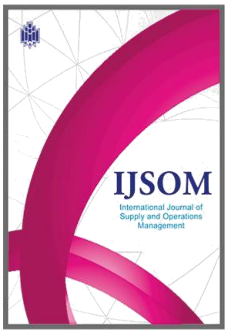
International Journal of Supply and Operations Management

IJSOM

November 2020, Volume 7, Issue 4, pp. 350-372
ISSN-Print: 2383-1359
ISSN-Online: 2383-2525
www.ijsom.com



Designing a Food Supply Chain Network under Uncertainty and Solving by Multi-Objective Metaheuristics

Hossein Ali Hassanpour [a,*], Mohammad Reza Taheri[a], Reza Rezanezhad[a]

[a] *Department of Industrial Engineering, Imam Hossein Comprehensive University, Tehran, Iran*

Abstract

Short life cycle products, especially food products, require a certain type of supply chain management due to their particular specifications such as perishability. On the other hand, the food distribution also requires special considerations and imparts more complexity compared with the distribution of other goods because in food distribution the quality of the food delivered to the customer should be considered as well as transportation costs. Therefore, in this paper, a new mathematical model is developed for integrating decisions regarding food supply and distribution under conditions of uncertainty (vehicles' travel time) with aims to minimize purchase and transportation costs and maximize customer satisfaction. Customer satisfaction relies upon the quality of the food delivered to the customers. The multi-objective model proposed in this paper is NP-hard. Hence, a developed version of NSGA-II called Multi-Objective Time Travel to History (MOTTH) algorithm, inspired from the idea of traveling through history, is proposed to solve the problem. In order to validate the performance of the proposed algorithm, the results of MOTTH algorithm are compared with the results obtained from an exact augmented epsilon-constraint method. Furthermore, a comparison is provided between the NSGA-II and MOTTH algorithms, the results of which indicate the superiority of the MOTTH metaheuristic algorithm.

Keywords: Foodstuffs; Perishable goods; Supply chain; Metaheuristic; Augmented epsilon-constraint.

1. Introduction

Satisfying the demand for food in today's world is humankind's one of the main issues. This has led governments to consider food safety and food quality improvement as their major goals. An important part of human life is entailed by food and as the middle layer, the food industry plays a key role in food supply management by intermediating and keeping the balance between farming and the final customer.

One of the concerns that food companies' managers have regarding food supply and distribution is the quality of the food delivered to the customers. This issue is caused due to the long duration of loading, transportation and delivery to the customers. Also, the sudden temperature alteration caused by repeatedly opening and closing the refrigerator during delivery results in decreased food quality and consequently reduced customer satisfaction and even may lead to more food wastage. Reports suggest that almost one-third of food produced annually is wasted (Gustavsson et al., 2011). Hence, the quality of food delivered to the customer is one of the most important criteria in the food supply chain, which depends on the travel time from the supplier to the customer, proper temperature, and the humidity level (Song & Ko, 2016; Nedović et al., 2016).

When a vehicle is delivering the demand of customers in a cargo, the long duration of transportation and repeated opening and closing the freezer reduce the quality of the remaining food in the vehicle (Hsu, Hung, & Li, 2007). Therefore, in this

* Corresponding author email address: hahassan@ihu.ac.ir

research, the purchase and delivery planning problem is studied in a two objective food supply chain. The customers' orders are given to the food production company. These orders are purchased according to the suppliers' production capacity and delivered using a heterogeneous transportation fleet, in a way that the purchase and transportation costs are minimized, in addition to maximizing customer satisfaction, which is the problem's main goal. Moreover, it is assumed in this study that the final customers' satisfaction relies on the delivered food quality, which itself depends on the transportation duration, the number of times the refrigerator is opened and closed, and the amount of time it is open. Since the travel time between two locations in the real world is not exact, the travel times in this study are considered uncertain and represented by triangular fuzzy numbers. Furthermore, several constraints such as the vehicles' setup times, the inability of suppliers to produce all products, and the inability of vehicles to carry all types of products are also considered in the model. This sort of supply chain is applicable to fields of military, ministries, and governmental organizations.

In the remainder of this paper, the literature review is conducted in section 2. In section 3, the problem is defined and its mixed-integer mathematical model is proposed. The exact augmented epsilon-constraint method and the NSGA-II and MOTTH metaheuristics are presented in section 4. In order to evaluate the metaheuristics, their results are compared with the ones obtained from the augmented epsilon-constraint method. Moreover, the results of the NSGA-II and MOTTH algorithms are also compared with each other. Eventually, conclusions and suggestions for future research are presented.

2. Literature review

Most reviewed studies suggest that temperature increase occurs in all stages of the cold supply chain (suppliers, distributors, retailers, and customers) and is not limited to specific types of foods.

Koseki and Isobe (2005) investigated containers that transport frozen fillets of tilapia fish in China. They found that the containers' temperature varies from -18.6°C to 16.8°C after six hours of transportation.

In Slovenia, Likar and Jevšnik (2006) announced that the temperature of the packaged frozen products such as chicken in the retailers' freezers fluctuates between 0°C and 15°C. The temperature fluctuation for products such as butter, cheese, and cream is between 0°C and 16°C. Also, for ice-cream products the temperature varies between -23°C and 10°C and the fluctuation for eggs is between 0°C and 17°C. Moreover, studies suggest that most staff in the cold supply chain do not possess sufficient knowledge.

In France, Derens et al. (2006) found that in 6.5% to 79.7% of times the frozen food has a higher temperature than the desired temperature while it is being delivered to the retailers by refrigerated vehicles.

