu_{fn}.\sum_{b\in B} Z_{nb}}{Q_{fn}(1-\theta_f)} + \sum_{m\in M}\sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda.o_f.\theta_f.\mu_{fn}.X_{nm}.Y_{mb}}{(1-\theta_f)^2} \\ &+ \sum_{m\in M}\sum_{n\in N}\sum_{f\in F}\frac{\lambda.o_f.\theta_f.\mu_{fn}.X_{nm}}{(1-\theta_f)} + \sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda.o_f.\theta_f.\mu_{fn}.Z_{nb}}{(1-\theta_f)}\end{aligned} \quad (1)$$

$$\begin{aligned}Min\ OBF_2 &= \sum_{m\in M}\sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda\mu_{fn}.X_{nm}.c_{fmb}.Y_{mb}}{(1-\theta_f)^2} + \sum_{m\in M}\sum_{n\in N}\sum_{f\in F}\frac{\lambda\mu_{fn}.X_{nm}.c_{fnm}}{(1-\theta_f)} \\ &+ \sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda\mu_{fn}.Z_{nb}.c_{fnb}}{(1-\theta_f)} + \sum_{m\in M}\sum_{f\in F} co_{fm}.INV_{fm} + \sum_{n\in N}\sum_{f\in F} co_{fn}.INV_{fn}\end{aligned} \quad (2)$$

$$Max\ OBF_3 = \sum_{b\in B} g_b.W_b \quad (3)$$

$s.t.$:

$$Y_{mb} \le W_b, \forall m \in M, b \in B \quad (4)$$

$$Z_{nb} \le W_b, \forall n \in N, b \in B \quad (5)$$

$$X_{nm} \le \sum_{b\in B} Y_{mb}, \forall n \in N, m \in M \quad (6)$$

$$\sum_{n\in N} \mu_{fn}.X_{nm} \le cap_{fm}, \forall m \in M, f \in F \quad (7)$$

$$\sum_{f\in F} \mu_{fn}.X_{nm} \le cap_v.U_v, \forall m \in M, n \in N \quad (8)$$

$$\sum_{m\in M} X_{nm} + \sum_{b\in B} Z_{nb} = 1, \forall n \in N \quad (9)$$

$$\sum_{b\in B} Y_{mb} \le 1, \forall m \in M \quad (10)$$

$$Q_{fn} = \sqrt{\left(\frac{2\lambda.a_{fn}.\mu_{fn}.\sum_{b\in B} Z_{nb}}{h_{fn}(1-\theta_f)}\right)}, \forall n \in N, f \in F \quad (11)$$

$$Q_{fm} = \sqrt{\left(\frac{2\lambda.A_{fm}.\sum_{n\in N}\mu_{fn}.X_{nm}}{H_{fm}(1-\theta_f)}\right)}, \forall m \in M, f \in F \quad (12)$$

$$D_{fm} = \frac{\sum_{n\in N}\mu_{fn}.X_{nm}}{1-\theta_f}, \forall m \in M, f \in F \quad (13)$$

$$U_{fm} = \sum_{n\in N}\sum_{l\in N}\rho_{nl}.\sigma_{fn}.\sigma_{fl}.X_{nm}.X_{lm}, \forall m \in M, f \in F \quad (14)$$

$$L_{fm} = \sum_{b\in B} l_{fmb}.Y_{mb}, \forall m \in M, f \in F \quad (15)$$

$$SS_{fm} = Z_\alpha\sqrt{\sum_{n\in N}\sum_{l\in N}\sum_{b\in B}\rho_{nl}.\sigma_{fn}.\sigma_{fl}.X_{nm}.X_{lm}.l_{fmb}.Y_{mb}}, \in M, f \in F \quad (16)$$

$$R_{fm} = Z_\alpha\sqrt{\sum_{n\in N}\sum_{l\in N}\sum_{b\in B}\rho_{nl}.\sigma_{fn}.\sigma_{fl}.X_{nm}.X_{lm}.l_{fmb}.Y_{mb}} + \frac{\sum_{n\in N}\sum_{b\in B}\mu_{fn}.X_{nm}.l_{fmb}.Y_{mb}}{1-\theta_f}, \forall m \in M, f \in F \quad (17)$$

$$INV_{fm} = \frac{Q_{fm}}{2} + SS_{fm}, \forall m \in M, f \in F \quad (18)$$

$$SS_{fn} = Z_\alpha.\sigma_{fn}.\sqrt{\sum_{b\in B} l_{fnb}.Z_{nb}}, \forall n \in N, f \in F \quad (19)$$

$$INV_{fn} = \frac{\mu_{fn}.\sum_{m\in M} X_{nm}.l_{fnm}}{2} + \frac{Q_{fn}}{2} + Z_{\alpha}.\sigma_{fn}.\sqrt{\sum_{b\in B} l_{fnb}.Z_{nb}}, \forall n \in N, f \in F \quad (20)$$

$$R_{fn} = Z_{\alpha}.\sigma_{fn}.\sqrt{\sum_{b\in B} l_{fnb}.Z_{nb}} + \sum_{b\in B} \mu_{fn}.l_{fnb}.Z_{nb}, \forall n \in N, f \in F \quad (21)$$

$$a_n \le \sum_{m\in M} t_{fnm}.X_{nm} + \sum_{b\in B} t_{fnb}.Z_{nb} \le b_n, \forall n \in N, f \in F \quad (22)$$

$$c_m \le \sum_{b\in B} t_{fmb}.Y_{mb} \le d_m, \forall m \in M, f \in F \quad (23)$$

Equation (1) shows the total costs of the distribution chain network of agricultural items. In this regard, there are costs such as the establishment of a supplier, transportation costs, costs of ordering and maintaining perishable goods, and costs of product failure. Equation (2) minimizes the amount of greenhouse gas emissions caused by the transfer and storage of perishable products between the three levels of supplier, distribution center, and retailer. Relationship (3) deals with the sustainability aspects of the problem and increases the amount of employment dependent on the establishment of suppliers. Relationship (4) shows that if a supplier is selected, services can be provided to the distribution centers from that supplier. Relationship (5) also shows that if a supplier is selected, it is possible to provide services to retailers from that supplier. Relationship (6) If the distribution center provides services to a certain retailer, it must have received the products and services from the supplier in advance. Equation (7) guarantees that the distribution center cannot distribute products beyond its capacity. Equation (8) calculates the number of means of transportation used in the distribution of products between distribution centers and retailers. Relationship (9) guarantees that each retailer can receive goods and products from only one distribution center. Relationship (10) guarantees that each distribution center can receive goods and services from at most one supplier. Equations (11) and (12) show the optimal order quantity of perishable products for the distribution center and the retailer. Equation (13) and (14) calculates the demand for perishable products. In these relationships, the daily demand of products for retailers follows a normal distribution function in the form of $(\mu_{fn}, \sigma_{fn}^2)$. Therefore, according to the interactions between retailers, the product demand in the distribution center will follow a multivariate normal distribution $(\mu_{fn}, \sigma_{fn}^2)$. Relationship (15) shows the lead time of the distribution center. Equations (16) and (17) calculate the confidence inventory and its re-travel point for a distribution center. Equation (18) shows the total inventory of the distribution center, including the trust inventory and the seller's inventory. Equation (19) shows the retailer's confidence inventory and equation (20) shows the retailer's total inventory. Equation (21) shows the retailer's reorder point. Relationships (22) and (23) show the time window for the timely delivery of perishable items to distribution centers and retailers.

