

A Combined Transportation Model for the Fruit and Vegetable Supply Chain Network

Javid Ghahremani-Nahr ^a, Seyyed Esmaeil Najafi ^b, Hamed Nozari ^{c,*}

^a Faculty Member of Academic Center for Education, Culture and Research (ACECR), Tabriz, Iran

^b Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

^c Faculty of Industrial Engineering, Iran University of Science and Technology

Received 26 December 2021; Revised 12 April 2022; Accepted 13 April 2022

Abstract

This research has modeled the problem of combined transportation in the fruits and vegetable supply chain under uncertainty. The designed model includes four echelons: cultivation, packaging, distribution, and customer centers that aim to meet customer demand for perishable products (fruits and vegetables) under conditions of uncertainty in different scenarios. The presence of multiple vehicles in the supply chain network at additional costs has led to the model showing the most suitable combined transport based on the model solution results using the CPLEX method. Data, and as the probability increases or decreases, the amount of transfer time decreases. The result of changes in uncertainty rates also shows that with increasing uncertainty rates, the demand increases. As a result, more transportation options are used, which has led to an increase in product transfer time. The most crucial sensitivity analysis regarding the time of corruption found that the possibility of using high-speed vehicles has been provided by increasing corruption time. Besides, transfer time has decreased due to the chance of storing perishable products and avoiding unwanted transportation. Furthermore, by analyzing the objective function and computational time in larger size issues using SCA and GA algorithms, it was observed that there is no significant difference between the mean indices. And the SCA algorithm has a higher efficiency than the GA algorithm in obtaining the value of the objective function in an acceptable time.

Keywords: Fruit and Vegetable Supply Chain; Combined Transportation; Product Perishability; Robust Fuzzy Stochastic Optimization Method.

1. Introduction

In a supply chain environment, time latency has a significant impact on the success of perishable products. Therefore, the main concern is to develop a comprehensive optimization approach in a supply chain environment for perishable products. Integrating the production, inventory, and distribution of perishable products into a supply chain environment is challenging for staff and researchers. The optimal standard supply chain model may not work for perishable products. Thus, there is a comprehensive model that focuses on the integration of processes (Jouzdani & Govindan, 2021). Shorter product life, temperature control, the need for accurate transaction capability, many product types, and a large volume of goods used, are significant challenges in a supply chain environment for perishable products (Khandelwal et al., 2021). A globally competitive business environment has led to increasing collaboration between companies as members of the global supply chain network (Biuki et al., 2020). A supply chain network as a process is composed of all activities related to supply, production, distribution, warehousing, and transportation.

Regarding global supply chain management, how to transfer products between different countries is also

discussed. Thus, due to the geographical location of each country, it is not possible to access all land, sea, rail, and air routes. Therefore, combined transportation is employed to transfer products between countries (Ghahremani Nahr et al., 2021). Thus, the transfer of products between the origin and the destination can be done through several transportation options, encountering some problems (Nahr et al., 2021). One of the problems of combined transmission in the supply chain network is reducing transmission time. Most of the production of perishable products is stored for several months, and only a part of this product enters the market directly after harvest. Therefore, most small and large producers prefer to keep these relatively sensitive products for several months to supply the used fruit and a reasonable price due to market demand. Thus, suitable places to store large volumes of manufactured products and have a program is necessary (Amiri et al., 2020). Also, because most of the existing warehouses were traditional, every year, a large number of products in these warehouses suffer from a decline in quality, which has been produced with great effort and cost. The current structure of distributing perishable products (fruits and vegetables) has disadvantages such as lack of good product quality, long customer access to end products, and lack of appropriate distribution facilities (Rizvi et al., 2020). In addition to

causing severe problems for the export of products, this leads to the loss of agricultural resources and domestic customers (Rizou et al., 2020). The rapid distribution of perishable goods is of particular importance today, and the failure to quality these products creates many costs. Small and medium farmers are often involved with truck access, warehouses, and the distribution of infrastructure to deliver their products quickly and efficiently to retailers and consumers (Nozari et al., 2021). To make this easier, especially for small and medium-sized farmers, the USDA has proposed the creation of a so-called regional "food hub" service to deliver its products to the market faster. USDA's work definition of a food center is a facility located in the center with a business management structure that facilitates the aggregation, storage, processing, distribution, or marketing of local food products produced in the area. Food centers need active coordination and business management for widespread access to retailers for small to medium-sized farmers' markets (Nozari et al., 2022).

In this way, consumers' access to fresh and healthy food may potentially increase. In addition, by relying on regional mid-range food centers rather than direct retail markets, more locations, including food-deprived areas and food deserts, could potentially be covered. And then allow them to be sent to multiple destinations (Szmelter-Jarosz et al., 2021; Trivedi et al., 2021). The importance of the rapid distribution of perishable products such as fruits and vegetables has led to this article modeling and solving a fruit and vegetable supply chain network. The main goal is to reduce product transfer time by making location distribution and routing decisions. Due to the uncertainty in the amount of demand, this parameter is considered uncertain, and the possible robust fuzzy stochastic optimization method is used to control it. Also, in this paper, SCA and GA meta-heuristic algorithms are used to solve sample problems.

The structure of the article is as follows. The second part presents the research background, and the research gap is determined. The third section discusses the problem of modeling the fruits and vegetable supply chain under uncertainty. This section also presents the initial solution to the problem using SCA and GA algorithms. In the fourth section, numerical examples in small and large sizes are analyzed by CPLEX, SCA, and GA methods, and finally, in the fifth section, the model's conclusions are presented.

2. Literature Review

Mousavi et al. (2015) designed a distributor-retailer network for a location-allocation inventory control problem to find the optimal number of packages and distributors' locations. The distance between distributors and retailers is Euclidean and Euclidean square. AUD and IQD discounts are purchased. They used a modified fruit fly optimization (FFO) algorithm to solve the problem. Etemadnia et al. (2015) examined the wholesale locations

(hubs) in food supply chain systems on a national scale to facilitate the efficient transfer of food from production areas to places of consumption. The proposed mathematical formula is a complex integer linear programming (MILP) problem that minimizes the cost of the entire network, which includes the cost of transporting goods and locating facilities. They used a scenario-based study to examine the model's sensitivity to parameter changes and showed how they affect optimal locations and the number of wholesale facilities. Gardas et al. (2017) conducted a study to identify and model the causes of post-harvest mortality of fruits and vegetables in Indian tissue. They identified fourteen critical factors through a review of the literature and expert opinions. They used the Interpretive Structural Modeling (ISM) approach to establish interrelationships between defined factors and determine critical criteria with a high driving force. The developed ISM model was designed to guide supply chain members at different levels to achieve sustainability in social, economic, and ecological dimensions and increase the supply chain efficiency of fruits and vegetables by eliminating vital factors that cause post-harvest losses.

Yin et al. (2017) modeled the issue of vegetable supply chain quality by linear programming of mixed integers to ensure the quality of vegetables and reduce system costs. This model was used in a red pepper supply chain. It was found that this model is helpful for the production and distribution process in the vegetable supply chain and for designing the vegetable supply chain. Tama et al. (2018) conducted a study using the system dynamics simulation method to develop a model and scenario by coordinating the supply quantity among supply chain actors based on the newspaper sales inventory model. The results show that supply chain coordination increases the overall supply chain profit, although there will always be players who have experienced a decline in profit. The coordination scenario between the farmer, distributor, and wholesaler with a value increase of 10.49%, had the highest growth in the gain of the entire supply chain compared to other coordination scenarios.

Hua et al. (2018) proposed a method for optimizing the distribution of offshore logistics network nodes in the fruit and vegetable supply chain based on the ant colony algorithm and modeled the problem of optimizing the distribution of offshore logistics nodes. They used an improved ant colony algorithm to optimize Used the nautical logistics node distribution and then solved the value of the objective function. Experimental results showed that the cost of the proposed method in this paper is low. Raut et al. (2019) A study on the issue of maximum food losses in the fruit and vegetable supply chain due to quality and mismatch between supply and demand and loss of fruits and vegetables due to improper transportation and lack of proper cold transportation such as facilities/suppliers provided cold supplies or inadequate infrastructure. They proposed a unique multi-criteria fuzzy decision approach to improve food losses through procurement providers. Furthermore, they applied Fuzzy-

DEMATEL and fuzzy-analytic hierarchical process analysis tools.