In Canada, Rediers et al. (2009) found that the temperature of chicory salad fluctuates up to 16°C, in which the transportation stage is responsible for 2°C.

Koutsoumanis et al. (2010) studied the pasteurized milk supply chain and realized that the temperature fluctuates between 3.6°C and 10.9°C above the desired temperature during transportation and between 0°C and 11.7°C after they are delivered to the retailers.

In Iceland, it was found that in the transportation of fresh salmon fillets, 35% of the times during air transportation and 18% of the times during maritime transportation, their temperature was higher than the desired level (0±1°C) (Martinsdóttir et al., 2010). In this regard, Mai et al. (2012) reported that in 17% and 36.1% of the time required for the air transportation of haddock fillet and cod loins, the temperature was more than above 5°C above the proper temperature.

In the US, Pelletier et al. (2011) demonstrated that the temperature in the strawberry supply chain fluctuates between 0.7°C and 3.7°C in the preservation, transportation, and retail stages. Moreover, a considerable number of strawberries spoil due to insufficient humidity.

In Finland, Lundén et al. (2014), claimed that the workers do not notice the temperature increase in the food along the supply chain. For instance, in 50% and 46.2% of times, the minced meat and ready-to-cook fish were 3°C above the proper temperature for 30 minutes.

In Spain, Zubeldia et al. (2016) discovered that the temperature in the upper shelves of the retailers' freezers is above the desired temperature, especially in summer. Hence, the lifetime of products such as smoked salmon, cooked chicken, and fresh cheese is reduced by 40%, 57%, and 25%, respectively.

These studies indicate the deviations from the desired temperature in the cold supply chain in developed countries. However, there is little information regarding the cold supply chain in developing countries.

There are many studies conducted regarding the supply-distribution network in the frozen food supply chain under uncertainty, some of which are described in the following.

Ghare and Schrader (1963) were the first to investigate the inventory model for perishable products. Tarantilis and Kiranoudis (2001) solved the heterogeneous Vehicle Routing Problem (VRP) by developing an algorithm based on the acceptance threshold in order to achieve a schedule for the milk distribution vehicles. In another paper, they studied the vehicle routing problem for fresh meat distribution from warehouses to customers in a region of Athens. They presented a probabilistic heuristic for solving the problem (Tarantilis & Kiranoudis, 2002).

Osvald and Stirn (2008) presented an algorithm for fresh vegetable distribution, in which perishability is a crucial criterion. They considered constraints such as delivery time windows and transportation time between two locations. Rong et al. (2011) conducted a study on the production and distribution integration in the food supply chain with considering food quality. They presented a mixed-integer linear programming model for food quality reduction by integrating production and distribution. They also conducted a case study for designing and implementing food distribution systems considering the two criteria of food quality and costs. Brito et al. (2012) considered the distribution of frozen products in the cold supply chain in environments containing uncertainty and indeterminate data optimization, which decision-makers often deal with (fuzzy vehicle routing problem with time windows). Their goal was to minimize the costs related to the shortest route and preventing the delivered products' quality reduction. They included constraints, such as service times and solved the problem using fuzzy linear programming and fuzzy optimization. Wang and Hong (2015) intended to plan and select an optimization model for cold product distribution and routing with variable customer demand. Their purpose was to minimize distribution costs considering time windows. The distribution routing was optimized by the saving algorithm. They eventually compared the optimal routes in the forms of probabilistic distribution model (probabilistic demand) and an exact distribution model.

Song and Ko (2016) studied the routing problem of refrigerated and non-refrigerated vehicles for delivering several types of perishable foods. They took into account different assumptions, such as the geographical location, customers' demand, vehicles' capacity, the maximum delivery time, the number of refrigerated and non-refrigerated vehicles. The problem's objective function was to maximize the customer satisfaction level, which depends on food freshness. They presented a non-linear mathematical model and a heuristic to solve the problem. Lesmawati et al. (2016) presented a genetic algorithm for optimizing the frozen food distribution problem in the cold supply chain with aims to minimize transportation costs, which include the departure cost of the loaded vehicle and the arrival cost of the empty vehicle. Hsiao et al. (2017) investigated the food distribution problem in the cold supply chain with the purpose of formulating a distribution plan for meeting the customers' needs for several types of frozen food with predetermined quality levels and the minimum possible costs. They developed a Biogeography-Based-Optimization (BBO) algorithm in order to solve the problem. Joshi et al. (2018) investigated the effect of the cold supply chain and product variety on the qualitative properties of packaged modified mushrooms throughout the distribution stage using a mathematical model. A sensitivity analysis was also conducted in order to examine the influence of different parameters on the mushrooms' quality.

Carson and East (2018) studied the position of the cold supply chain in New Zealand exports. For this purpose, they selected the four industries of dairy, red meat, gardening, and seafood. Their goal was to improve energy efficiency in the refrigerating process. Ndraha et al. (2019) examined the frozen foods' temperature conditions during transportation and delivery to the final customer in Taiwan. For this purpose, the products' temperature specifications were recorded and their remaining lifetime was estimated in different scenarios using the Monte Carlo algorithm with 10000 iterations.

Ghomi-Avili et al. (2019) presented a multi-objective model of a supply chain network with price-dependent demand, shortage, and random disruptions in reverse logistics. This network is contained the five layers of producer, supplier, control centers, distribution centers, and market. The customers' demand was simulated based on the two linear and exponential behaviors. The problem's objective functions were: increasing the income, reducing the delivery time to the customer, and decreasing the number of missing customers.