In this article, to deal with the uncertainties in the parameters of the model, which includes cost and supply parameters, Jimenez's fuzzy method is used because of its high efficiency. In addition to maintaining the linearity of the problem, this method does not increase the number of objective functions and inequality constraints. Jimenez et al.'s (2007) fuzzy method are programmed based on the expected value and the expected interval. Due to the computational efficiency and simplicity, the triangular fuzzy distribution method has been used to deal with the inaccurate parameters of the model. Suppose $\tilde{C}$ is a triangular fuzzy number, the membership function of this fuzzy number $\mu\tilde{C}(x)$ is defined as relation (24):

$$\mu\tilde{C}(x) = \begin{cases} f_c(x) = \dfrac{x - c_p}{c_m - c_p} & if\ c_p \le x \le c_m \\ 1 & if\ x = c_m \\ g_c(x) = \dfrac{c_o - x}{c_o - c_m} & if\ c_m \le x \le c_o \\ 0 & if\ x < c_p\ or\ x > c_o \end{cases} \quad (24)$$

The expected distance EI and the mathematical expectation EV of the triangular fuzzy number are calculated from the following relations:

$$EI(\tilde{C}) = [E_1^c, E_2^c] = \left[\int_0^1 f_c^{-1}(x)dx, \int_0^1 g_c^{-1}(x)dx\right] = \left[\frac{1}{2}(c_m + c_p), \frac{1}{2}(c_o + c_m)\right] \quad (25)$$

$$EV(\tilde{C}) = \frac{E_1^c + E_2^c}{2} = \frac{c_p + 2c_m + c_o}{4} \quad (26)$$

For the pair of fuzzy numbers $\tilde{a}$ and $\tilde{b}$, the degree of $\tilde{a}$ being greater than $\tilde{b}$ is defined by the following relation:

$$\mu_M(\tilde{a}, \tilde{b}) = \begin{cases} 1 & if\ E_1^a > E_2^b \\ \dfrac{E_2^a - E_1^b}{E_2^a - E_1^b - (E_1^a - E_2^b)} & if 0 \epsilon [E_1^a - E_2^b, E_2^a - E_1^b] \\ 0 & if\ E_2^a < E_1^b \end{cases} \quad (27)$$

$\mu_M(\tilde{a}, \tilde{b}) \ge \alpha$ means that at least in degree α, $\tilde{a}$ is greater than $\tilde{b}$ and is defined as $\tilde{a} \ge_{\alpha} \tilde{b}$. In addition to what was said, for the pair of fuzzy numbers $\tilde{a}$ and $\tilde{b}$ where $\tilde{a}$ is equal to $\tilde{b}$ we have: a ̃≥_(α/2) $\tilde{a} \ge_{\frac{\alpha}{2}} \tilde{b}, \tilde{a} \le_{\frac{\alpha}{2}} \tilde{b}$. Now consider the following fuzzy programming model in which all parameters are considered fuzzy:

$$Min\ Z = \tilde{c}^t x$$
$$\tilde{a}_i x \geq \tilde{b}_i, \forall i = 1,2, \dots, l$$
$$\tilde{a}_i x = \tilde{b}_i, \forall i = l+1, \dots, m \quad (28)$$
$$x \geq 0$$

According to the Jimenez method, for the case where $\tilde{a}$ is greater than $\tilde{b}$ we have:

$$\frac{E_2^{a_i x} - E_1^{b_i}}{E_2^{a_i x} + E_1^{b_i} - E_1^{a_i x} - E_2^{b_i}} \geq \alpha, \forall i = 1, \dots, l \quad (29)$$

For the case where $\tilde{a}$ is equal to $\tilde{b}$ we have:

$$\frac{\alpha}{2} \leq \frac{E_2^{a_i x} - E_1^{b_i}}{E_2^{a_i x} + E_1^{b_i} - E_1^{a_i x} - E_2^{b_i}} \leq 1 - \frac{\alpha}{2}, \forall i = l+1, \dots, m \quad (30)$$

According to the above relations, we have

$$\left[(1-\alpha)E_2^{a_i x} + \alpha E_1^{a_i x}\right]x \geq (1-\alpha)E_1^{b_i} + \alpha E_2^{b_i}, \forall i = 1, \dots, l$$
$$\left[\left(1-\frac{\alpha}{2}\right)E_2^{a_i x} + \frac{\alpha}{2}E_1^{a_i x}\right]x \geq \left(1-\frac{\alpha}{2}\right)E_1^{b_i} + \frac{\alpha}{2}E_2^{b_i}, \forall i = l+1, \dots, m \quad (31)$$
$$\left[\left(1-\frac{\alpha}{2}\right)E_1^{a_i x} + \frac{\alpha}{2}E_2^{a_i x}\right]x \leq \left(1-\frac{\alpha}{2}\right)E_2^{b_i} + \frac{\alpha}{2}E_1^{b_i}, \forall i = l+1, \dots, m$$

Based on the above proofs, the following new parameters have been placed in the final model to control the non-deterministic parameters instead of the non-deterministic parameters of the previous model:

$$H_{fm} \sim \frac{H_{fm}^1 + 2H_{fm}^2 + H_{fm}^3}{4}$$
$$h_{fn} \sim \frac{h_{fn}^1 + 2h_{fn}^2 + h_{fn}^3}{4}$$
$$\mu_{fn} = \alpha.\frac{\mu_{fn}^2 + \mu_{fn}^3}{2} + (1-\alpha).\frac{\mu_{fn}^1 + \mu_{fn}^2}{2}$$
$$t_{fmb} \sim \frac{t_{fmb}^1 + 2t_{fmb}^2 + t_{fmb}^3}{4} \quad (32)$$
$$t_{fnm} \sim \frac{t_{fnm}^1 + 2t_{fnm}^2 + t_{fnm}^3}{4}$$
$$t_{fnb} \sim \frac{t_{fnb}^1 + 2t_{fnb}^2 + t_{fnb}^3}{4}$$
$$\sigma_{fn} = \left(\frac{\mu_{fn}^3 - \mu_{fn}^1}{3.2}\right)^2$$

Therefore, the final controlled model of the problem is as follows:

$$Min\ OBF_1 = \sum_{b\in B} p_b.W_b + \sum_{m\in M}\sum_{b\in B} q_{mb}.Y_{mb} + \sum_{v\in V} f_v.U_v +$$
$$\sum_{m\in M}\sum_{b\in B}\sum_{n\in N}\sum_{f\in F} \frac{\left(\lambda\left[\alpha.\frac{\mu_{fn}^2 + \mu_{fn}^3}{2} + (1-\alpha).\frac{\mu_{fn}^1 + \mu_{fn}^2}{2}\right].X_{nm}.\left[\frac{t_{fmb}^1 + 2t_{fmb}^2 + t_{fmb}^3}{4}\right].Y_{mb}\right)}{\left(1-\theta_f\right)^2} + \quad (33)$$
$$\sum_{m\in M}\sum_{n\in N}\sum_{f\in F} \frac{\left(\lambda\left[\alpha.\frac{\mu_{fn}^2 + \mu_{fn}^3}{2} + (1-\alpha).\frac{\mu_{fn}^1 + \mu_{fn}^2}{2}\right].X_{nm}.\left[\frac{t_{fnm}^1 + 2t_{fnm}^2 + t_{fnm}^3}{4}\right]\right)}{\left(1-\theta_f\right)} +$$

$$\sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\begin{pmatrix}\lambda\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right]\\ .Z_{nb}.\left[\frac{t_{fnb}^1+2t_{fnb}^2+t_{fnb}^3}{4}\right]\end{pmatrix}}{(1-\theta_f)}+\sum_{m\in M}\sum_{f\in F}\frac{\lambda.A_{fm}.D_{fm}}{Q_{fm}}+$$

$$\sum_{m\in M}\sum_{f\in F}\left[\frac{H_{fm}^1+2H_{fm}^2+H_{fm}^3}{4}\right].INV_{fm}+\sum_{n\in N}\sum_{f\in F}\left[\frac{h_{fn}^1+2h_{fn}^2+h_{fn}^3}{4}\right].INV_{fn}+$$

$$\sum_{n\in N}\sum_{f\in F}\frac{\lambda.a_{fn}.\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].\sum_{b\in B}Z_{nb}}{Q_{fn}(1-\theta_f)}+$$

$$\sum_{m\in M}\sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda.o_f.\theta_f.\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].X_{nm}.Y_{mb}}{(1-\theta_f)^2}+$$

$$\sum_{m\in M}\sum_{n\in N}\sum_{f\in F}\frac{\lambda.o_f.\theta_f.\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].X_{nm}}{(1-\theta_f)}+$$

$$\sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda.o_f.\theta_f.\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].Z_{nb}}{(1-\theta_f)}$$

$$Min\ OBF_2=\sum_{m\in M}\sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].X_{nm}.c_{fmb}.Y_{mb}}{(1-\theta_f)^2}+$$

$$\sum_{m\in M}\sum_{n\in N}\sum_{f\in F}\frac{\lambda\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].X_{nm}.c_{fnm}}{(1-\theta_f)}+ \quad (34)$$

$$\sum_{b\in B}\sum_{n\in N}\sum_{f\in F}\frac{\lambda\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].Z_{nb}.c_{fnb}}{(1-\theta_f)}+$$

$$\sum_{m\in M}\sum_{f\in F}co_{fm}.INV_{fm}+\sum_{n\in N}\sum_{f\in F}co_{fn}.INV_{fn}$$

$$Max\ OBF_3=\sum_{b\in B}g_b.W_b \quad (35)$$

$s.t.$:

$$Y_{mb}\le W_b,\forall m\in M,b\in B \quad (36)$$

$$Z_{nb}\le W_b,\forall n\in N,b\in B \quad (37)$$

$$X_{nm}\le\sum_{b\in B}Y_{mb},\forall n\in N,m\in M \quad (38)$$

$$\sum_{n\in N}\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].X_{nm}\le cap_{fm},\forall m\in M,f\in F \quad (39)$$