Sathapatyanon & Kuwornu (2019) examined the role of cooperative networks in the fruit supply chain in Thailand using preliminary data from three cooperatives in the eastern and southern regions of Thailand. The results of the t-test showed that marketing fruits through cooperative networks have advantages such as increasing bargaining power, improving fruit quality, reducing production and harvesting costs, and better access to market information and high-value markets. Liao et al. (2020) considered a six-echelon MILP model to determine the optimal location and number of facilities required to design a closed-loop supply chain network for citrus boxes, considering environmental and economic issues. They developed a new hybrid linear mathematical model for a CLSC and introduced emission taxes to control and reduce environmental pollution. Three leading meta-heuristic algorithms and two combined methods were used and adjusted to solve the proposed model. Sahebjamnia et al. (2020) developed a new operations research model to design a citrus supply chain network. They solved the problem on a large scale using three well-known meta-heuristic algorithms, MOPSO, NSGA-II, and MOICA. They evaluated the performance of the MOPSO, MOICA, and NSGAI algorithms to find the Pareto solution to the citrus supply chain problem. A new nonlinear programming model of mixed integers was also designed to find the location of facilities, flow, and transportation issues of the citrus supply chain network. Rzaei et al. (2021) presented an integrated supply chain network model using a mathematical planning method to optimize fruit production, storage and distribution plans to reduce costs for several presentation periods. They aimed to determine the amount of fruit purchased from suppliers, providing refrigerated storage and optimal distribution. To validate their model, they used a case study of the apple crop in the cities of West and East Azerbaijan, in Iran, in 2019.

Widi et al. (2021) conducted a study to identify pre-epidemic fruit supply chain management, analyze emerging challenges due to outbreaks, and present a fruit supply chain design in response to the Covid-19 epidemic. They interviewed several vital individuals throughout the chain, from producers to end customers, and used qualitative analysis within the food supply chain network. Their results showed that the supply chain was not optimally implemented. Jabarzadeh et al. (2020) presented a closed-loop supply chain optimization problem for a perishable agricultural product to minimize total network costs and carbon dioxide emissions from various network activities and maximize demand response simultaneously. Formulated a linear programming model of multi-objective mixed numbers and used the LP-Metric method and Tchebycheff weight method to solve the optimization model. The computational time to find the optimal Pareto solutions using the Tchebycheff weight method was twice that of the LP-Metric process. Patidar

et al. (2020), in their study on the reconstruction of India's fresh agricultural food supply chain network, proposed the consolidation of crops by forming clusters of farmers and transferring them from these cluster centers to the market. They formulated a multi-period, multi-product, mixed-integer nonlinear programming model to design a four-tier supply chain, considering farmers' clustering and crop corruption. A real case study was performed to validate the formulated model.

Hosseini-Motlagh et al. (2021) studied the case of the wheat supply chain in Iran and the institutions involved in it. By optimizing a new mathematical model, they optimized the total cost of designing a wheat supply chain network. Their proposed model integrates wheat collection, production, inventory, and distribution categories. Intrinsic uncertainty in supply, demand, related costs, and climate change highlighted the role of uncertainty in the mathematical optimization model. Then they used a robust approach to deal with the inevitable uncertainty of the parameters. The proposed model overcame the complexity of uncertainty and performed better than the definitive model. Yu et al. (2021) developed an evolutionary game model based on the relationship between agricultural suppliers and urban dwellers in the financing system. They analyzed the financing game model using evolutionary game theory and Matlab software. The results showed that ESS in the financing game between agricultural suppliers and urban residents could be improved by reducing the cost of GAPSC and increasing its operational capacity of GAPSC. Ronaghi (2021) conducted a study to provide a model for assessing the maturity of China's blockchain technology in the agricultural supply chain. The dimensions of the China block were ranked by agricultural experts using the SWARA method and a model for assessing the adequacy of the China blockchain using each size. China blockchain technology and its dimensions were designed. He tested the proposed model using data collected by a questionnaire in a company's supply chain activities in the agricultural sector. The findings showed that smart contracts, IoT, and transaction records are the most critical dimensions of the Chinese blockchain. The supply chain studied in digital documents is in good condition. Wang et al. (2021) analyzed the network model for the distribution of organic vegetables. They developed an algorithm for solving the nonlinear problem and provided numerical analysis to show the proposed solution. An improved location selection model for the Organic Vegetable Distribution Center and Sorting Center was presented. They studied a confirmed case of an agricultural supply chain in Zhengzhou city to validate the model.

Fakhrzad & Goodarzian (2021) examined a four-echelon citrus supply chain including gardeners, distribution centers, citrus warehouses, and fruit markets. They developed a nonlinear mixed-integer programming (MINLP) model that minimizes total cost and maximizes citrus supply chain profits. Due to the complexity of the

proposed model in large samples, Ant Colony Optimization and Simulated Annealing were used. Jiao et al. (2021) proposed a model for cold chain transportation of fresh fruits and vegetables and storage in a low-temperature refrigeration environment. The target model consists of three parts: the cost of fuel used in the car, the cost of refrigeration transport with Cold chains, and the cost of losing whole fruits and vegetables. The improved ant colony algorithm was used to find fruits and vegetables' optimal cold chain transport path. The results showed that the research method could have the best comprehensive advantage by performing the task of transporting fruits and vegetables in the shortest time and at the lowest cost. Salehi-Amiri et al. (2021) designed a robust closed-loop supply chain network for the walnut industry to optimize the overall costs of the chain using complex integer linear programming, forward and reverse logistics, the delivery of goods, and return products. They used five meta-heuristic algorithms to identify the best solutions. They provided sensitivity analyzes to study the model results. Chouhan et al. (2021) proposed three hybrid meta-heuristic algorithms, H-GASA, H-KASA, and H-RDASA, to solve the complexity of designing and handling a multi-layered sugarcane closed-loop supply chain network. They examined the performance of the algorithms using Taguchi experiments and identified the best combination of parameters. In addition, they generated a set of test problems to ensure the capability of the proposed model. The results showed that H-KASA works better in small-size problems and H-RDASA works in medium and large-size problems. Aghaei Fishani et al. (2022) developed a fuzzy green supply chain management problem considering the location-allocation routing problem. They used a hybrid meta-heuristic approach to solve the model. Arasteh (2022) proposed a mathematical model to optimize inventory management costs in the supply chain by determining safety stock placement. Nozari et al. (2022) designed a multi-stage stochastic inventory management model for transport companies, including several modes. They used the robust-fuzzy-probabilistic method to control the uncertainty parameters.

Various papers have been designed on the food supply chain, medicine, etc., in each of which there are research gaps. Considering the research gap, this paper presents a comprehensive model of the fruits and vegetables supply chain, in which different scenarios are considered in the customer demand. Therefore, a new method for controlling uncertain parameters is presented in this paper (Robust Fuzzy Stochastic Method). Various methods based on meta-heuristic algorithms (GA and SCA) with appropriate initial solutions have been used to solve it. Based on the literature review, the main features of the article can be described as follows:

- Considering the corruption of products in combined transport

- Use of new methods to control uncertainty in possible situations
- Use of meta-heuristic algorithms using the efficient initial solution
- Considering the different aspects of sustainability in the problem

3. Problem Definition and Modelling

The importance of the supply chain of perishable products, including fruits and vegetables, has led to the modeling of a supply chain network problem in this part of the article, taking into account the perishability of products (fruits and vegetables). According to Figure (1), the supply chain network considers four echelons farms, packaging centers, distribution centers, and customers. The cultivation centers send the harvested fruits and vegetables to the packaging centers for packaging, observing their time of decay. After packing fruits and vegetables, packing centers send them to distribution centers for sale in stores and delivery to customers. In the proposed model, fruit and vegetable perishability is considered to deliver the products to customers before spoilage. The primary purpose is to locate packaging centers and product distribution centers. The optimal allocation of vehicles to transport fruit and vegetable packages is also a tactical decision. This article makes the above findings to minimize the transfer time of fruit and vegetable products from cultivation centers to customers. The network implementation budget is also limited during this period. Besides, the strategic and tactical decisions will be made following the intended budget.

According to Figure (1), the transfer of fruits and vegetables along the supply chain network is done by different vehicles (combined transportation). Therefore, choosing the type of vehicle to transfer the products due to budget constraints is another tactical decision that the model makes. Thus, the combined transportation model in the fruit and vegetable supply chain network can be defined according to the following assumptions

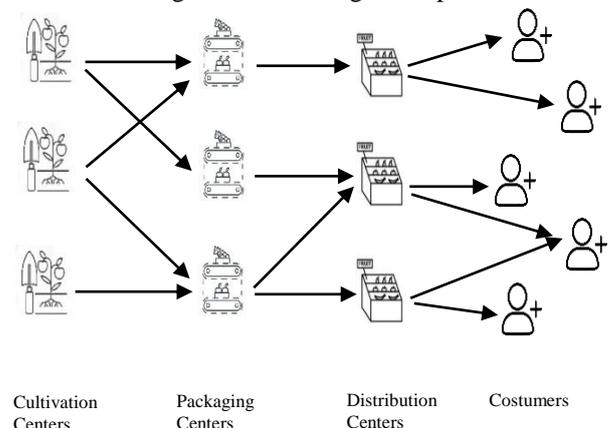


Fig. 1. Fruit and vegetable supply chain network.