Mohebalizadehgashti et al. (2020) modeled the multi-product, multi-period, multi-layer food supply chain with environmental considerations. Their goals were to reduce costs, reduce emissions, and increase facilities capacity. They used the augmented epsilon-constraint approach for solving the model. They also utilized the decision tree to deal with the model's uncertainty. (In their model, financial factors were assumed to be uncertain)

Table 1. Categorized researches of the literature

Paper	Network design										Constraints			Objective function		Solving method		
	Goal		Period		Product		Parameter											
								Probabilistic										
	Single-objective	Multi-objective	Single-period	Multi-period	Single-product	Multi-product	Deterministic	demand	travel time	financial factors	Vehicles setup time	Purchase from the supplier	Transportation using vehicles	Quality	Costs	Exact methods	Heuristics	Metaheuristics
Tarantilis and Kiranoudis (2001)	*		*		*		*								*			*
Tarantilis and Kiranoudis (2002)	*		*		*		*								*			*
Osvald and Stirn (2008)	*		*		*		*								*		*	
Rong et al. (2011)	*			*	*		*								*	*		
Brito et al. (2012)		*	*		*				*					*	*	*		
Wang and Hong (2015)	*		*		*			*							*	*		*
Song and ko (2016)	*		*			*	*							*			*	
Lesmawati et al. (2016)	*		*		*		*								*			*
Hsiao et al. (2017)	*		*			*	*								*			*
Ghomi-Avili et al. (2019)		*		*		*	*								*	*		
Mohebalizadehgashti et al. (2020)		*		*	*					*					*	*		
The present study		*		*		*			*		*	*	*	*	*	*		*

The deterministic and probabilistic parameters shown in Table 1 are used in network design (such as demand, travel time, financial factors, and parameters related to transportation).

The literature review indicates that in almost no studies the maximization of the delivered products' quality and costs minimization were considered simultaneously. On the other hand, this study takes into account the real conditions of a food supply chain and a distribution network, such as uncertain travel times, vehicle setup constraints, the inability of suppliers to supply all types of products, and the inability of vehicles to transport all types of products. These assumptions increase the problem's complexity. Hence, this research's contributions are as follows:

1. Presenting a mathematical model of the supply chain and distribution network in order to simultaneously maximize the delivered products' quality and minimize costs.
2. Using an exact augmented epsilon-constraint approach to solve the problem in small sizes.
3. Using a TTH metaheuristic with non-dominated sorting, called MOTTH, for solving the problem in large sizes.

3. Problem description

The problem in this study includes a three-layer food supply chain. The first layer encompasses the food suppliers. Since the problem is a multi-product supply chain, a supplier is not able to supply all types of products and is only capable of supplying some of them.

The second layer is the heterogeneous transportation fleet and operates as a VRP whereby a vehicle can collect food from a supplier and deliver it to the customers in different locations. This results in reducing costs and using vehicles more efficiently. Moreover, the vehicle setup time constraint is also considered in the problem. The transportations fleet consists of several refrigerated vehicles with different capacities and velocities. Each vehicle has fixed and variable costs and the variable cost depends on the traveled distance. As the supply chain is multi-product and each product requires specific temperature and storage conditions, a vehicle is not able to transport all types of foods. Hence, each type of product requires a particular type of vehicle for transportation. On the other hand, considering the climate and traffic conditions, travel time is not deterministic. Therefore, the time uncertainty is also taken into account in this study.

The third layer is composed of the final customers, whom their location and demand are specified and exact.

Since the products investigated in this study are food, the quality of the products delivered to customers is importantfor the customers. The quality of the delivered food to customers directly affects their satisfaction. Therefore, it is assumed in this study that the products' quality depends on the transportation time, the number of times the freezer is opened and closed, and the amount of time it remains open.

3.1. Model assumptions

There are *N* orders and *NR* products, which should be purchased from *NS* suppliers. One supplier is not capable of providing all types of orders. Also, the purchase cost of each unit of product from each supplier is predefined and differs between the suppliers.

After being purchased, the *N* orders should be delivered to the customers using *NV* vehicles. These vehicles are heterogeneous- that is, their average capacity and velocity are different. The products' quality reduction rates with respect to the traveled time and the amount of time the freezer is open are different in each vehicle, due to the difference in their properties (e.g. the freezer's quality, insulation, etc.). Moreover, the vehicles are not able to transport all types of products.

In order to efficiently utilize the transportation fleet, it is allowed to use the vehicles for several customers. In other words, each vehicle may load and deliver the orders of different customers in one cargo. In addition, after delivering the products to the customers, the vehicles are not omitted from the fleet and may be used again.

Each vehicle has a setup time and is available after its setup time. For instance, a vehicle may be unavailable in the time zero due to breakdown.

All vehicles are located in one place in the initial point of scheduling. This place is called terminal.

Climate and traffic conditions are considered in the delivery of products to the customers. Hence, delivery times are not exact. Since the travel time equals the distance between the two locations divided by the average velocity and the distance is constant, the average velocity is uncertain and indicated by triangular fuzzy numbers.

Product shortage is not allowed.

The supply and distribution planning in the food supply chain is performed for different periods.

The purpose of this model is to determine the number of products that should be purchased from a supplier and deliver the products to the final customer using a specific vehicle in a way that the customer satisfaction, which depends on the delivered product's quality, is maximized and the total purchase costs and vehicles' fixed and variable costs are minimized.

3.2. The mathematical model of the problem

In this section, the mixed-integer model of the problem is presented.