$$\sum_{f\in F}\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].X_{nm}\le cap_v.U_v,\forall m\in M,n\in N \quad (40)$$

$$\sum_{m\in M}X_{nm}+\sum_{b\in B}Z_{nb}=1,\forall n\in N \quad (41)$$

$$\sum_{b\in B}Y_{mb}\le 1,\forall m\in M \quad (42)$$

$$Q_{fn}=\sqrt{\left(\frac{2\lambda.a_{fn}.\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].\sum_{b\in B}Z_{nb}}{\left[\frac{h_{fn}^1+2h_{fn}^2+h_{fn}^3}{4}\right](1-\theta_f)}\right)},\forall n\in N,f\in F \quad (43)$$

$$Q_{fm}=\sqrt{\left(\frac{2\lambda.A_{fm}.\sum_{n\in N}\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].X_{nm}}{\left[\frac{H_{fm}^1+2H_{fm}^2+H_{fm}^3}{4}\right](1-\theta_f)}\right)},\forall m\in M,f\in F \quad (44)$$

$$D_{fm}=\frac{\sum_{n\in N}\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].X_{nm}}{1-\theta_f},\forall m\in M,f\in F \quad (45)$$

$$U_{fm}=\sum_{n\in N}\sum_{l\in N}\rho_{nl}.\left[\left(\frac{\mu_{fn}^3-\mu_{fn}^1}{3.2}\right)^2\right].\left[\left(\frac{\mu_{fl}^3-\mu_{fl}^1}{3.2}\right)^2\right].X_{nm}.X_{lm},\forall m\in M,f\in F \quad (46)$$

$$L_{fm}=\sum_{b\in B}l_{fmb}.Y_{mb},\forall m\in M,f\in F \quad (47)$$

$$SS_{fm}=Z_\alpha\sqrt{\sum_{n\in N}\sum_{l\in N}\sum_{b\in B}\rho_{nl}.\left[\left(\frac{\mu_{fn}^3-\mu_{fn}^1}{3.2}\right)^2\right].\left[\left(\frac{\mu_{fl}^3-\mu_{fl}^1}{3.2}\right)^2\right].X_{nm}.X_{lm}.l_{fmb}.Y_{mb}},\forall m\in M,f\in F \quad (48)$$

$$R_{fm}=Z_\alpha\sqrt{\sum_{n\in N}\sum_{l\in N}\sum_{b\in B}\rho_{nl}.\left[\left(\frac{\mu_{fn}^3-\mu_{fn}^1}{3.2}\right)^2\right].\left[\left(\frac{\mu_{fl}^3-\mu_{fl}^1}{3.2}\right)^2\right].X_{nm}.X_{lm}.l_{fmb}.Y_{mb}}+\frac{\sum_{n\in N}\sum_{b\in B}\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].X_{nm}.l_{fmb}.Y_{mb}}{1-\theta_f},\forall m\in M,f\in F \quad (49)$$

$$INV_{fm}=\frac{Q_{fm}}{2}+SS_{fm},\forall m\in M,f\in F \quad (50)$$

$$SS_{fn}=Z_\alpha.\left[\left(\frac{\mu_{fn}^3-\mu_{fn}^1}{3.2}\right)^2\right].\sqrt{\sum_{b\in B}l_{fnb}.Z_{nb}},\forall n\in N,f\in F \quad (51)$$

$$INV_{fn}=\frac{\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].\sum_{m\in M}X_{nm}.l_{fnm}}{2}+\frac{Q_{fn}}{2}+Z_\alpha.\left[\left(\frac{\mu_{fn}^3-\mu_{fn}^1}{3.2}\right)^2\right].\sqrt{\sum_{b\in B}l_{fnb}.Z_{nb}},\forall n\in N,f\in F \quad (52)$$

$$R_{fn}=Z_\alpha.\left[\left(\frac{\mu_{fn}^3-\mu_{fn}^1}{3.2}\right)^2\right].\sqrt{\sum_{b\in B}l_{fnb}.Z_{nb}}+\sum_{b\in B}\left[\alpha.\frac{\mu_{fn}^2+\mu_{fn}^3}{2}+(1-\alpha).\frac{\mu_{fn}^1+\mu_{fn}^2}{2}\right].l_{fnb}.Z_{nb},\forall n\in N,f\in F \quad (53)$$

$$a_n\le\sum_{m\in M}\left[\frac{t_{fnm}^1+2t_{fnm}^2+t_{fnm}^3}{4}\right].X_{nm}+\sum_{b\in B}\left[\frac{t_{fnb}^1+2t_{fnb}^2+t_{fnb}^3}{4}\right].Z_{nb}\le b_n,\forall n\in N,f\in F \quad (54)$$

$$c_m\le\sum_{b\in B}\left[\frac{t_{fmb}^1+2t_{fmb}^2+t_{fmb}^3}{4}\right].Y_{mb}\le d_m,\forall m\in M,f\in F \quad (55)$$

Considering the multi-objective nature of the mathematical model presented in this section, multi-objective decision-making methods such as epsilon constraint and multi-objective meta-heuristic algorithms such as NSGA II and MOGWO have been used to solve the problem. In this problem, there is a combination of facility location, vehicle routing, and allocation problems. It has been shown in many articles that location problems are among NP-hard problems (Chobar et al., 2022). Therefore, the minimum level of difficulty of the mathematical

model presented in this article is equal to the level of difficulty of the location problems. According to this issue, the model of the sustainable distribution network of agricultural items with high perishability is one of the NP-hard problems.

4. Solution methods

In this part of the research, various solution methods have been proposed to solve the problem in different sizes. The solution methods proposed in this research include the epsilon constraint method as an exact method and the meta-heuristic algorithms NSGA II and MOGWO as approximate methods. Also, the initial answer designed to achieve the solutions is stated in this section.

4.1.Constraint epsilon method

The epsilon constraint method is one of the well-known approaches to facing multi-objective problems, which solves this type of problem by transferring all the objective functions except one of them at each stage. One of the major advantages of this method is that it is possible to control the number of generated answers and the intervals according to the criteria of the decision-maker. In this problem, this method has been used to solve the problem in a small size.

4.2. MOGWO algorithm

Wolves have a very precise and orderly social dominance hierarchy (Mirjalili et al., 2016). In this hierarchy, leaders include one male and one female, which are called α. α is the main responsible for making decisions about hunting, where to sleep when to wake up, etc. α decisions are announced to the group; However, some democratic behavior has also been observed where an α obeys other wolves in the pack. In congregations, the whole herd confirms α by keeping itself low. The α wolf is also the dominant wolf because the orders must be executed by the group. Alpha wolves are only allowed to mate in packs. It is noteworthy that α is not necessarily the strongest member of the herd, but the best member in terms of management in the herd. The second level in the hierarchy of gray wolves is β. β are subordinate wolves that assist α in decision-making or other pack decisions. Wolf β can be male or female and he is the best replacement for α if he dies or grows old. β executes α's commands throughout the herd and gives feedback to α.

The ω wolf is the lowest class in the gray wolf hierarchy. The wolf ω plays the role of the victim. Usually, ω wolves must obey all high-level and dominant wolves. They are the last wolves allowed to eat. If the wolf is not an α or ω, it is called a δ. δ wolves must be functions of α and β. However, they dominate ω.

When designing the gray wolf algorithm, to mathematically model the social hierarchy of wolves, α is considered as the most suitable solution. Subsequently, β and δ are the second and third suitable solutions. The rest of the candidate solutions are assumed as (X). To hunt, gray wolves must find and surround prey. Therefore, the following equations update the positions of the wolves around the prey.

$$\vec{D} = |\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)| \tag{56}$$
$$\vec{X}(t+1) = \vec{X}(t) - \vec{A}.\vec{D} \tag{57}$$

In the above example, $\vec{C}$ and $\vec{A}$ are coefficient vectors$\overrightarrow{X_p}$is the position vector of prey and $\vec{X}$ is the position vector of gray wolves. It is a balancing act between siege and hunting. Therefore, the search radius must be optimized during the process, for this purpose, the equations related to the two coefficients used in the above relationships are as follows.

$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a} \tag{58}$$
$$\vec{C} = 2\overrightarrow{r_2} \tag{59}$$

The above equations enable gray wolves to update their position around the prey. As a result, the following equations are used for hunting.