- The problem under consideration is multi-period and multi-product (perishable with a limited lifespan),

- Demand and transfer costs are considered uncertain.
- Several scenarios with a specific probability of occurrence are evaluated for each scenario,
- Budget constraints (economic supply chain sustainability) are considered, and
- Distribution centers have the possibility of transferring products between them.

3.1. Modeling the problem of combined transportation in the supply chain of fruits and vegetables

For modeling, the Indices, parameters, and decision variables of the problem are defined as follows:

Indices:

$l = \{1, \dots, L\}$	Index of Cultivation Centers
$k = \{1, \dots, K\}$	Index of product packaging centers
$j, j' = \{1, \dots, J\}$	Index of distribution centers
$i = \{1, \dots, I\}$	Customer Index
$p = \{1, \dots, P\}$	Product Index (Fruits and Vegetables)
$t = \{1, \dots, T\}$	Time period index
$r = \{1, \dots, T\}$	Product packaging time index
$v = \{1, \dots, V\}$	Vehicle Index
$s = \{1, \dots, S\}$	Scenario Index

Parameters:

FK_k	The cost of selecting and locating the packing center k
FJ_j	The cost of selecting and locating a distribution center j
FV_v	Cost of using the vehicle v
Tr_{lkp}	The cost of transporting product p between the cultivation center l and the packaging center k in scenario s
Tr_{kjp}	The cost of transporting product p between the packing center k and the distribution center j in scenario s
$Tr_{jj'}$	The cost of transporting the product between the distribution centers j and j' in scenario s
Tr_{jip}	The cost of transporting the product between the distribution center j and the customer i in scenario s
SV_v	Speed of vehicle v
Dis_{lk}	Distance between cultivation center l and packing center k
Dis_{kj}	Distance between packing center k and distribution center j
Dis_{jj}	Distance between distribution centers j and j'
Dis_{ji}	Distance between distribution center j and customer i
H_{kp}	Maintenance cost of product p in the packaging center k
H_{jp}	maintenance cost of Product p in the distribution center j
B_t	Budget available for network deployment over time t
\overline{Dem}	Uncertain customer demand i of product p in

st_p	Life of product p
Cap_v	The capacity of vehicle v
Cap_{l_c}	The capacity of culture center l of crop p
Cap_k	The capacity of the packing center k of product p
Cap_{j_p}	The capacity of the distribution center j of product p
ϑ_s	Probability of occurrence of scenario s

Decision variables:

S_{lkp}	The amount of product p transferred between the culture center l and the packaging center k in period t in scenario s
T_{kjr}	The amount of product p transferred between the packing center k and the distribution center j over time t in scenario s
$X_{jj'}$	The value of product p transferred between the distribution centers j and j' in period t in scenario s
U_{jip}	The value of product p transferred between the distribution center j and the customer i in period t in scenario s
T_{kjr}	The amount of product p transferred between packing center k and distribution center j over time t and packing at time r in scenario s
Q_{kp}	Inventory level product p in packing center k in period t and packing in time r in scenario s
Q'_{jpi}	Inventory level product p in the distribution center j in period t in scenario s
SV_{lk}	If the transfer of products between the cultivation center l and the packing center k in period t in scenario s is done by vehicle v , the value is 1, and otherwise, it is 0.
TV_k	If the transfer of products between the packing center k and the distribution center j in period t in scenario s is done by vehicle v , the value is 1 and otherwise, it is 0.
XV_{j}	If the transfer of products between the distribution centers j and j' in period t in scenario s is done by vehicle v , the value is 1 and otherwise, it is 0.
UV_{ji}	If the transfer of products between the distribution center j and customer i in period t in scenario s is done by vehicle v , the value is 1 and otherwise, it is 0.
OK_k	If the packing center is selected in place k , it will be 1 and otherwise, it will be 0.
OJ_j	If the distribution center is selected at location j , it will be 1, otherwise it will be 0.

According to the stated indices, parameters, and decision variables, combined transportation modelling in the fruit and vegetable supply chain network is performed as follows:

$$\begin{aligned} \text{Min} Z &= \sum_{s=1}^S \vartheta_s \left[\sum_{l=1}^L \sum_{k=1}^K \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{lk} SV_{lkvts}}{SV_v} \right. \\ &+ \sum_{k=1}^K \sum_{j=1}^J \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{kj} TV_{kjvts}}{SV_v} \\ &+ \sum_{j=1}^J \sum_{j'=1}^J \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{jj'} XV_{jj'vts}}{SV_v} \\ &\left. + \sum_{j=1}^J \sum_{i=1}^I \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{ji} UV_{jivts}}{SV_v} \right] \end{aligned}$$

s. t.:

$$\sum_{r=1}^t Q_{kptrs} = \sum_{l=1}^L S_{lkpts} \quad (1)$$

$$- \sum_{j=1}^J T_{kjpts}, \forall k, p, t = 1 < st_p, s$$

$$\sum_{r=1}^t Q_{kptrs} = \sum_{r=1}^{t-1} Q_{kpt-1rs} + \sum_{l=1}^L S_{lkpts} \quad (2)$$

$$- \sum_{j=1}^J T_{kjpts}, \forall k, p, 1 < t < st_p, s$$

$$\sum_{r=t+1-st_p}^t Q_{kptrs} = \sum_{r=t+1-st_p}^{t-1} Q_{kpt-1rs} \quad (3)$$

$$+ \sum_{l=1}^L S_{lkpts} - \sum_{j=1}^J T_{kjpts}, \forall k, p, t \geq st_p, s$$

$$T_{kjpts} = \sum_{r=1}^t M_{kjptrs}, \forall k, j, p, t < st_p, s \quad (4)$$

$$T_{kjpts} = \sum_{r=t+1-st_p}^t M_{kjptrs}, \forall k, j, p, t \geq st_p, s \quad (5)$$

$$Q_{kptrs} = \sum_{l=1}^L \sum_{l=1}^L S_{lkpts} \quad (6)$$

$$- \sum_{j=1}^J M_{kjptrs}, \forall k, p, t = r, s$$

$$Q_{kptrs} = Q_{kpt-1rs} - \sum_{j=1}^J M_{kjptrs}, \forall k, p, t - r < st_p, s \quad (7)$$

$$Q'_{jpts} = Q'_{jpt-1s} + \sum_{k=1}^K T_{kjpts} + \sum_{j'=1}^J X_{j'jpts} \quad (8)$$

$$- \sum_{j'=1}^J X_{jj'pts} - \sum_{i=1}^I U_{jipts}, \forall j, p, t, s$$

$$\sum_{j=1}^J U_{jipts} \geq \widetilde{Dem}_{ipts}, \forall i, p, t, s \quad (9)$$

$$\sum_{k=1}^K FK_k OK_k + \sum_{j=1}^J FJ_j OJ_j +$$

$$\sum_{k=1}^K \sum_{p=1}^P \sum_{r=1}^t \vartheta_s H_{kp} Q_{kptrs} +$$

$$\sum_{j=1}^J \sum_{p=1}^P \vartheta_s H_{jp} Q'_{jpts} +$$

$$\sum_{l=1}^L \sum_{k=1}^K \sum_{p=1}^P \vartheta_s \widetilde{Tr}_{lkps} S_{lkpt} +$$

$$\sum_{k=1}^K \sum_{j=1}^J \sum_{p=1}^P \vartheta_s \widetilde{Tr}_{kjps} T_{kjpts} +$$

$$\sum_{j=1}^J \sum_{j'=1}^J \sum_{p=1}^P \vartheta_s \widetilde{Tr}_{jj'ps} X_{jj'pts} + \quad (10)$$

$$\sum_{j=1}^J \sum_{i=1}^I \sum_{p=1}^P \vartheta_s \widetilde{Tr}_{jips} U_{jipts} +$$

$$\sum_{l=1}^L \sum_{k=1}^K \sum_{v=1}^V \vartheta_s FV_v SV_{lkvts} +$$

$$\sum_{k=1}^K \sum_{j=1}^J \sum_{v=1}^V \vartheta_s FV_v TV_{kjvts} +$$

$$\sum_{j=1}^J \sum_{j'=1}^J \sum_{v=1}^V \vartheta_s FV_v XV_{jj'vts} +$$

$$\sum_{j=1}^J \sum_{i=1}^I \sum_{v=1}^V \vartheta_s FV_v UV_{jivts} \leq B_t, \forall t, s$$