Indices

The number of customers	NC	The number of suppliers	NS
The number of vehicles	NV	The number of products	NR
Customers	i,j	Suppliers	s
Vehicles	v	Products	r
The cargo	b	The scheduling period	t
The transportation priority of an order in a vehicle	p		

Parameters

The amount of area occupied by one unit of the type r product	$Size^r$
The capacity of the v^{th} vehicle	Cap_v
The setup time of the v^{th} vehicle in the t^{th} period	$VehInAv_v^t$
The average velocity of the v^{th} vehicle (fuzzy triangular number)	$\widehat{VS}_v$

The distance between the terminal and the s^{th} supplier	$TDIS_s$
The distance between the s^{th} supplier and the i^{th} customer	$SDIS_{si}$
The distance between the i^{th} and the j^{th} customer	DIS_{ij}
The maximum satisfaction for the r^{th} product	SAT^r
The satisfaction reduction rate when the v^{th} vehicle transports the r^{th} product (per unit of distance)	RED_v^r
The satisfaction reduction rate when the v^{th} vehicle's freezer is opened for delivering the r^{th} product (per unit of time)	O_v^r
The time for which the freezer remains open for unloading one unit of the type r product	$Time^r$
The purchase price of the r^{th} product from the s^{th} supplier in the t^{th} period	$Cost_s^{rt}$
The supply capacity of the s^{th} supplier for the r^{th} product in the t^{th} period	SU_s^{rt}
The fixed cost of the v^{th} vehicle for transporting the r^{th} product in the t^{th} period	TF_v^{rt}
The variable cost of the v^{th} vehicle for transporting the r^{th} product in the t^{th} period (per unit of distance)	ACX_v^{rt}
The i^{th} customer's demand for the r^{th} product in the t^{th} period	D_i^{rt}
A $NR \times NS$ matrix. If the supplier s is capable of providing the product r, it $G(r,s)$ equals 1; otherwise, it equals 0.	G
A $NR \times NV$ matrix. If the vehicle v is capable of transporting the product r, it $N(r,s)$ equals 1; otherwise, it equals 0	N
A large number	M

The decision variables

If there is demand from the i^{th} customer for the r^{th} product in the t^{th} period, it equals 1; otherwise, it equals 0	H_i^{rt}
If the s^{th} supplier satisfies the demand of the r^{th} product form the i^{th} customer in the t^{th} period, it equals 1; otherwise, it equals 0	X_{si}^{rt}
If the i^{th} customer's r^{th} order have the p^{th} priority in the b^{th} cargo of the v^{th} vehicle in the t^{th} period, it equals 1; otherwise, it equals 0	T_{vbip}^{rt}
The amount of the r^{th} product in the b^{th} cargo of the v^{th} vehicle with the p^{th} priority for the i^{th} customer in the t^{th} period	AX_{vbip}^{rt}
The loading time of the v^{th} vehicle for transporting the b^{th} cargo of the r^{th} order of the i^{th} customer in the t^{th} period	$Load_{ibv}^{rt}$
The r^{th} product's delivery time to the i^{th} customer in the t^{th} period	$Delivery_i^{rt}$
The satisfaction level of the i^{th} customer when the v^{th} vehicle delivers the r^{th} product	ICS_{iv}^r
The purchase amount of the r^{th} product from the s^{th} supplier in the t^{th} period	PU_s^{rt}

The mathematical model is presented as follows:

$$Max\ z_1 = \sum_t \sum_i \sum_v \sum_r \sum_b \sum_p TICS_{vbip}^{rt} \quad (1)$$

$$Min\ z_2 = f_1 + f_2 + f_3 \quad (2)$$

$$f_1 = \sum_t \sum_s \sum_r (Cost_s^{rt} \times PU_s^{rt})$$

$$f_2 = \sum_v \sum_r \sum_t \sum_b \sum_i \sum_p (TF_v^{rt} \times T_{vbip}^{rt})$$

$$f_3 = \sum_r \sum_v ((\sum_t \sum_s \sum_i \sum_b ACX_v^{rt} \times SDIS_{si} \times TXSAX_{svbi1}^{rt}) + (\sum_t \sum_i \sum_{j \neq i} \sum_b \sum_{p \neq 1} ACX_v^{rt} \times DIS_{ij} \times TTAX_{vbijp(p-1)}^{rt}))$$

$$D_i^{rt} \geq H_i^{rt} \qquad \forall\, i.r.t \quad (3)$$

$$D_i^{rt} \leq M \times H_i^{rt} \qquad \forall\, i.r.t \quad (4)$$

$$\sum_s X_{si}^{rt} = H_i^{rt} \qquad \forall\, i.r.t \quad (5)$$

$$\sum_v \sum_b \sum_p T_{vbip}^{rt} = H_i^{rt} \qquad \forall\, i.r.t \quad (6)$$

$$\sum_{i} T_{vbip}^{rt} \leq 1 \qquad \forall\, v.b.p.t.r \tag{7}$$

$$\sum_{i} T_{v(b+1)i1}^{rt} \leq \sum_{i} T_{vbi1}^{rt} \qquad \forall\, v.b.t.r \tag{8}$$

$$\sum_{i} T_{vbi(p+1)}^{rt} \leq \sum_{i} T_{vbip}^{rt} \qquad \forall\, v.b.p.t.r \tag{9}$$

$$\sum_{i}\sum_{p} Size^{r} \times D_{i}^{rt} \times T_{vbip}^{rt} \leq Cap_{v} \qquad \forall\, r.v.b.t \tag{10}$$