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_1.\vec{X}_\delta - \vec{X}\right| \tag{60}$$
$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\vec{D}_\delta \tag{61}$$
$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{62}$$

4.3. NSGA II algorithm

The genetic algorithm starts by randomly generating an initial population of chromosomes while satisfying the bounds or constraints of the problem (Deb et al., 2002). In other words, chromosomes are strings of proposed values for the problem's decision variables, each representing a possible answer to the problem. Chromosomes are derived from successive replications called generations. During each generation, these chromosomes are evaluated according to the optimization goal, and the chromosomes that are considered to be a better answer to the problem in question have a greater chance of reproducing the answers to the problem. It is very important to formulate the evaluation function of chromosomes in a way that helps the speed of convergence of calculations towards the general optimal solution. Because in the genetic algorithm, the value of the evaluation function must be calculated for each chromosome, and because we are usually faced with a considerable number of chromosomes in many problems, the time-consuming calculation of the evaluation function can practically make use of the genetic algorithm practically impossible in some problems; Therefore, based on the obtained values of the objective function in the population of strings, each string is assigned a fitness number. This fitness number will determine the selection probability for each field. Based on this selection probability, a set of fields is first selected. To produce the next generation, new chromosomes called children are created by combining two chromosomes from the current generation using the combination operator or by modifying the chromosome using the mutation operator. So the new strings replace strings from the initial population so that the number of strings population is constant in different calculation iterations. The random mechanisms that act on the selection and removal of strands are such that the strands that have more fitness have a higher probability to combine and produce new strands and are more resistant in the replacement stage than other strands. In this way, the population of sequences in a competition based on the objective function during different generations is completed and increased by the value of the objective function in the population of strings, so that after several years, the algorithm converges to the best chromosome, which hopefully represents the optimal or suboptimal solution. is optimal for the given problem. In general, in this algorithm, while new points of the solution space are searched for by genetic operators in each computation iteration, the selection mechanism explores the process of searching for areas of the space where the statistical average of the objective function is higher. Usually, the new population that replaces the previous population is more fit. This means that the population improves from generation to generation. The search will be successful when we have reached the maximum possible generation or convergence has been achieved or the stopping criteria have been met and as a result, the best chromosome obtained from the last generation is selected as the estimated optimal solution or the optimal solution for the problem.

4.4. The initial answer to the problem

The most important part of the implementation of any algorithm is the appropriate definition of the initial answer to solve the problem. Each of the algorithms is suitable for their operators to improve the initial solution and achieve the best solution. Figure (2) shows an example of the initial solution used in solving the problem. In this figure, 10 retailers, 3 distribution centers, 3 suppliers, and 2 types of perishable agricultural products are considered.

Node	1	2	3	4	5	6	7	8	9	10
Solution1	10	2	6	8	9	4	7	3	5	1
Solution2	1	1	0	1	3	3	2	2	2	0
Solution3	2	2	1	2	3	3	1	1	1	3

Fig. 2 . The initial answer to the problem of the distribution network of agricultural products

In figure (2) a matrix $3 * |N|$It is introduced as the initial answer, in which the first line is a set of permuted random numbers of length $|N|$ which includes decisions related to the routing of retailers. The second line contains a set of random numbers between 0 and $|M|$It is defined according to the allocation of distribution centers to retailers. Finally, the third line contains random numbers between 1 and $|B|$ and is considered proportional to the allocation of suppliers to distribution centers. Therefore, the initial answer is decoded according to the following steps:

Step 1: According to the sequence presented in the first line and the number of distributors in the second line, products are distributed to retailers. For example, according to figure (2), it can be seen that distributor number (2) has been assigned to two retailers, 10 and 2. Therefore, the products will be distributed first to 10 retailers and then to 2 retailers.

Step 2: According to the third line, suppliers are assigned to distribution centers. For example, according to figure (2), it can be seen that supplier (2) is responsible for supplying agricultural products to distributor number (1).

Step 3: If the value 0 is entered for the second line (distribution centers), it means that the supplier supplies the retailer's customers directly.

Step 4: After determining the optimal route and allocating different centers to each other, the actual demand of retailers is determined and the optimal amount of products ordered by retailers and distribution centers is obtained.

Step 5: The total number of heterogeneous devices used by the header between the levels of the distribution network is obtained.

Step 6: Based on the allocations made between the centers and the time of vehicle transfer, the penalty function is used if the time window is exceeded.

Step 7: If the amount of distribution of agricultural products exceeds the capacity of the distribution center, the penalty function is used.

Step 8: The value of the objective functions is calculated in each iteration.

Figure (3) shows the decoding of the initial solution presented in Figure (2).

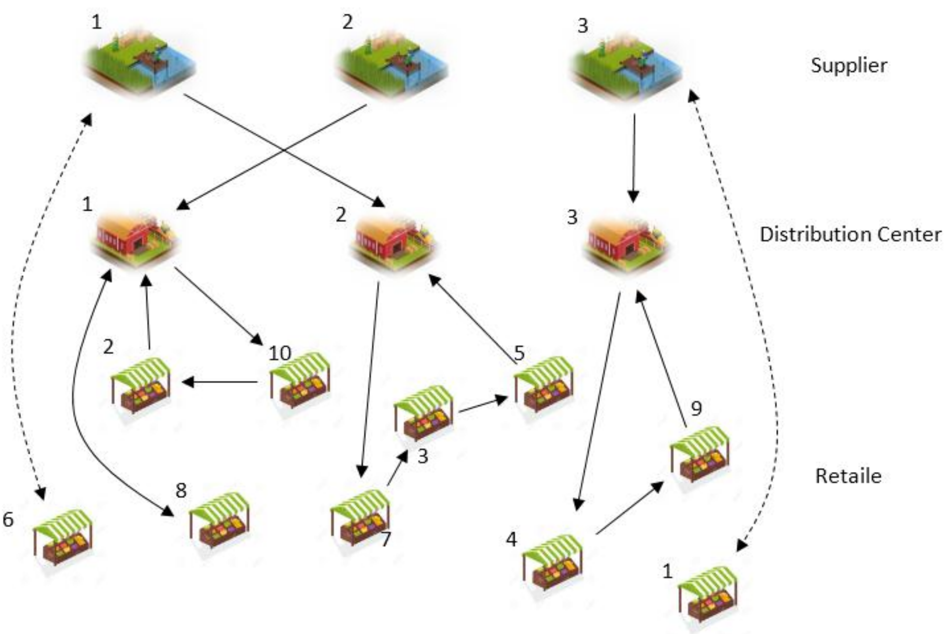

Fig. 3. Deciphering the initial solution to the problem of a sustainable distribution network of agricultural products

5. Analysis of numerical examples

5.1. Analysis of a small numerical example

After presenting the initial answer and explaining different solution methods, in this section, to analyze a numerical example in a small size with 6 retailers, 5 distribution centers, 4 suppliers of raw materials, 2 types of perishable products, and 6 types of transportation and The quote is taken into account. Due to the developmental nature of the mathematical model, random data has been used to value the parameters according to the table (1).

Table 1

Interval limits of problem parameters based on the uniform distribution function

Parameter	Range	Parameter	Range
f_v	$\sim U[30,50]$	t_{fmb}	$\sim U([20,30],[30,40],[40,45])$
A_{fm}	$\sim U[20,30]$	t_{fnm}	$\sim U([10,15],[15,20],[20,25])$
c_{fmb}	$\sim U[5,8]$	t_{fnb}	$\sim U([20,30],[30,40],[40,45])$
h_{fn}	$\begin{pmatrix} 2*\sim U[-0.5,0.5], \\ 3*\sim U[-0.5,0.5], \\ 4*\sim U[-0.5,0.5] \end{pmatrix}$	H_{fm}	$\begin{pmatrix} 3*\sim U[-0.5,0.5], \\ 4*\sim U[-0.5,0.5], \\ 5*\sim U[-0.5,0.5] \end{pmatrix}$
a_{fn}	$\sim U[10,18]$	c_{fnm}	$\sim U[2,5]$
μ_{fn}	$\sim U([40,50],[50,60],[60,70])$	c_{fnb}	$\sim U[5,8]$
θ_f	$\sim U[0.05,0.1]$	co_{fm}	$\sim U[1,3]$
ρ_{nl}	$\sim U[0.8,1.2]$	co_{fn}	$\sim U[1,3]$
l_{fmb}	$3*\sim U[1,5]$	λ	120
l_{fnm}	$\sim U[1,5]$	o_f	$\sim U[3,5]$
l_{fnb}	$3*\sim U[1,5]$	Z_α	1.96
cap_{fm}	$\sim U[300,500]$	g_b	$\sim U[50,300]$
cap_v	$\sim U[120,150]$	$[a_n, b_n]$	[0,200]
p_b	$\sim U[1000,1200]$	$[c_n, d_n]$	[0,200]
q_{mb}	$\sim U[50,100]$		

After designing the numerical example and random data, the epsilon method of limitation has been used to solve the problem in a small size. In the section presenting the results of efficient solutions in Table (2), the value of the uncertainty rate is considered equal to 0.5.