$$S_{lkpts} \leq \sum_{v=1}^V Cap_v SV_{lkvts}, \forall l, k, p, t, s \quad (11)$$

$$T_{kjpts} \leq \sum_{v=1}^V Cap_v TV_{kjvts}, \forall k, j, p, t, s \quad (12)$$

$$X_{jj'pts} \leq \sum_{v=1}^V Cap_v XV_{jj'vts}, \forall j, j', p, t, s \quad (13)$$

$$U_{jipts} \leq \sum_{v=1}^V Cap_v UV_{jivts}, \forall j, i, p, t, s \quad (14)$$

$$\sum_{k=1}^K S_{lkpts} \leq Cap_{lp}, \forall l, p, t, s \quad (15)$$

$$\sum_{j=1}^J T_{kjpts} + \sum_{r=1}^t Q_{kptrs} \leq Cap_{kp} OK_k, \forall k, p, t, s \quad (16)$$

$$\sum_{i=1}^I U_{jipts} + \sum_{j'=1}^J X_{jj'pts} + Q_{jpts} \leq Cap_{jp} OJ_j, \forall j, p, t, s \quad (17)$$

$$Q_{kptrs} = 0 \forall k, p, t < r, s \quad (18)$$

$$S_{lkpts}, T_{kjpts}, X_{jj'pts}, U_{jipts}, Q_{kptrs}, Q_{jpts} \geq 0 \forall k, l, j, j', i, r, t, p, s \quad (19)$$

$$SV_{lkvts}, TV_{kjvts}, XV_{jj'vts}, UV_{jivts}, OK_k, OJ_j \quad (21)$$

$$\in \{0,1\} \forall l, k, j, j', i, v, t, s$$

The objective function (1) Minimizes the transfer time of perishable fruits and vegetables from cultivation centers to customers and the supply chain network. In this regard, based on the speed of each transfer option, the total transfer time from cultivation centers to the final customer is minimized. Therefore, the model intends to use vehicles with the least transfer time available based on budget. Constraints (2) to (4) indicate the product inventory level by considering spoilage time in different periods in the packing center. Constraints (5) and (6) show the total flow of perishable products from the packaging center to the distribution center and at the time of product packaging. Constraints (7) and (8) indicate the inventory level of a packing center based on the packing time of the product. Limit (9) to the inventory level of products in different periods in distribution centers. Constraint (10) ensures that customer demand for any product is met in any period. Constraints (11) indicate the budget constraints available for each time. Constraints (12) to (15) mean the type of vehicle used to transport fruit and vegetable products based on the vehicle limit. Constraint (16) to (18) states that the maximum capacity of the selected facility can be used if the potential facility is set and located. Constraint (19) shows the logical relation of the problem. Constraints (20) and (21) indicate the gender and type of decision variables.

3.2. Robust fuzzy stochastic optimization

In probabilistic models, the minimum confidence level for imposing indefinite constraints should be determined by decision preferences. As can be seen, in the proposed models, the objective function is not sensitive to deviation from its expected value, which means that the achievement of robust solutions in the base model is not guaranteed. In such cases, a high risk may be imposed on decision-making on many real issues, especially in strategic decisions where solution consolidation is critical. Therefore, the uncertain, indefinite fuzzy programming approach for the problem is used to deal with this inefficient situation. This approach takes advantage of the significant advantages of robust-fuzzy and stochastic programming, which clearly distinguishes it from other uncertainty programming approaches. The robust fuzzy stochastic optimization model is as follows:

$$MinZ = E[Z] + \omega \sum_s \vartheta_s \{E[Z] - E[Z_s] + 2\theta_s\}$$

$$+ \eta \sum_i \sum_p \sum_t \sum_s \vartheta_s \left[Dem_{i,p,t,s}^4 \right. \quad (22)$$

$$\left. - \frac{(\alpha_s - \lambda) Dem_{i,p,t,s}^4 + (1 - \alpha_s) Dem_{i,p,t,s}^3}{1 - \lambda} \right]$$

s. t. :

$$E[Z] = \sum_{s=1}^S \vartheta_s \left[\sum_{l=1}^L \sum_{k=1}^K \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{lk} SV_{lkvts}}{SV_v} \right. \quad (23)$$

$$+ \sum_{k=1}^K \sum_{j=1}^J \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{kj} TV_{kjvts}}{SV_v}$$

$$+ \sum_{j=1}^J \sum_{j'=1}^J \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{jj'} XV_{jj'vts}}{SV_v}$$

$$\left. + \sum_{j=1}^J \sum_{i=1}^I \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{ji} UV_{jivts}}{SV_v} \right]$$

$$E[Z_s] = \vartheta_s \left[\sum_{l=1}^L \sum_{k=1}^K \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{lk} SV_{lkvts}}{SV_v} \right. \quad (24)$$

$$+ \sum_{k=1}^K \sum_{j=1}^J \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{kj} TV_{kjvts}}{SV_v}$$

$$+ \sum_{j=1}^J \sum_{j'=1}^J \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{jj'} XV_{jj'vts}}{SV_v}$$

$$\left. + \sum_{j=1}^J \sum_{i=1}^I \sum_{v=1}^V \sum_{t=1}^T \frac{Dis_{ji} UV_{jivts}}{SV_v} \right], \forall s$$

$$\sum_{j=1}^J U_{jipst} \geq (1 - \alpha_s) Dem_{ipts}^3 \quad (25)$$

$$+ \alpha_s Dem_{ipts}^4, \forall i, p, t, s$$

$$Eqs(2 - 9) \& (11 - 21) \quad (26)$$

In Equation (22), the first expression refers to the expected value of the first objective function using the mean values of the uncertain parameters of the model. The second statement refers to the cost of the penalty for deviating more than the expected value of the first objective function (optimality sustainable). The third sentence also shows the total cost of the demand deviation penalty (uncertain parameter). Therefore, the parameter ω of the weighting coefficient of the objective function η is the cost of the penalty for not estimating the demand. The parameters α_s represent the correction coefficients in the value of fuzzy surfaces of numbers, which should be a number between 0.1 and 0.9. Equations (23) and (24) show the mathematical expectation of network-related costs in all scenarios and each scenario, respectively. Equation (24) shows the other limitations used in the model.

3.3. Initial solution

The complexity of supply chain network models has been demonstrated in many articles. The supply chain network model includes capacity facility location and flow optimization (Ghahremani-Nahr et al., 2020). Therefore, the model complexity can be reduced to the complexity of the problem of locating capacity facilities. On the other

hand, Np-Hard has been proven to be a potential location facility in various articles (Ghahremani-Nahr et al., 2020). As a result, it can be concluded that the supply chain network model is designed NP-Hard, and SCA and GA meta-heuristic algorithms are used to solve it. In the following, the initial solution to the problem is provided for encoding and decoding.

Priority-based encoding modification was introduced by Ghahremani et al. (2020). The supply chain network is divided into its constituent levels in this encoding. Each echelon is considered in the design of the primary chromosome according to the capacity, demand, type of vehicle, etc. Figure (2) shows an example of the initial solution and its decoding for a supply chain network echelon. The priority-based decoding modified in Figure (2) follows the following four steps:

Step 1- First, the most significant priority (number) is selected from the chromosomes related to the sources. If the resource is able to supply all the depots, the importance of the other resources will be reduced to zero. In this case, locating is done on resources that do not have zero priority.

Step 2 - The highest priority (number) from the whole chromosome is selected as the first allocation level.

Step 3- Based on the shipping cost, the lowest shipping cost is estimated from the allocation level selected from step (2) (source/depot) with the new allocable level (depot/source), and the second allocation level is determined.

Step 4 - After determining the source and depot, the minimum amount of depot demand and resource capacity is considered the optimal allocation amount. After the allocation operation, the depot demand amount and the resource capacity are updated.

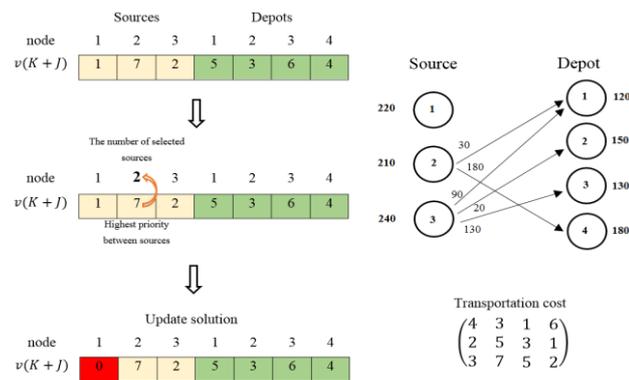


Fig. 2. Modified priority-based encoding and decoding.