$$Load_{i1v}^{rt} \geq VehInAv_{v}^{t} + \frac{TDIS_{s}}{\widehat{VS}_{v}} - M(2 - T_{v1i1}^{rt} - X_{si}^{rt}) \qquad \forall\, r.i.v.s.t \tag{11}$$

$$Load_{ibv}^{rt} \geq TDelivery_{v(b-1)jp}^{rt} + \frac{SDIS_{sj}}{\widehat{VS}_{v}} \times T_{v(b-1)jp}^{rt} - M(3 - T_{vbi1}^{rt} - T_{v(b-1)jp}^{rt} - X_{si}^{rt}) \qquad \forall\, i \neq j.r.v.\ b \neq 1.s.p.t \tag{12}$$

$$Delivery_{i}^{rt} \geq Load_{ibv}^{rt} + \frac{SDIS_{si}}{\widehat{VS}_{v}} - M(2 - T_{vbi1}^{rt} - X_{si}^{rt}) \qquad \forall\, r.i.b.v.s.t \tag{13}$$

$$Delivery_{i}^{rt} \geq TDelivery_{vbj(p-1)}^{rt} + \frac{DIS_{ij}}{\widehat{VS}_{v}} \times T_{vbj(p-1)}^{rt} - M(2 - T_{vbip}^{rt} - T_{vbj(p-1)}^{rt}) \qquad \forall\, i \neq j.r.v.b.\ p \neq 1.t \tag{14}$$

$$ICS_{iv}^{r} \leq SAT^{r} - \frac{SDIS_{si}}{\widehat{VS}_{v}} \times RED_{v}^{r} \times TX_{svbi1}^{rt} - Time^{r} \times O_{v}^{r} \times D_{i}^{rt} \times TX_{svbi1}^{rt} \qquad \forall\, i.r.v.b.s.t \tag{15}$$

$$ICS_{jv}^{r} \leq TICS_{vbi(p-1)}^{rt} - \frac{DIS_{ij}}{\widehat{VS}_{v}} \times RED_{v}^{r} \times T_{vbi(p-1)}^{rt} - Time^{r} \times O_{v}^{r} \times D_{i}^{rt} \times T_{vbi(p-1)}^{rt} + M(2 - T_{vbjp}^{rt} - T_{vbi(p-1)}^{rt}) \qquad \forall i \neq j.v.b.r.\ p \neq 1.t \tag{16}$$

$$PU_{s}^{rt} = \sum_{i} D_{i}^{rt} \times X_{si}^{rt} \qquad \forall\, s.r.t \tag{17}$$

$$PU_{s}^{rt} \leq SU_{s}^{rt} \qquad \forall\, s.r.t \tag{18}$$

$$X_{si}^{rt} = 0 \qquad \forall\, r.t.s.i \mid G(r.s) = 0 \tag{19}$$

$$T_{vbip}^{rt} = 0 \qquad \forall\, r.t.v.b.i.p \mid N(r.v) = 0 \tag{20}$$

$$AX_{vbip}^{rt} = T_{vbip}^{rt} \times D_{i}^{rt} \qquad \forall\, r.t.v.b.i.p \tag{21}$$

$$\sum_{p} AX_{vbip}^{rt} = SAX_{vbi}^{rt} \qquad \forall\, r.t.v.b.i \tag{22}$$

$$TICS_{vbip}^{rt} \leq M \times T_{vbip}^{rt} \qquad \forall\, r.t.v.b.i.p \tag{23}$$

$$TICS_{vbip}^{rt} \leq ICS_{iv}^{r} \qquad \forall\, r.t.v.b.i.p \tag{24}$$

$$TICS_{vbip}^{rt} \geq ICS_{iv}^{r} - M \times (1 - T_{vbip}^{rt}) \qquad \forall\, r.t.v.b.i.p \tag{25}$$

$$2 \times TX_{svbip}^{rt} \leq T_{vbip}^{rt} + X_{si}^{rt} \qquad \forall\, r.t.s.v.b.i.p \tag{26}$$

$$TX_{svbip}^{rt} \geq T_{vbip}^{rt} + X_{si}^{rt} - 1 \qquad \forall\, r.t.s.v.b.i.p \tag{27}$$

$$TXSAX_{svbip}^{rt} \leq SAX_{vbi}^{rt} \qquad \forall\, r.t.s.v.b.i.p \tag{28}$$

$$TXSAX_{svbip}^{rt} \leq M \times TX_{svbip}^{rt} \qquad \forall\, r.t.s.v.b.i.p \tag{29}$$

$$TXSAX_{svbip}^{rt} \geq SAX_{vbi}^{rt} - M \times (1 - TX_{svbip}^{rt}) \qquad \forall\, r.t.s.v.b.i.p \tag{30}$$

$$2 \times TT_{vbijp(p-1)}^{rt} \leq T_{vbip}^{rt} + T_{vbj(p-1)}^{rt} \qquad \forall\, i \neq j.r.v.b.\ p \neq 1.t \tag{31}$$

$$TT_{vbijp(p-1)}^{rt} \geq T_{vbip}^{rt} + T_{vbj(p-1)}^{rt} - 1 \qquad \forall\, i \neq j\,.r.v.b.\; p \neq 1.t \tag{32}$$

$$TTAX_{vbijp(p-1)}^{rt} \leq AX_{vbip}^{rt} \qquad \forall i \neq j.r.t.v.b.p \neq 1 \tag{33}$$

$$TTAX_{vbijp(p-1)}^{rt} \leq\; M \times TT_{vbijp(p-1)}^{rt} \qquad \forall i \neq j.r.t.v.b.p \neq 1 \tag{34}$$