Table 2
The set of efficient solutions for a small-size numerical example with the epsilon constraint method

Solution	OBF_1	OBF_2	OBF_3
1	1354487.37	504498.9	168
2	1386248.67	510545.3	175
3	1428745.68	513164.3	190
4	1456645.67	518786.7	198
5	1496745.68	520468.7	210
6	1534575.25	523745.7	224
7	1576242.35	528794.2	232
8	1624775.36	532494.3	238
9	1674982.15	534187.7	243

According to the results of table (2), it can be seen that with the increase in the total costs of the distribution network of agricultural items, due to the change in the type of routing and location of facilities, the amount of greenhouse gas emissions has also gone out of optimality and increased. Also, with the change in the number and location of facilities, the number of created jobs has increased. The results show that 9 different efficient solutions have been created through the epsilon constraint method.

To check the outputs of the model, the location, routing, and allocation made for the first efficient solution are considered. Therefore, the output results of the decision variables of this efficient solution are shown in figure (4).

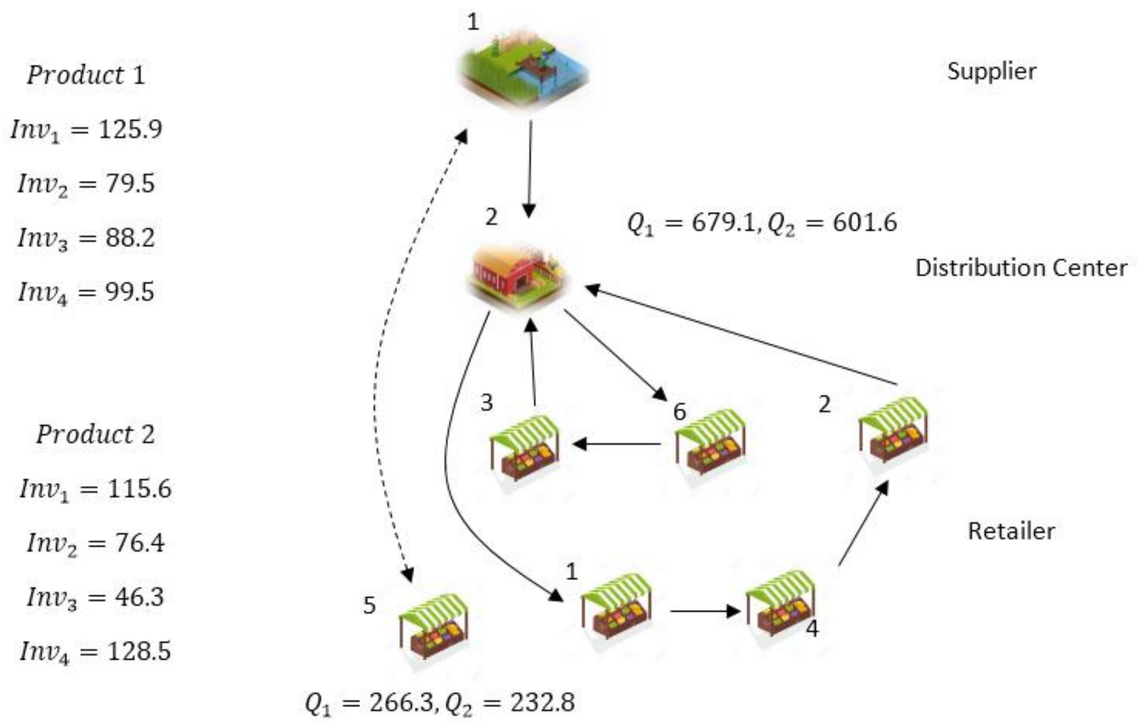

Fig. 4. The set of outputs of effective solution number 1

After checking the effective solutions and the output of the mathematical model, the sensitivity analysis of the problem under the change in the important parameters of the problem has been discussed.

5.2. Sensitivity analysis

The change in the parameters of the problem leads to changes in the decision variables and of course the objective functions of the problem, which leads to better decision-making by managers. In this section, the sensitivity analysis of the model presented in this article has discussed some of the most important parameters of the problem. Due to the indeterminacy of the proposed model and the use of the fuzzy programming method in controlling the parameters, the changes in the values of the objective functions of the problem have been shown under the change in the rate of indeterminacy. Table (3) shows the changes in the values of the objective functions of the problem under changes in the uncertainty rate between 0.1 and 0.9.

Table 3

Changes in the values of the objective functions of the problem under changes in the uncertainty rate.

α	OBF_1	OBF_2	OBF_3
0.1	1312478.34	448247.21	154
0.2	1326746.25	459742.53	154
0.3	1338475.34	471657.24	154
0.4	1344458.26	483982.51	168
0.5	1354487.37	504498.90	168
0.6	1369784.25	516874.33	168
0.7	1379848.38	529795.34	177
0.8	1389745.25	541792.57	177
0.9	1400149.74	553982.03	186

By examining the results of table (3), it can be seen that with the increase in the uncertainty rate, due to the increase in the potential and actual demand and the increase in the number of orders and storage of perishable items in the distribution network, the costs of the network have increased and also due to the increase in the amount of transfer of items. In agriculture, the amount of greenhouse gas emissions have also increased. Also, it can be seen that with the increase in the uncertainty rate, the employment rate has increased due to the increase in the amount of supply and demand and the need for human resources.

In another analysis, the changes in the values of the objective functions of the problem have been investigated under the change in the capacity of the vehicle. In this case, in Table (5), the values of the objective functions of the problem of reducing the capacity of vehicles are shown.

Table 4

Changes in the values of the objective functions of the problem under vehicle capacity reduction

Reduce Vehicle Capacity (%)	OBF_1	OBF_2	OBF_3
0	1354487.37	504498.90	168
5	1358945.30	508676.41	168
10	1359974.20	510498.98	168
15	1362145.34	512496.48	168
20	1365276.06	514985.22	168
25	1368637.48	516974.67	168

By examining the results of table (4), it can be seen hat by reducing the capacity of vehicles, the use of vehicles with a higher cost or a change in the routing of the vehicle and its greater use has occurred, and this has led to the creation of a distance from the optimal point. As a result, the total costs as well as the amount of greenhouse gas emissions have increased in this case. While the decrease in vehicle capacity has not affected the employment rate.

Finally, in another analysis, the effect of the perishability of agricultural items on the changes in the values of the objective functions has been investigated. An increase in the rate of perishability leads to rapid spoilage and destruction of goods. Therefore, these changes should be considered in the design of the distribution network of agricultural items. Table (5) shows the changes in the values of the objective functions of the problem under the increasing rate of the perishability of items.

Table 5
Changes in the values of the objective function of the problem under increasing the rate of corruption

Increase θ (%)	OBF_1	OBF_2	OBF_3
0	1354487.37	504498.90	168
5	1361782.26	509465.77	168
10	1376451.35	512354.25	168
15	1387465.67	515687.64	168
20	1398465.34	518648.66	168
25	1403548.62	521846.67	168

According to the results of table (5), it can be seen that with the increase in the rate of the perishability of agricultural products, there was a larger amount of goods to meet the demand of customers due to its destruction, and this has led to an increase in the amount of production and storage. Based on this, the costs related to production, reordering, maintenance, and transportation have also increased. Due to the increase in the number of orders and production, the emission of greenhouse gases has also increased.

Figure (5) shows the changes in each of the objective function values of the problem, relative to the changes in the uncertainty rate, vehicle capacity, and also corruption rate.