Due to the multi-echelon supply chain network design, the final initial solution designed is as shown in Figure (2). Since the problem is considered a multi-product and multi-period. Therefore, considering the product and time, a final chromosome from Figure (3) should be produced and decoded according to the steps provided in the above section.

Product (P)- Period (T)

	Cultivation and packaging center		Packaging and distribution center		Between distribution centers		Between the distribution center and the customer	
Nodes	L	K	K	J	J	J	J	I
Priority	$v(L + K)$		$v(K + J)$		$v(J + J)$		$v(J + I)$	

Fig. 3. Modified priority-based for multi-echelon supply chain

After presenting the initial solution for the proposed multi-echelon supply chain problem, Figure (4) shows the model decoding solution steps and feasibility assurance.

<p>Step 1. Decoding the initial solution between Distribution centers and Customers based on Figure (2) Input: $I , J , Tr_{j'ps}, st_p, Cap_{jp}, Cap_v, Dem_{ipts}$ Output: $U_{j'pts}, UV_{j'vts}, OJ_j$ If Eqs (25-15) won't be feasible, use the penalty function (Add a big value to the OBF).</p>
<p>Step 2. Decoding the initial solution between Distribution centers based on Figure (2) and output Step 1 Input data: $J , Tr_{j'ps}, st_p, Cap_{jp}, Cap_v$ The input of step 1: OJ_j Output: $X_{j'pts}, XV_{j'vts}, Q'_{jpts}$ If Eqs (18-14) won't be feasible, use the penalty function (Add a significant value to the OBF).</p>
<p>Step 3. Decoding the initial solution between Packaging and distribution center based on Figure (2) and output Step 2 Input data: $J , K , Tr_{kps}, st_p, Cap_{kp}, Cap_v$ The input of step 2: $OJ_j,$ $\sum_j' X_{j'pts} + \sum_i U_{j'pts} -$ $\sum_j' X_{j'pts}$ (The amount of product required by the center) Output: $T_{kpts}, TV_{kvt}, Q_{kptrs}, M_{kjptrs}, OK_k$ If Eqs (9-5-6-13-17-19) won't be feasible, use the penalty function (Add a considerable value to the OBF).</p>
<p>Step 4. Decoding the initial solution between Cultivation and packaging center based on Figure (2) and output Step 3 Input data: $L , K , Tr_{lps}, st_p, Cap_{lp}, Cap_v$ The input of step 2: $OK_k,$ $\sum_j T_{kpts}$ (The amount of product required by the center) Output: S_{lkpts}, SV_{lkvts} If Eqs (2-3-4-7-8-12-16) won't be feasible, use the penalty function (Add an immense value to the OBF).</p>
<p>Step 5. Examine Eq (11) based on the inputs of steps 1 to 4. Input data: $FK_k, FJ_j, FV_v, H_{kp}, H_{jp}, B_t, \vartheta_s$ The input of steps 1 to 4: all decision variable If Eq (11) won't be feasible, use the penalty function (Add a considerable value to the OBF).</p>
<p>Step 6. Calculate the value of the objective function based on Eqs (22-23-24) plus the penalty function Input data: $SV_v, \vartheta_s, Dis_{lk}, Dis_{kj}, Dis_{ji}, Dis_{j'}$ The input of steps 1 to 4: all decision variable</p>

Fig. 4. Decoding solution steps and feasibility assurance

Due to the use of two algorithms, GA and SCA, the operators of each algorithm are examined. Since the search space of the two algorithms is continuous, the operators of each algorithm generate new solutions in the continuous space. Eventually, after forming new solutions based on a corrective mechanism, the continuous space becomes a discrete space.

The SCA Operators

The SCA algorithm is a population-based algorithm that tries to achieve near-optimal values for each problem by creating random solutions. This algorithm consists of two different steps. In the first step (former phase), an optimization algorithm abruptly combines the unexpected solutions in the set of keys with a high rate of randomness to find the promising regions of the search space. In the second step (exploitation phase), however, there are gradual changes in the random solutions, and random variations are considerably less than those in the exploration phase. In this work, the following position updating equations are proposed for both steps (Mirjalili, 2016):

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 * \sin(r_2) * |r_3 P_i^t - X_i^t|, & r_4 < 0.5 \\ X_i^t + r_1 * \cos(r_2) * |r_3 P_i^t - X_i^t|, & r_4 \geq 0.5 \end{cases} \quad (27)$$

Where X_i^t is the position of the current solution in i^{th} dimension at t^{th} iteration, $r_1/r_2/r_3$ are random numbers, P_i^t is the position of the destination point in i^{th} dimension, and $||$ indicates the absolute value. Also r_4 is a random number in $[0,1]$. SCA can balance exploration and exploitation to find the promising regions of the search space and eventually converge to the global optimum. The range of sine and cosine in Eq (28) is changed adaptively to balance exploration and exploitation, using the following Equation:

$$r_1 = a - t \frac{a}{T} \quad (28)$$

Where t is the current iteration, T is the maximum number of iterations, and a is a constant

The GA Operators

The GA has two operators of crossover and mutation, which are described below. Figure (5) illustrates the operator with a two-point crossover.

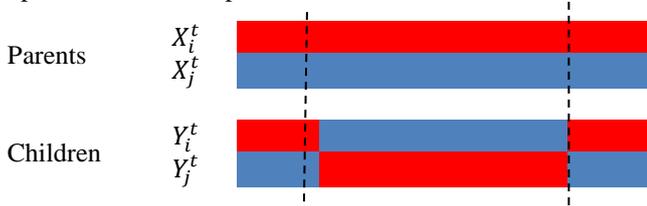


Fig. 5. Two-point crossover operator

Two crossover points in the two-point crossover are chosen randomly from the parent chromosomes. The genes between them in the parent's chromosome are swapped. Figure (6) shows the performance of the mutation operator.



Fig. 6. Mutation operator

This operator replaces the selected gene with a random amount.

The search area in the chromosome of the designed supply chain network is discrete, and it means that any individual from the population components can't have an arbitrary value. Allowable values are limited to natural numbers from 1 to N. Therefore, continuous search area must be changed to the discrete search area in the algorithms. Figure (7) is shown an example of shipment in the solution search area.

Random number in continuous space	0.125	0.362	0.418	0.342	0.599	0.908	0.142
Nodes	1	2	3	4	5	6	7
Random number in continuous space	0.908	0.599	0.418	0.362	0.342	0.142	0.125
Priority in discrete space	6	5	3	2	4	7	1

Fig. 7. An example of shipment in the solution search area

In Figure (7), select the most considerable number in the continuous space of the chromosome. The position of this number is the first gene of the new solution.

In the following, small and large problems are analysed with different solution methods. Therefore, first, a problem is designed in small size and solved using the CPLEX method. Then, SCA and GA algorithms are used to solve sample problems in larger sizes.

4. Model Analysis

4.1. Numerical example of small size

In this section, the designed model is analyzed. Therefore, random data based on the uniform distribution function has been used due to the lack of access to real-world data. Hence the considered problem includes three cultivation centers, four packaging centers, four distribution centers, five customer cluster centers, two products (fruits and vegetables) and four periods (days), and four types of vehicles. It is in two different scenarios. Table (1) shows the interval limits of the problem parameters based on the uniform distribution function.

Table 1
The value of the important parameters of the problem based on the uniform distribution function

Parameter	Amount
FK_k, FJ_j	$\sim U [10000,12000]$
FV_v	$\sim U [500,700]$
$Tr_{lkps}, Tr_{kjp}, Tr_{jj'ps}, Tr_{jips}$	$\sim U [20,30]$
SV_v	$\sim U [80,120]$
H_{kp}, H_{jp}	$\sim U [5,10]$
B_t	400000
st_p	2
Cap_v	$\sim U [300,400]$
Cap_{lp}	$\sim U [3000,4500]$
Cap_{kp}	$\sim U [2500,3500]$
Cap_{jp}	$\sim U [1500,2500]$
$Dis_{ik}, Dis_{kj}, Dis_{jj'}, Dis_{ji}$	$\sim U [100,150), (150,200), (200,250), (250,300)$
Dem_{ipts}	$\sim U [(100,150), (150,200), (200,250), (250,300)]$

Due to the designed model uncertainty and the robust fuzzy stochastic method to control, the problem is

analyzed considering the uncertainty rate of 0.5 for scenarios 1 and 2. Also, the corruption time is assumed as two days. In addition, the probability of occurrence of each of the scenarios is 50%. By solving the above example, the value of the objective function of the problem is 3604.42 time units. Considering the four types of vehicles, Figure (8) deals with the type of vehicle selected to transfer products between different levels of the supply chain network. Several sensory analyses have been performed to investigate the effect of changes in the problem parameters on the objective function of the designed model. First, the difference in the objective function value in exchange for changes in the probability of occurrence of the scenarios is investigated. Therefore, in nine different cases, the occurrence probability of the first and second scenarios is changed according to Table (2), where the value of the objective function is shown.