$$TTAX_{vbijp(p-1)}^{rt} \geq AX_{vbip}^{rt} - M \times (1 - TT_{vbijp(p-1)}^{rt}) \qquad \forall i \neq j.r.t.v.b.p \neq 1 \tag{35}$$

$$TDelivery_{vbip}^{rt} \leq M \times T_{vbip}^{rt} \qquad \forall\, r.t.v.b.i.p \tag{36}$$

$$TDelivery_{vbip}^{rt} \leq Delivery_{i}^{rt} \qquad \forall\, r.t.v.b.i.p \tag{37}$$

$$TDelivery_{vbip}^{rt} \geq Delivery_{i}^{rt} -\; M \times (1 - T_{vbip}^{rt}) \qquad \forall\, r.t.v.b.i.p \tag{38}$$

$$\begin{array}{ll} Load_{ibv}^{rt} \geq 0 & Delivery_{i}^{rt} \geq 0 \\ ICS_{iv}^{r} \geq 0 & PU_{s}^{rt} \geq 0 \\ AX_{vbip}^{rt} \geq 0 & X_{si}^{rt} \in (0.1) \\ H_{i}^{rt} \in (0.1) & T_{vbip}^{rt} \in (0.1) \end{array} \tag{39}$$

3.2.1. Describing the model's objective functions and constraints

Equation 1 indicates the maximization of customer satisfaction and Equation 2 represents the minimization of the costs, including product purchase costs and vehicles fixed and variable costs (f_1, f_2, and f_3 respectively indicate the products' purchase costs, the vehicles' fixed costs, and the vehicles' variable costs). Equations 3 and 4 suggest that if the i^{th} customer does not have demand for the r^{th} product, then H_i^{rt} equals zero; Otherwise, it equals one. Equation 5 ensures that the r^{th} order of the i^{th} customer is purchased and Equation 6 guarantees that the purchased product of the i^{th} customer is assigned to a cargo and given a transportation priority in the v^{th} vehicle. Equation 7 prevents the orders of two customers in the period *t* from being allocated to the same cargo with the same priority. Equation 8 indicated that if no orders are assigned to the b^{th} cargo in the t^{th} period, then no orders must be assigned to the $b+1^{th}$ cargo. Equation 9 assures that if no orders are allocated to the p^{th} priority of the b^{th} cargo, then no orders are allocated to the $p+1^{th}$ priority of the b^{th} cargo, either.

Equation 10 implies that the area occupied by the orders in a cargo should not exceed the transportation capacity of the v^{th} vehicle. Equation 11 determines the loading time of the r^{th} order of the i^{th} customer for the first cargo of the v^{th} vehicle. Equation 12 determines the loading time of the r^{th} order of the i^{th} customer in the v^{th} vehicle for all $b \neq 1$ cargos. Equation 13 calculates the delivery time of the r^{th} order to the i^{th} customer using the v^{th} vehicle when it has the first delivery priority. Equation 14 determines the delivery time of the r^{th} order to the i^{th} customer with the p^{th} priority, while the j^{th} customer has the $p\text{-}1^{th}$ delivery priority. The satisfaction level of the customer from the products' quality in the first delivery priority by the v^{th} vehicle is represented by the Equation 15, and Equation 16 determine the satisfaction level of other customers from the products' quality that have the priority of $p \neq 1$ by the v^{th} vehicle. Equation 17 indicates the amount of the r^{th} product that should be purchased from s^{th} supplier. Equation 18 suggests that the purchase amount must not exceed the supplying capacity of the s^{th} supplier. Equations 19 and 20 respectively represent the supplier's inability to provide all product types and the vehicles' inability to transport all product types. Equation 21 determines the amounts of products in each transportation priority in each cargo. Equation 22 indicated the total amount of products in each cargo of each vehicle. Equations 23 to 38 are intended for model linearization. Eventually, Equation 39 defines the decision variables' signs.

3.3. The corresponding deterministic model

In this paper, it is assumed that the products' delivery duration affects their quality. In order to better reflect the ambiguity of real-world decision making in this problem, the delivery time is not certain. Since the travel time equals the distance between the two locations divided by the average velocity and the distance is constant, the average velocity is uncertain. Due to computational efficiency simplicity in data collection, the triangular fuzzy distribution is used to model the uncertain nature of the parameter $\widetilde{VS}_v$. For this purpose, $\widetilde{VS}_v$ is considered as $\widetilde{VS}_v = (VS_{1v}.VS_{2v}.VS_{3v})$.

Furthermore, in order to convert the problem's probabilistic model, which includes uncertain coefficients constraints 11, 12, 13, 14, 15 and 16, to the corresponding deterministic model, the Jimenes method is used. This method significantly efficient in terms of computation because it retains the linear property of the model and does not increase the number of unequal constraints (Jimenes et al., 2007).