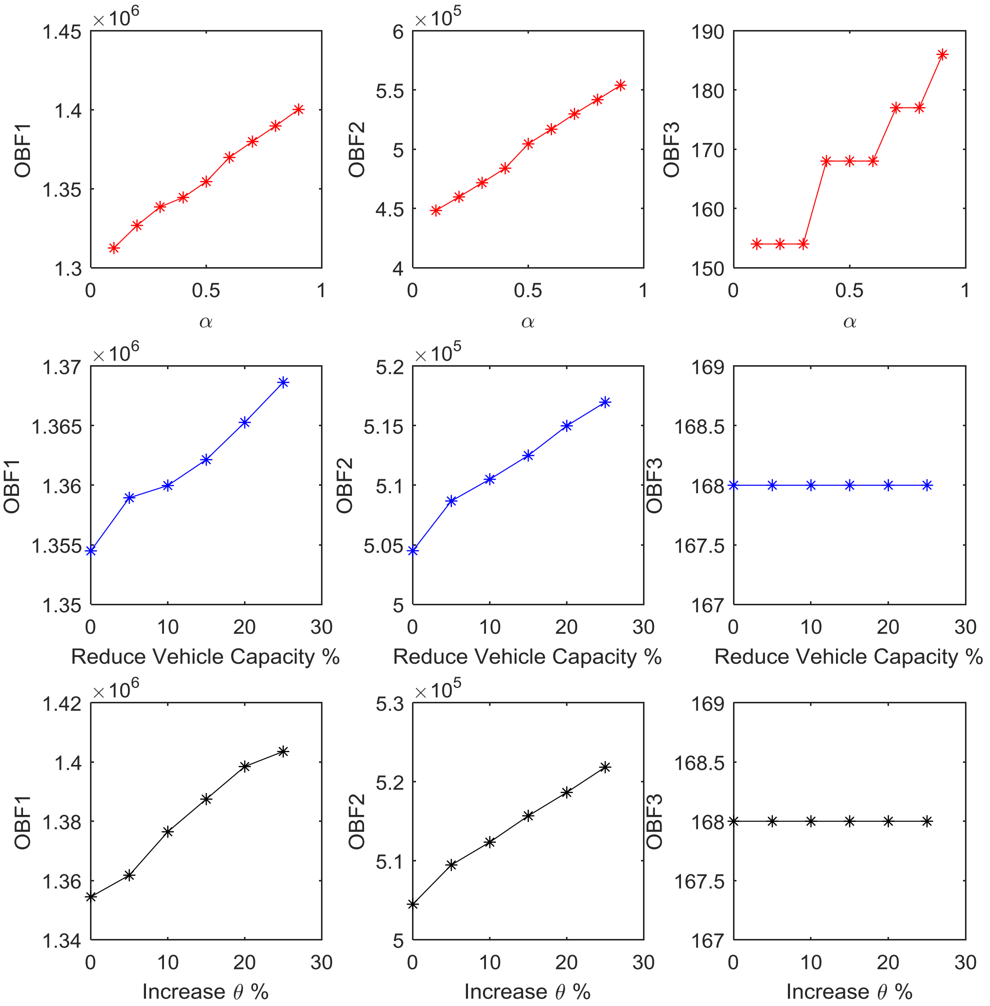

Fig. 5. Changes in the values of the objective functions of the problem under changes in the model parameters

5.3. Analysis of numerical examples in larger sizes

After the sensitivity analysis of the designed problem, numerical examples in larger dimensions are solved. Since the use of meta-heuristic algorithms has been suggested to solve numerical examples in larger sizes, therefore, the parameters of NSGA II and MOGWO algorithms have been discussed first. It should be noted that the results of these two algorithms will be compared with each other.

In Taguchi's method, at first, the appropriate factors should be identified and then the levels of each factor should be selected, and then the appropriate test plan should be determined for these control factors. After the test plan is determined, tests are performed and the tests are analyzed to find the best combination of parameters. In this research, 3 levels are considered for each factor. Since the outputs of each experiment will be a set of effective answers; The following relationship is used to determine the answer to each test.

$$S_i = \left|\frac{NPF + MSI + SM + CPU_{time}}{4}\right| \quad (63)$$

$$RPD = \frac{S_i - S_i^*}{S_i^*} \quad (64)$$

In the above relationships, S_i is the answer of each of the tests, S_i^* is the best test answer obtained, NPF is the number of effective answers obtained, MSI is the largest range of answers, SM is the metric distance index, and CPU_{time} is the computing time. Based on the experiments carried out using the Taguchi method, the value of the optimal parameters of each algorithm has been obtained in the form of a table (6). Figure (6) also shows the average graph of the S/N ratio in meta-heuristic algorithms.

Table 6

Optimal parameters of meta-heuristic algorithms by Taguchi method

Algorithm	*Parameter*	*Best Value*
NSGA II	Max it	200
	N pop	200
	Pc	0.9
	Pm	0.08
MOPSO	Max it	200
	N Wolf	200
	A	1
	C	2

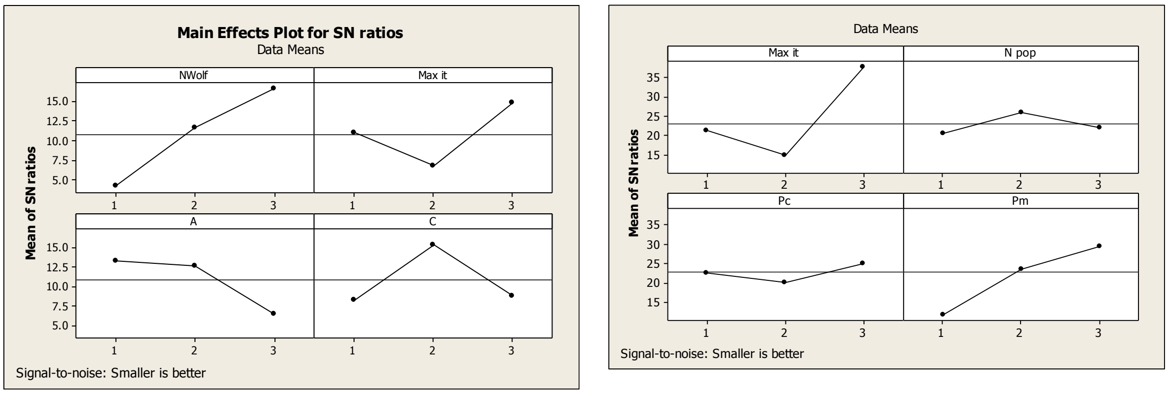

Fig. 6. Average graph of S/N ratio in meta-heuristic algorithms

5.4. Analysis of numerical examples in different sizes

After setting the parameters of meta-heuristic algorithms, in this section, 15 numerical examples of different sizes have been analyzed. Table (7) shows the size of numerical examples in different sizes. The numerical example number (1) is equal to the small-size numerical example presented in the previous section.

Table 7

Size of numerical examples in different sizes

Sample Problem	*N*	*M*	*B*	*F*	*V*
1	6	5	4	2	6
2	10	5	5	2	8
3	15	8	8	2	10
4	20	8	8	3	12

5	25	12	12	3	15
6	30	12	12	3	20
7	35	15	15	4	20
8	40	15	15	4	20
9	50	20	20	4	30
10	60	20	20	5	30
11	70	25	25	5	30
12	80	25	25	5	30
13	90	25	25	6	35
14	100	25	25	6	35
15	120	25	25	6	35

As stated, 15 numerical examples have been solved in larger designs and problem sizes using different solution methods. Numerical example number (1) is equal to the numerical example of small size, hence the set of efficient solutions obtained from solving numerical example number (1) with NSGA II and MOGWO algorithms is shown in table (8). Also, in Figure (7), the Pareto front obtained by solving numerical examples of different sizes is compared.

Table 8.
Effective solutions obtained from solving the numerical example number (1) with different methods

Solution	*NSGA II*			*MOPSO*		
	OBF_1	OBF_2	OBF_3	OBF_1	OBF_2	OBF_3
1	1375441.87	507954.81	173	1375471.81	506029.58	169
2	1385676.34	508384.63	177	1391653.27	506931.56	175
3	1388097.72	509654.12	180	1404220.33	507972.37	179
4	1397302.10	510697.13	183	1413628.30	510413.51	182
5	1421204.06	511823.08	193	1447564.44	512397.18	190
6	1454438.67	512745.44	200	1447811.94	513255.20	191
7	1469414.53	513666.32	205	1475554.07	513534.25	200
8	1482974.16	517042.59	208	1476975.06	514681.62	202
9	1515080.85	523189.30	220	1483150.70	514736.79	205
10	1575589.39	526606.82	230	1490945.65	514891.17	207
11	1577313.29	526620.67	232	1497678.86	515295.97	209
12	1593815.85	528460.52	235	1503417.83	516806.61	212
13	1609774.41	528868.71	235	1506541.65	517329.06	215
14	1630172.45	529240.38	240	1515449.74	519047.22	218
15	1634138.33	529265.46	242	1522471.98	519536.67	221
16	-	-	-	1559257.76	520825.89	224
17	-	-	-	1579434.20	523420.43	230
18	-	-	-	1623274.16	525602.09	235
19	-	-	-	1629240.20	526091.49	236

The results of Table (8) show that the NSGA II algorithm has obtained 15 efficient solutions and the MOGWO algorithm has obtained 19 efficient solutions, which is more than the number of efficient solutions obtained from the epsilon method. In these results, it can be seen that by increasing the value of the third objective function, the value of the first and second objective functions has also increased.

The results of table (8) and figure (7) show that the obtained efficient solutions are very close to each other and all the indicators are also close to each other. Therefore, it can be said that the effectiveness of the algorithms in solving numerical examples of different sizes is much higher than the epsilon method. Table (9) shows the comparison indices of efficient solutions in different numerical examples.