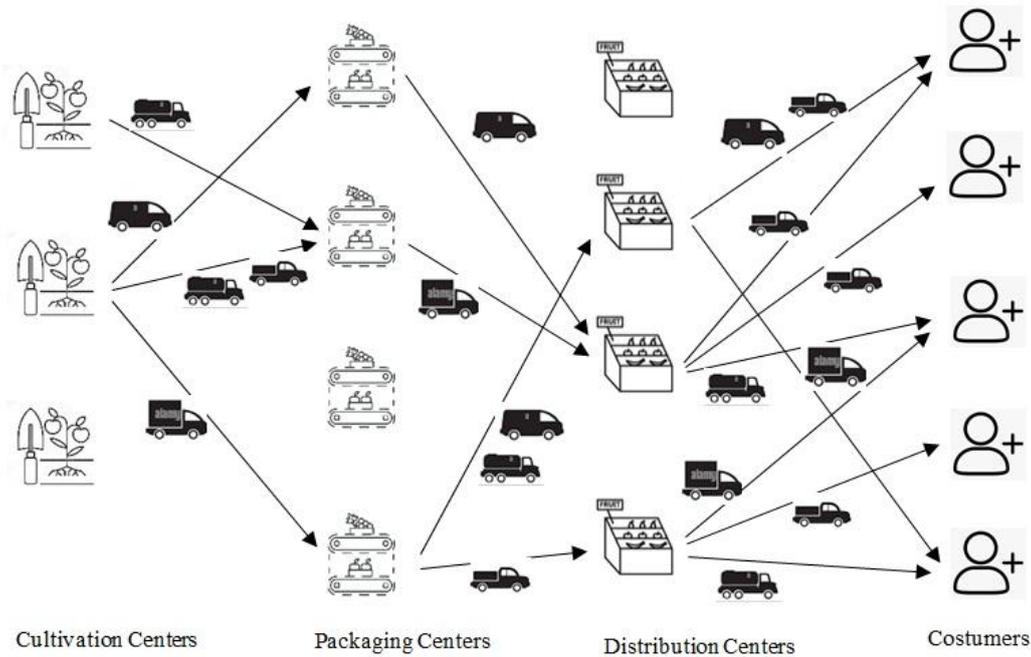


Fig. 8. Optimal allocation and type of vehicle allocated at each echelon of the supply chain network

Table 2
Changes in the value of the objective function in exchange for changes in the probability of occurrence of different scenarios

$(\vartheta_1, \vartheta_2)$	OBF	$(\vartheta_1, \vartheta_2)$	OBF	$(\vartheta_1, \vartheta_2)$	OBF
(0.1,0.9)	2999.67	(0.4,0.6)	3582.85	(0.7,0.3)	3427.38
(0.2,0.8)	3270.74	(0.5,0.5)	3604.42	(0.8,0.2)	3207.62
(0.3,0.7)	3468.54	(0.6,0.4)	3556.01	(0.9,0.1)	2908.96

Table (2) demonstrates that when the probability of occurrence of scenarios 1 and 2 is equal to 50%, the value of the objective function is at its maximum value. By decreasing one of the probabilities in the first or second scenario, the value of the objective function decreases. On the other hand, due to the uncertainty of demand, the sensitivity analysis of the value of the objective function in exchange for reducing the uncertainty rate in the first scenario and increasing the uncertainty rate in the second scenario is discussed. Table (3) shows these changes in

the value of the objective function in exchange for changes in the expressed uncertainty rate.

Table 3
Changes in the value of the objective function in exchange for the rate change in uncertainty

(α_1, α_2)	OBF	(α_1, α_2)	OBF	(α_1, α_2)	OBF
(0.1,0.9)	3653.28	(0.4,0.6)	3617.26	(0.7,0.3)	3590.0
(0.2,0.8)	3637.60	(0.5,0.5)	3604.42	(0.8,0.2)	3575.5
(0.3,0.7)	3623.67	(0.6,0.4)	3604.06	(0.9,0.1)	3567.3

Table (3) shows that in exchange for decreasing the uncertainty rate in the first scenario and increasing the uncertainty rate in the second scenario, the value of the objective function has improved, due to the increase in total demand and, consequently, increased product

transfers between levels. Hence, increasing the number of transfers, the number of vehicles used increases, and as a result, the transfer time has increased.

Also, due to the limited investment budget in the designed model, changes in the objective function in exchange for budget changes are examined in this section. According to the initial model, assuming a budget of 400,000 units, the value of the objective function is 3604.42 units. In this section, the budget amount is changed from 370,000 to 430,000. And in return, the amount of the objective function is shown in Table (4).

Table 4
Changes in the amount of the objective function in exchange for changes in the amount of the budget

B_t	OBF	B_t	OBF
370000	3612.36	410000	3602.04
380000	3612.67	420000	3601.42
390000	3611.48	430000	3592.57
400000	3604.42		

According to Table (4), it can be seen that with the increase in the amount of budget, it is possible to establish centres and facilities close to retailers for faster delivery of perishable products, as well as the use of high-speed vehicles at a higher cost. Hence, with the increase in budget, the transfer time has decreased. Table (5) also examines the value of the objective function of the problem in exchange for the change in product spoilage time.

Table 5
Changes in the value of the objective function in exchange for changes in corruption time

st_p	OBF	st_p	OBF
1	3620.46	4	3595.61
2	3604.42	5	3590.20
3	3601.39		

Table (5) illustrates that with the increase in corruption time, due to the possibility of storing perishable products and avoiding unwanted transportation, it is possible to use high-speed vehicles (due to the possibility of using the maximum budget). Therefore, this has led to a reduction in transfer time. Finally, in the last analysis, the amount of changes in the objective function of the problem in exchange for possible changes in the speed of the combined transport is examined. In this analysis, assuming changes in transport speed from 0.85 to 1.15, the value of the objective function is calculated and shown in Table (6).

Table 6
Change the value of the objective function in exchange for changes in transport speed

SV_v	OBF	SV_v	OBF
0.85	3621.26	1.05	3597.36
0.9	3612.18	1.10	3590.15
0.95	3610.25	1.15	3581.36
1	3604.42		

Table (6) shows that the transfer time has decreased by increasing the transfer speed of vehicles and the constant distance between the facilities. Figure (9) shows the trend of changes in the value of the objective function in exchange for changes in the various parameters presented.

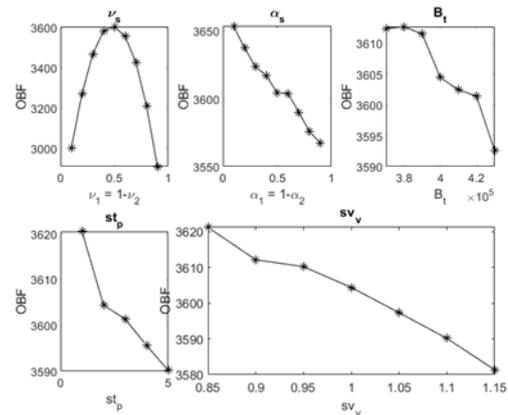


Fig. 9. Trend of changes in the value of the objective function in exchange for changes in various parameters of the problem

Given the complexity of supply chain network design, including capacity facility location issues and optimal flow allocation, GA and SCA meta-heuristic algorithms have been used to solve other numerical examples. Therefore, before solving the small size numerical model and examining the efficiency of these two algorithms to achieve the value of the objective function and computational time, the parameter of the two algorithms has been adjusted by the Taguchi method.