For this reason, consider the following fuzzy mathematical planning model, in which all parameters are defined in the fuzzy form:

$Min\ Z = \tilde{c}x$
$s.t$
$\tilde{a}_i x \geq \tilde{b}_i \qquad i=1,\dots,l$
$\tilde{a}_i x = \tilde{b}_i \qquad i=l+1,\dots,m$
$x \geq 0$

The deterministic model obtained using Jimenes' method (Jimenes et al., 2007) is as follows:

$$Min\ Z = EV(\tilde{c})x$$
$$s.t$$
$$\left[(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}\right]x \geq \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i} \qquad i = 1.\dots.l$$
$$\left[\left(1-\frac{\alpha}{2}\right)E_2^{a_i} + \frac{\alpha}{2}E_1^{a_i}\right]x \geq \frac{\alpha}{2}E_2^{b_i} + \left(1-\frac{\alpha}{2}\right)E_1^{b_i} \qquad i = 1+l.\dots.m$$
$$\left[\frac{\alpha}{2}E_2^{a_i} + \left(1-\frac{\alpha}{2}\right)E_1^{a_i}\right]x \leq \left(1-\frac{\alpha}{2}\right)E_2^{b_i} + \frac{\alpha}{2}E_1^{b_i} \qquad i = 1+l.\dots.m$$
$$x \geq 0$$

where:

$$EV(\tilde{c}) = \frac{c^p + 2c^m + c^o}{4}$$
$$E_1^c = \frac{1}{2}(c^p + c^m)$$
$$E_2^c = \frac{1}{2}(c^m + c^o)$$

and the α set (α-cut), indicated by $\tilde{A}_\alpha$, is a set whose members is the fuzzy set of $\tilde{A}$ have membership functions equal to or greater than α.

$$\tilde{A}_\alpha = \{x \in X | \mu_{\tilde{A}}(x) \geq \alpha\}$$

Therefore, the constraints 11, 12, 13, 14, 15, 16 are converted to the equations 40, 41, 42, 43, 44, and 45.

$$Load_{i1v}^{rt} \geq VehInAv_v^t + \left(\alpha \times \frac{\frac{TDIS_s}{VS_{2v}} + \frac{TDIS_s}{VS_{1v}}}{2} + (1-\alpha) \times \frac{\frac{TDIS_s}{VS_{3v}} + \frac{TDIS_s}{VS_{2v}}}{2}\right) - M(2 - T_{v1i1}^{rt} - X_{si}^{rt}) \qquad \forall\, r.i.v.s.t \tag{40}$$

$$Load_{ibv}^{rt} \geq TDelivery_{v(b-1)jp}^{rt} + \left(\alpha \times \frac{\frac{SDIS_{sj}}{VS_{2v}} + \frac{SDIS_{sj}}{VS_{1v}}}{2} + (1-\alpha) \times \frac{\frac{SDIS_{sj}}{VS_{3v}} + \frac{SDIS_{sj}}{VS_{2v}}}{2}\right) \times T_{v(b-1)jp}^{rt} - M(3 - T_{vbi1}^{rt} - T_{v(b-1)jp}^{rt} - X_{si}^{rt}) \qquad \forall\, i \neq j.r.v.\ b \neq 1.s.p.t \tag{41}$$

$$Delivery_i^{rt} \geq Load_{ibv}^{rt} + \left(\alpha \times \frac{\frac{SDIS_{sj}}{VS_{2v}} + \frac{SDIS_{sj}}{VS_{1v}}}{2} + (1-\alpha) \times \frac{\frac{SDIS_{sj}}{VS_{3v}} + \frac{SDIS_{sj}}{VS_{2v}}}{2}\right) - M(2 - T_{vbi1}^{rt} - X_{si}^{rt}) \qquad \forall\, r.i.b.v.s.t \tag{42}$$

$$Delivery_i^{rt} \geq TDelivery_{vbj(p-1)}^{rt} + (\alpha \times \frac{\frac{DIS_{ij}}{VS_{2v}} + \frac{DIS_{ij}}{VS_{1v}}}{2} + (1-\alpha) \times \frac{\frac{DIS_{ij}}{VS_{3v}} + \frac{DIS_{ij}}{VS_{2v}}}{2}) \times T_{vbj(p-1)}^{rt} - M(2 - T_{vbip}^{rt} - T_{vbj(p-1)}^{rt}) \quad \forall\, i \neq j.r.v.b.\; p \neq 1.t \tag{43}$$

$$ICS_{iv}^{r} \leq SAT^{r} - (\alpha \times \frac{\frac{SDIS_{si}}{VS_{2v}} + \frac{SDIS_{si}}{VS_{1v}}}{2} + (1-\alpha) \times \frac{\frac{SDIS_{si}}{VS_{3v}} + \frac{SDIS_{si}}{VS_{2v}}}{2}) \times RED_v^{r} \times TX_{svbi1}^{rt} - Time^{r} \times O_v^{r} \times D_i^{rt} \times TX_{svbi1}^{rt} \quad \forall\, i.r.v.b.s.t \tag{44}$$

$$ICS_{jv}^{r} \leq TICS_{vbi(p-1)}^{rt} - (\alpha \times \frac{\frac{DIS_{ji}}{VS_{2v}} + \frac{DIS_{ji}}{VS_{1v}}}{2} + (1-\alpha) \times \frac{\frac{DIS_{ji}}{VS_{3v}} + \frac{DIS_{ji}}{VS_{2v}}}{2}) \times RED_v^{r} \times T_{vbi(p-1)}^{rt} - Time^{r} \times O_v^{r} \times D_i^{rt} \times T_{vbi(p-1)}^{rt} + M(2 - T_{vbjp}^{rt} - T_{vbi(p-1)}^{rt}) \quad \forall i \neq j.v.b.r.\; p \neq 1.t \tag{45}$$

4. The proposed solving method

In this section, first, the augmented epsilon-constraint method is presented as the exact solving method. Then, the NSGA-II and MOTTH algorithms are introduced.