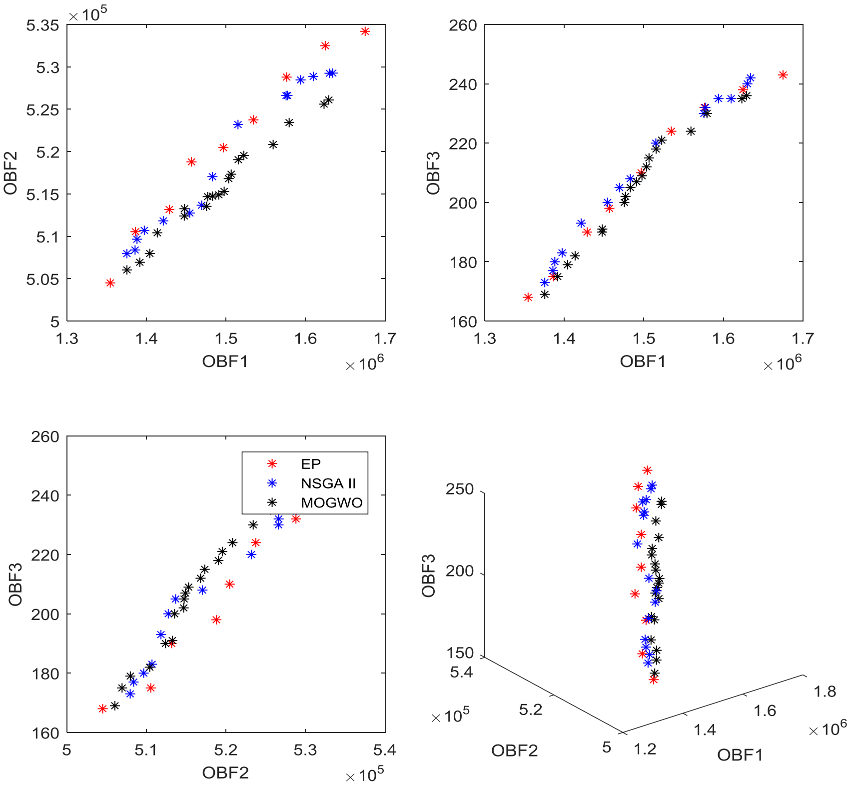

Fig. 7. Comparison of the Pareto front resulting from solving the numerical example number (1)

Table 9.
Average indices obtained from solving numerical examples of different size

					limit Epsilon				NSGA II			
Sample Problem	NPF	MSI	SM	CPU-Time	NPF	MSI	SM	CPU-Time	NPF	MSI	SM	CPU-Time
1	8	8712.34	0.57	843.41	15	6889.75	0.56	21.34	19	6559.05	0.69	24.67
2	15	8347.20	0.64	>1000	18	8579.76	0.56	32.69	23	8593.45	0.57	36.97
3	16	7984.16	0.48	>1000	20	8673.55	0.69	47.10	27	8013.27	0.67	53.60
4	-	-	-	-	18	6084.02	0.70	68.94	36	7168.40	0.56	78.67
5	-	-	-	-	23	6501.84	0.70	98.73	30	6967.33	0.61	110.37
6	-	-	-	-	27	8119.40	0.70	134.10	36	7898.43	0.68	148.67
7	-	-	-	-	32	6856.15	0.50	172.34	27	7479.90	0.43	190.33
8	-	-	-	-	39	8975.02	0.45	215.84	29	7645.85	0.53	239.87
9	-	-	-	-	40	7163.59	0.67	260.44	27	7549.12	0.53	290.22
10	-	-	-	-	36	7817.19	0.68	315.21	23	8284.87	0.43	346.09
11	-	-	-	-	29	6935.51	0.62	370.69	36	6583.04	0.54	406.57
12					28	7903.12	0.40	432.79	24	7227.00	0.50	477.26
13					32	6943.15	0.63	493.15	28	6248.67	0.48	536.94
14					29	7353.34	0.73	556.67	34	6543.28	0.39	623.28
15	-	-	-	-	30	8456.34	0.52	637.19	35	7543.23	0.61	744.26
Average	-	-	-	-	27.33	7550.11	0.607	257.148	28.93	7353.65	0.548	287.18

Based on the results of Table 9, it can be seen that the NSGA II algorithm has the highest MSI value and the lowest average computing time compared to the MOGWO algorithm. Also, the MOGWO algorithm has a higher efficiency in obtaining the average metric distance index and the number of efficient solutions than the NSGA II algorithm. On the other hand, it can be seen that the problem-solving time by the epsilon method is much higher than meta-heuristic algorithms. So that this method has not been able to solve numerical examples greater than 3. Figure (8) shows the average comparison indices between NSGA II and MOGWO algorithms.

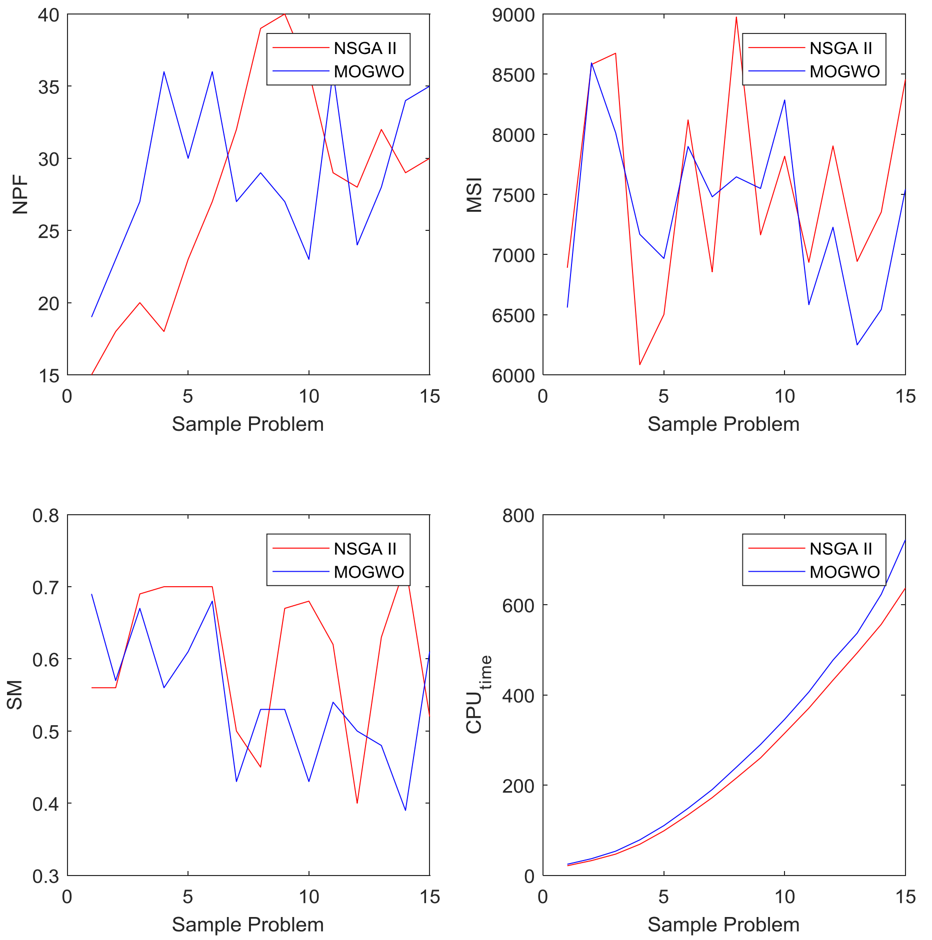

Fig. 8. The average indicators of the comparison of efficient solutions in numerical examples of different sizes

The results of the analysis also show that there is no significant difference between the comparison indices of the solution methods, and as a result, the efficiency of these algorithms is proven in terms of solving the problem in a shorter time.

6. Conclusion and Future Suggestions

In this paper, a mathematical model of the stable distribution network of agricultural items under uncertainty is presented. The most important goals that were addressed in this article were determining the optimal location of suppliers, determining the optimal route for the distribution of agricultural items, assigning suppliers to distribution centers, and determining the amount of inventory and the optimal order point. To control the parameters of this model, the probabilistic fuzzy method has been used. The developed model simultaneously optimizes 3 objective functions total cost minimization, greenhouse gas emission mitigation minimization, and employment rate maximization. The results of solving the model using the epsilon method show that to reduce the emission of greenhouse gases, the route of transferring items and the location of facilities should be changed, which leads to an increase in total costs in the distribution network of agricultural items. Also, with the increase in the number of tehsils in this issue, the employment rate has increased. By changing the most important parameters of the problem and performing a sensitivity analysis, it was also observed that with the increase in the uncertainty rate in the network, the amount of real demand of the retailers for agricultural products has increased and this has led to an increase in the amount of production, accumulated inventory and reorder point. Therefore, the total costs and the amount of greenhouse gas emissions have also increased. Also, the increase in the amount of production has led to an increase in the employment rate in the distribution network of relief items. On the other hand, with the increase in corruption in the network, the value of the first and second objective functions has also increased due to the increase in the number of production and maintenance of agricultural products.