Table (7) shows the levels of the proposed parameters of the two meta-heuristic algorithms, SCA and GA, and the optimal value obtained by the Taguchi method, which is influenced by the mean S / N ratio diagrams. Three levels are determined for each parameter in the Taguchi method, and numerical tests are performed based on the Taguchi method. The RPD should be determined according to Equation (29) to determine the optimal level of parameters. After deciding on the RPD, the average S / N ratio chart is analyzed.

$$RPD_i = \frac{(AlgSol_i - BestSol)}{BestSol} \tag{29}$$

Table 7
Proposed levels and the optimal value of meta-heuristic algorithm parameters

Algorithm	Parameter	Level 1	Level 2	Level 3	The optimal amount
GA	Max it	100	150	200	200
	Npop	50	100	150	100
	P_m	0.03	0.04	0.05	0.03
	P_c	0.7	0.8	0.9	0.9
SCA	Max it	100	150	200	200
	Npop	50	100	150	150
	a	1	1.5	2	1.5

After setting the parameter of meta-heuristic algorithms to evaluate the performance of the algorithms, the numerical example stated in the previous section is examined. Hence the convergence of the algorithms in achieving the near-optimal solution is shown in Figure (10).

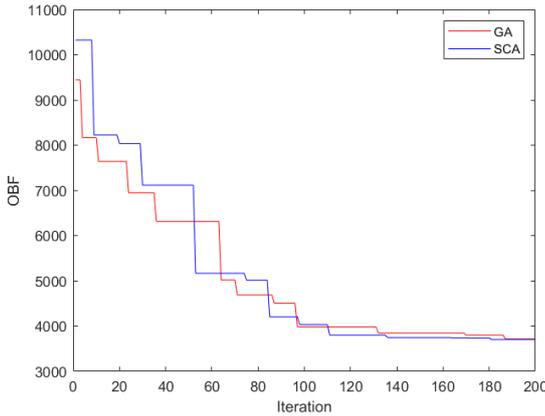


Fig. 10. Convergence of algorithms to achieve the near-optimal solution in a small size numerical example

After solving the problem with meta-algorithms and the CPLEX method, the value of the objective function obtained by different solving techniques and the computational time obtained is shown in Table (8).

Table 8
The value of the objective function and the computational time obtained in solving the small size problem

Method of solution	objective function	Percentage of relative difference	Computational time
GA	3711.34	2.97 %	45.18
SCA	3702.18	2.71 %	38.16
Cplex	3604.42	-	493.15

The results obtained from solving the small size numerical example show that the meta-heuristic algorithms have achieved outstanding results much shorter than the CPLEX method. The maximum percentage of relative difference obtained is less than 3%. Therefore, it can be said that the efficiency of algorithms in solving the fruit and vegetable supply chain problem is very high.

4.2. Numerical example of large size

Due to the high efficiency of meta-heuristic algorithms in solving numerical examples of larger sizes, ten numerical models have been designed and solved according to Table (9). Each designed numerical example is solved three times by each algorithm, and the mean of the objective function and computational time are shown in Table (10).

Table 9
Size of numerical examples in a larger size

Numerical examples	L	K	J	I	P	T	V	S
1	5	6	5	7	3	4	6	3
2	6	8	6	8	3	4	7	3
3	7	10	7	10	3	6	7	3
4	8	12	10	15	4	6	8	4
5	10	15	12	18	4	6	10	4
6	12	18	15	20	4	8	12	4
7	15	20	18	23	5	8	15	5
8	18	23	20	25	5	8	15	5
9	20	25	23	30	5	8	20	5
10	25	28	25	35	5	8	25	5

According to the measurements in Table (9), the mean of the objective function and the computational time obtained from solving numerical examples are presented in Table (10).

Table 10
Mean objective function and computational time obtained from solving numerical examples

Numerical examples	GA		SCA	
	OBF	CPU - Time	OBF	CPU - Time
1	8326.14	52.18	8214.66	48.16
2	9514.67	68.24	9472.05	55.22
3	11679.47	88.03	11764.82	73.71
4	15994.26	112.46	16234.11	100.37
5	19742.34	167.92	18465.37	134.67
6	23476.45	276.18	22974.50	197.45
7	30175.64	412.36	31248.67	310.28
8	36882.14	624.17	37625.47	504.67
9	42674.64	945.07	41352.71	766.24
10	50146.77	1342.34	49347.67	1145.37
mean	24861.25	408.89	24760.00	333.61

According to Table (10), it can be seen that the SCA algorithm has performed better than the GA algorithm in terms of achieving the objective function in a shorter time. Therefore, Figure (11) shows the mean of the objective function and computational time in different numerical examples.

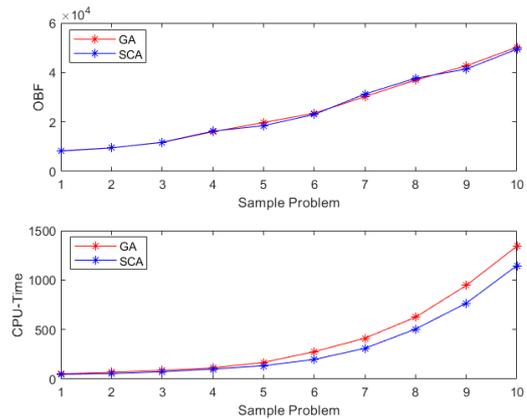


Fig. 11. Mean objective function and computational time obtained from solving numerical examples with SCA and GA algorithms

Based on Figure (11) and the results obtained from Table (10), it can be stated that with increasing the size of the problem, the solution time has grown exponentially. Additionally, the SCA algorithm has been more efficient than the GA algorithm regarding the mean objective function and computational time. In the following, the significant difference between the mean indices between SCA and GA algorithms in numerical examples of larger sizes with T-Test is investigated. Table (11) shows the results of the T-Test. If the P-value is less than 0.05, it indicates a significant difference between the means of the index.

Table 11
T-Test results in the significant difference of indicators

Indicator	number of samples	Mean difference	Confidence interval (95%)	T-Value	P-Value
OBF	30	191	(-13515 13897)	0.03	0.977
CPU-Time	30	75	(-305 456)	0.42	0.682

According to Table (11), there is no significant difference between the means of the objective function and the computational time between the two algorithms, SCA and GA.

5. Conclusion

In this paper, the problem of reducing the transmission time in the supply chain network of perishable products (fruits and vegetables) is modeled by considering combined transport under uncertainty. Therefore, a multi-echelon model consisting of cultivation centers, packaging centers, distributors, and customers was considered to meet retailers' demand for perishable products under conditions of uncertainty. Therefore, the robust fuzzy stochastic method was used to control the model. The proposed model included decisions about the location variables of distribution centers and the number of inventory reserves, the number of perishable products transferred, and the type of hybrid means of transportation. The model results showed that the maximum value of the objective function occurs when the first and second scenarios occur with a probability of 50%, and with increasing or decreasing this probability, the transfer time decreases. Also, the result of changes in uncertainty rates showed that with rising uncertainty rates, the demand increases. As a result, more means of transportation are used for transportation, which leads to a rise in transfer time.

On the other hand, by increasing the budget, the transfer time has decreased due to the possibility of using high-speed vehicles. Finally, in the most critical sensitivity analysis regarding corruption time, we found that increasing corruption time, considering the option of storing perishable products and avoiding unwanted transportation, the possibility of using high-speed vehicles (due to the possibility of using the maximum budget) is provided. Therefore, this has led to a reduction in transfer time. Due to the complexity of the supply chain network design, the SCA and GA algorithms were used to solve numerical examples. Therefore, the results showed that the maximum relative difference in the objective function obtained is less than 3% compared to the CPLEX method, while the problem-solving time is much shorter. As a result, by designing 10 numerical examples in larger sizes, the mean and computational time obtained were analyzed and it was found that there is no significant difference between the mean of the obtained indices between the solution methods. Therefore, by examining

the results, it is observed that the value of the objective function obtained from the algorithms is very close to each other, and this has been achieved due to the proper design of the initial solution. As a result, due to better results of SCA algorithm than GA algorithm, this algorithm was proposed to implement the problem of supply chain network of fruits and vegetables.

References

- Aghaei Fishani, B., Mahmoodirad, A., Niroomand, S., & Fallah, M. (2022). Developing a Fuzzy Green Supply Chain Management Problem Considering Location Allocation Routing Problem: Hybrid Meta-Heuristic Approach. *Journal of Optimization in Industrial Engineering*, 15(1), 161-174.
- Amiri, S. A. H. S., Zahedi, A., Kazemi, M., Soroor, J., & Hajiaghahi-Keshteli, M. (2020). Determination of the optimal sales level of perishable goods in a two-echelon supply chain network. *Computers & Industrial Engineering*, 139, 106156.
- Arasteh, A. (2022). Optimizing inventory management costs in supply chains by determining safety stock placement. *Journal of Optimization in Industrial Engineering*, 15(1), 1-15.
- Biuki, M., Kazemi, A., & Alinezhad, A. (2020). An integrated location-routing-inventory model for sustainable design of a perishable products supply chain network. *Journal of Cleaner Production*, 260, 120842.
- Chouhan, V. K., Khan, S. H., & Hajiaghahi-Keshteli, M. (2021). Metaheuristic approaches to design and address multi-echelon sugarcane closed-loop supply chain network. *Soft Computing*, 25(16), 11377-11404.
- Etemadnia, H., Goetz, S. J., Canning, P., & Tavallali, M. S. (2015). Optimal wholesale facilities location within the fruit and vegetables supply chain with bimodal transportation options: An LP-MIP heuristic approach. *European Journal of Operational Research*, 244(2), 648-661.
- Fakhrzad, M. B., & Goodarzian, F. (2021). A new multi-objective mathematical model for a Citrus supply chain network design: Metaheuristic algorithms. *Journal of Optimization in Industrial Engineering*, 14(2), 127-144.
- Gardas, B. B., Raut, R. D., & Narkhede, B. (2017). Modeling causal factors of post-harvesting losses in vegetable and fruit supply chain: An Indian perspective. *Renewable and sustainable energy reviews*, 80, 1355-1371.
- Gahremani Nahr, J., Pasandideh, S. H. R., & Niaki, S. T. A. (2020). A robust optimization approach for multi-objective, multi-product, multi-period, closed-loop green supply chain network designs under uncertainty and discount. *Journal of industrial and production engineering*, 37(1), 1-22.
- Gahremani-Nahr, J., Nozari, H., & Sadeghi, M. E. (2021). Investment modeling to study the performance of dynamic networks of insurance

- companies in Iran. *Modern Research in Performance Evaluation*.
- Hosseini-Motlagh, S. M., Samani, M. R. G., & Abbasi Saadi, F. (2021). Strategic optimization of wheat supply chain network under uncertainty: a real case study. *Operational research*, 21(3), 1487-1527.
- Hua, J., Gu, S., & Zhang, L. (2018). Optimal design of node distribution in maritime logistics network of fruit and vegetable supply chain. *Journal of Coastal Research*, (83 (10083)), 814-818.
- Jabarzadeh, Y., Yamchi, H. R., Kumar, V., & Ghaffarinasab, N. (2020). A multi-objective mixed-integer linear model for sustainable fruit closed-loop supply chain network. *Management of Environmental Quality: An International Journal*.
- Jiao, X., Xu, W., & Duan, L. (2021). Study on Cold Chain Transportation Model of Fruit and Vegetable Fresh-Keeping in Low-Temperature Cold Storage Environment. *Discrete Dynamics in Nature and Society*, 2021.
- Jouzani, J., & Govindan, K. (2021). On the sustainable perishable food supply chain network design: A dairy products case to achieve sustainable development goals. *Journal of Cleaner Production*, 278, 123060.
- Khandelwal, C., Singhal, M., Gaurav, G., Dangayach, G. S., & Meena, M. L. (2021). Agriculture Supply Chain Management: A Review (2010–2020). *Materials Today: Proceedings*, 47, 3144-3153.
- Liao, Y., Kaviyani-Charati, M., Hajiaghahi-Keshteli, M., & Diabat, A. (2020). Designing a closed-loop supply chain network for citrus fruits crates considering environmental and economic issues. *Journal of Manufacturing Systems*, 55, 199-220.
- Mirjalili, S. (2016). SCA: a sine cosine algorithm for solving optimization problems. *Knowledge-based systems*, 96, 120-133.
- Mousavi, S. M., Alikar, N., Niaki, S. T. A., & Bahreinnejad, A. (2015). Optimizing a location allocation-inventory problem in a two-echelon supply chain network: A modified fruit fly optimization algorithm. *Computers & Industrial Engineering*, 87, 543-560.
- Nahr, J. G., Nozari, H., & Sadeghi, M. E. (2021). Green supply chain based on artificial intelligence of things (AIoT). *International Journal of Innovation in Management, Economics and Social Sciences*, 1(2), 56-63.
- Nozari, H., Ghahremani-Nahr, J., & Szmelter-Jarosz, A. (2022). A multi-stage stochastic inventory management model for transport companies including several different transport modes. *International Journal of Management Science and Engineering Management*, 1-11.
- Nozari, H., Ghahremani-Nahr, J., Fallah, M., & Szmelter-Jarosz, A. (2022). Assessment of cyber risks in an IoT-based supply chain using a fuzzy decision-making method. *International Journal of Innovation in Management, Economics and Social Sciences*, 2(1).
- Nozari, H., Szmelter-Jarosz, A., & Ghahremani-Nahr, J. (2021). The Ideas of Sustainable and Green Marketing Based on the Internet of Everything—The Case of the Dairy Industry. *Future Internet*, 13(10), 266.
- Patidar, R., & Agrawal, S. (2020). Restructuring the Indian agro-fresh food supply chain network: a mathematical model formulation. *Clean Technologies and Environmental Policy*, 22(10), 2053-2077.
- Raut, R. D., Gardas, B. B., Narwane, V. S., & Narkhede, B. E. (2019). Improvement in the food losses in fruits and vegetable supply chain—a perspective of cold third-party logistics approach. *Operations Research Perspectives*, 6, 100117.
- Rizou, M., Galanakis, I. M., Aldawoud, T. M., & Galanakis, C. M. (2020). Safety of foods, food supply chain and environment within the COVID-19 pandemic. *Trends in food science & technology*, 102, 293-299.
- Rizvi, S. A. A., Asim, M., & Manzoor, S. (2020). Issues, Challenges, and Scope of Supply Chain Management in Fruits and Vegetables in Pakistan. *Int. European Extended Enablement in Sci., Engi. Magt*, 8(1), 20-30.
- Ronaghi, M. H. (2021). A blockchain maturity model in agricultural supply chain. *Information Processing in Agriculture*, 8(3), 398-408.
- Rzaei, M., Dabbagh, R., & Baba Zade, R. (2021). Presenting a supply chain model using a mathematical programming method to optimize product distribution plan in the fruit industry. *Iranian Journal of Agricultural Economics and Development Research*.
- Sahebjamnia, N., Goodarzian, F., & Hajiaghahi-Keshteli, M. (2020). Optimization of multi-period three-echelon citrus supply chain problem. *Journal of Optimization in Industrial Engineering*, 13(1), 39-53.
- Salehi-Amiri, A., Zahedi, A., Akbapour, N., & Hajiaghahi-Keshteli, M. (2021). Designing a sustainable closed-loop supply chain network for walnut industry. *Renewable and Sustainable Energy Reviews*, 141, 110821.
- Sathapatyanon, J., & Kuwornu, J. K. (2019). Assessment of the role of cooperative networks in the fruit supply chain in Thailand. *International Journal of Value Chain Management*, 10(1), 53-85.
- Szmelter-Jarosz, A., Ghahremani-Nahr, J., & Nozari, H. (2021). A neutrosophic fuzzy optimisation model for optimal sustainable closed-loop supply chain network during COVID-19. *Journal of Risk and Financial Management*, 14(11), 519.
- Tama, I. P., Akbar, Z., & Eunike, A. (2018, April). Implementation of system dynamic simulation method to optimize profit in supply chain network of vegetable product. In *IOP Conference Series: Materials Science and Engineering* (Vol. 337, No. 1, p. 012014). IOP Publishing.
- Trivedi, A., Sohal, A., Joshi, S., & Sharma, M. (2021). A two-stage optimization model for tactical planning in fresh fruit supply chains: A case study of Kullu,

- India. *International Journal of Supply and Operations Management*, 8(1), 18-28.
- Wang, A., Wang, Y., & Chen, Q. (2021). Analyzing Network Model for Organic Vegetable Distribution: A Case Study of Zhengzhou City. *Mobile Information Systems*, 2021.
- Widi, A., Sari, E. D., & Jahroh, S. (2021, February). The Change of Fruit Supply Chain in Response to Covid-19 Pandemic in West Java, Indonesia (Case Study of Anto Wijaya Fruit). In *Journal of Physics: Conference Series* (Vol. 1764, No. 1, p. 012036). IOP Publishing.
- Yin, H. L., & Wang, Y. M. (2017, July). An effective method for vegetable supply chain quality management. In *2017 36th Chinese Control Conference (CCC)* (pp. 7507-7510). IEEE.

This article can be cited: Ghahremani-Nahr, J., Najafi, S. E., & Nozari, H. (2022). A Combined Transportation Model for the Fruit and Vegetable Supply Chain Network. *Journal of Optimization in Industrial Engineering*, 15(2), 131-145.
Doi: 10.22094/joie.2022.1948231.1925