On the other hand, due to the problem being NP-hard, NSGA II and MOGWO algorithms were used to solve the problem in different sizes. The results showed that the epsilon constraint method was only able to solve sample problems up to number 3, and therefore it does not have the necessary efficiency to solve problems of other sizes. Also, by solving different numerical examples, it was observed that meta-heuristic algorithms were able to solve the model in a much shorter time than the epsilon constraint method, and there was no significant difference between their results. To develop the model and suggestions, some things can be considered, including the development of multi-objective meta-heuristic algorithms and their combination to achieve better results; considering different periods in the problem; Adding different levels of the distribution network of agricultural items.

Reference

Ada, N. (2022). Sustainable Supplier Selection in Agri-Food Supply Chain Management. *International Journal of Mathematical, Engineering and Management Sciences*, 7(1), 115.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation*, 6(2), 182-197.

Esteso, A., Alemany, M. M. E., & Ortiz, Á. (2021). Impact of product perishability on agri-food supply chains design. *Applied Mathematical Modelling*, 96, 20-38.

Chobar, A. P., Adibi, M. A., & Kazemi, A. (2022). Multi-objective hub-spoke network design of perishable tourism products using combination machine learning and meta-heuristic algorithms. *Environment, Development and Sustainability*, 1-28.

Ghasemkhani, A., Tavakkoli-Moghaddam, R., Rahimi, Y., Shahnejat-Bushehri, S., & Tavakkoli-Moghaddam, H. (2022). Integrated production-inventory-routing problem for multi-perishable products under uncertainty by meta-heuristic algorithms. *International Journal of Production Research*, 60(9), 2766-2786.

Iraj, M., Chobar, A. P., Peivandizadeh, A., & Abolghasemian, M. (2024). Presenting a two-echelon multi-objective supply chain model considering the expiration date of products and solving it by applying MODM. *Sustainable Manufacturing and Service Economics*, *3*, 100022.

Ghezavati, V. R., Hooshyar, S., & Tavakkoli-Moghaddam, R. (2017). A Benders' decomposition algorithm for optimizing distribution of perishable products considering postharvest biological behavior in agri-food supply chain: a case study of tomato. *Central European Journal of Operations Research*, 25(1), 29-54.

Giallanza, A., & Puma, G. L. (2020). Fuzzy green vehicle routing problem for designing a three echelons supply chain. *Journal of Cleaner Production*, 259, 120774.

Gruler, A., Panadero, J., de Armas, J., Pérez, J. A. M., & Juan, A. A. (2018). Combining variable neighborhood search with simulation for the inventory routing problem with stochastic demands and stock-outs. *Computers & Industrial Engineering*, 123, 278-288.

Gupta, M., Kaur, H., & Singh, S. P. (2021). Multi-echelon agri-food supply chain network design integrating operational and strategic objectives: a case of public distribution system in India. *Annals of Operations Research*, 1-58.

Harahap, A. Z. M. K., & Rahim, M. K. I. A. (2022). A Single Period Deterministic Inventory Routing Model for Solving Problems in the Agriculture Industry. *Journal of Applied Science and Engineering,* 25(6), 945-950.

Imran, M., Habib, M. S., Hussain, A., Ahmed, N., & Al-Ahmari, A. M. (2020). Inventory routing problem in supply chain of perishable products under cost uncertainty. *Mathematics,* 8(3), 382.

Jiménez, M., Arenas, M., Bilbao, A., & Rodrı, M. V. (2007). Linear programming with fuzzy parameters: an interactive method resolution. *European journal of operational research*, 177(3), 1599-1609.

Kresnanto, N. C., Putri, W. H., Lantarsih, R., & Harjiyatni, F. R. (2021, February). Challenges in transportation policy: speeding up a sustainable agri-food supply chain. *In IOP Conference Series: Earth and Environmental Science* (Vol. 662, No. 1, p. 012006). IOP Publishing.

Li, D., Cao, Q., Zuo, M., & Xu, F. (2020). Optimization of green fresh food logistics with heterogeneous fleet vehicle route problem by improved genetic algorithm. *Sustainability*, 12(5), 1946.

Li, Y., Chu, F., Chu, C., Zhou, W., & Zhu, Z. (2016, November). Integrated production inventory routing planning with time windows for perishable food. *In 2016 IEEE 19th International Conference on Intelligent Transportation Systems* (ITSC) (pp. 2651-2656). IEEE.

Mahjoob, M., Fazeli, S. S., Milanlouei, S., Tavassoli, L. S., & Mirmozaffari, M. (2022). A modified adaptive genetic algorithm for multi-product multi-period inventory routing problem. *Sustainable Operations and Computers*, 3, 1-9.

Mirjalili, S., Saremi, S., Mirjalili, S. M., & Coelho, L. D. S. (2016). Multi-objective grey wolf optimizer: a novel algorithm for multi-criterion optimization. *Expert Systems with Applications*, 47, 106-119.

Misni, F., Lee, L. S., & Seow, H. V. (2020). Hybrid harmony search-simulated annealing algorithm for location-inventory-routing problem in supply chain network design with defect and non-defect items. *Applied Sciences*, 10(18), 6625.

Onggo, B. S., Panadero, J., Corlu, C. G., & Juan, A. A. (2019). Agri-food supply chains with stochastic demands: A multi-period inventory routing problem with perishable products. *Simulation Modelling Practice and Theory*, 97, 101970.

Pratap, S., Jauhar, S. K., Paul, S. K., & Zhou, F. (2022). Stochastic optimization approach for green routing and planning in perishable food production. *Journal of Cleaner Production*, 333, 130063.

Mahdavimanshadi, M., Anaraki, M. G., Mowlai, M., & Ahmadirad, Z. (2024, May). A Multistage Stochastic Optimization Model for Resilient Pharmaceutical Supply Chain in COVID-19 Pandemic Based on Patient Group Priority. In *2024 Systems and Information Engineering Design Symposium (SIEDS)* (pp. 382-387). IEEE.

Saragih, N. I., Bahagia, N., & Syabri, I. (2019). A heuristic method for location-inventory-routing problem in a three-echelon supply chain system. *Computers & Industrial Engineering*, 127, 875-886.

Shirzadi, S., Ghezavati, V., Tavakkoli-Moghaddam, R., & Ebrahimnejad, S. (2021). Optimizing a sustainable inventory-routing problem in tomato agri-chain considering postharvest biological behavior. *Journal of Industrial Engineering International*, 17(2), 45-60.

Shirzadi, S., Ghezavati, V., Tavakkoli-Moghaddam, R., & Ebrahimnejad, S. (2021). Developing a green and bipolar fuzzy inventory-routing model in agri-food reverse logistics with postharvest behavior. *Environmental Science and Pollution Research*, 28(30), 41071-41088.

Song, L., & Wu, Z. (2022). An integrated approach for optimizing location-inventory and location-inventory-routing problem for perishable products. *International Journal of Transportation Science and Technology*.

Soysal, M., Bloemhof-Ruwaard, J. M., Haijema, R., & van der Vorst, J. G. (2018). Modeling a green inventory routing problem for perishable products with horizontal collaboration. *Computers & Operations Research*, 89, 168-182.

Taşkıner, T., & Bilgen, B. (2021). Optimization models for harvest and production planning in agri-food supply chain: A systematic review. *Logistics*, 5(3), 52.

Tavana, M., Tohidi, H., Alimohammadi, M., & Lesansalmasi, R. (2021). A location-inventory-routing model for green supply chains with low-carbon emissions under uncertainty. *Environmental Science and Pollution Research*, 28(36), 50636-50648.

Tirkolaee, E. B., Dashtian, Z., Weber, G. W., Tomaskova, H., Soltani, M., & Mousavi, N. S. (2021). An integrated decision-making approach for green supplier selection in an agri-food supply chain: Threshold of robustness worthiness. *Mathematics*, 9(11), 1304.

Zarean Dowlat Abadi, J., Iraj, M., Bagheri, E., RabieiPakdeh, Z., & Dehghani Tafti, M. R. (2022). A Multiobjective Multiproduct Mathematical Modeling for Green Supply Chain considering Location-Routing Decisions. *Mathematical Problems in Engineering*, 2022(1), 7009338.

Violi, A., Laganá, D., & Paradiso, R. (2020). The inventory routing problem under uncertainty with perishable products: an application in the agri-food supply chain. *Soft Computing*, 24(18), 13725-13740