4.1. The exact solving method

There are various methods for solving multi-objective problems, among which the augmented ε-constraint method is used in this paper. This method is a developed form of the ε-constraint method introduced by Chankong and Haimes (1983). It optimizes one objective function, while the other objective functions are converted into upper-bound or lower-bound constraints. These bounds are defined by different ε levels and provide the Pareto solution. However, the augmented ε-constraint method, presented by Mavrotas (2009), has drawn the attention of many researchers due to its significant advantages. For instance, it guarantees the efficiency of Pareto optimal solutions. Moreover, when the problem has more than two objective functions, it reduces the solving time (Mavrotas, 2009)

The steps of the augmented epsilon-constraint method are as follows:

Step 1: select an objective function as the main objective function. In this research, the first objective function (quality increase) is selected as the main objective function.

Step 2: form the pay-off table in order to find the range of the objectives that are transferred into constraints. To do this, solve the problem considering each objective function alone, and obtain the optimal and nadir values. In this study, there are two values for each objective function, which are used for obtaining the maximum and the minimum values of the objective functions.

Step 3: divide the interval between the optimal and nadir values for the secondary objective function (in this paper, the second objective function, which is cost reduction, is considered as the secondary objective function) into a predefined number (q) of segmentations. Each segmentation forms a new problem which should be solved separately.

Step 4: Change the proposed model as follows:

$Max\ Z_1$
$s.t.$
$Z_2 \leq Z_{2(min)} + v.\Delta\varepsilon_{z_2}$
$Where\ v=0,1,2,\ldots,q$
$\Delta\varepsilon_{z_2} = \frac{Z_{2(max)} - Z_{2(min)}}{q}$

Step 5: convert the objective functions that are transformed into a constraint, into an equation by adding slack or surplus variables. This results in the efficiency of the Pareto optimal solutions. Moreover, the slack or surplus variables should be added to the main objective function as well. Therefore, the model is formed as follows. In fact, the following mathematical model should be solved q times, separately:

$Max\ (Z_1+\beta * S_1)$
$s.t.$
Constraints 3-10, 17-39, and 40-45
$Z_2+S_1 = Z_{2(min)}+v.\Delta\varepsilon_{z_2}$
$v=0,1,2,\ldots,q$

where β is an arbitrarily small number, usually between 10-6 and 10-3, and does not have a considerable effect on the problem's main objective function. Moreover, the variable S_1 should equal zero or close to zero in order to obtain efficient Pareto optimal solutions. It should be noted that there is no single solution that optimizes both objective functions, simultaneously. Thus, a Pareto solution set should be obtained, which is calculated using the augmented ε-constraint method. The Pareto solution's optimality is guaranteed when there is no single solution capable of improving the first objective function without altering the second objective function's value. In order to solve the model, a random problem with the following parameters is generated, which is solved by the augmented ε-constraint method with q=7 using the GAMS 25.1.2 software on a computer with Corei5 2.5GHz CPU. Figure 1 illustrates the Pareto optimal solutions for the random problem. As indicated in this figure, with increasing the delivered products' quality, the costs are also increased, and vice versa. Nevertheless, the decision-maker chooses the final solution with regard to their current condition.

Table 2. The random problem's parameters

$NC=6$	$NS=3$	$NV=3$	$NR=3$
$t=1$		$SAT^r=100$	
SU_s^{rt}=300		α=0.4	
$VehInAv_v^t$=U{1,5}		$Size^r$= U{1,5}	
Cap_v=U{250,300}		$TDIS_s$=U{1,20}	
$SDIS_{si}$=U{1,20}		DIS_{ij}=U{1,20}	
D_i^{rt}=U{0,50}		$Cost_s^{rt}$=U{5,20}	
TF_v^{rt}= U{1,5}		ACX_v^{rt}= U{1,3}	
VS_v= U{1,6}		O_v^r=U(1,0)	
RED_v^r=U(1,0)		$Time^r$=U(1,0)	

$$G=N=\begin{matrix}1 & 0 & 0\\ 0 & 1 & 0\\ 0 & 0 & 1\end{matrix}$$

Table 3. Pay-off table to show the range of Z_2

Objective function	Z_1	Z_2
Maximize Z_1	1352.4	11152
Minimize Z_2	1293.8	9801

$$\Delta\varepsilon_{z_2} = \frac{11152-9801}{7} = 193$$

Table 4. The Pareto optimal solution

v	Z_1	Z_2
0	1293.8	9801
1	1299.1001	9994
2	1304.8	10187
3	1308.3001	10380
4	1309.7	10573
5	1310.0003	10766
6	1313.4002	10959
7	1352.4	11152

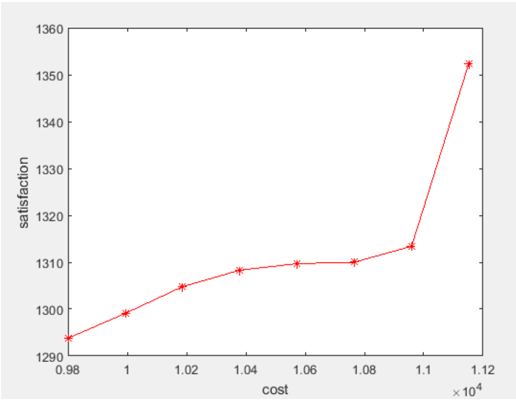


Figure 1. The Pareto optimal solution for the two-objective problem

The supply chain network design problem in this study is considered an NP-Hard problem due to its complexity. This means that in order to obtain the optimal or near-optimal solution for the problem in large sizes in a reasonable time, metaheuristic algorithms should be used. Hence, in this study, the NSGA-II and MOTTH algorithms are used to solve the problem.

4.2. The NSGA-II metaheuristic algorithm

First proposed by Srinivas and Deb (1994), NSGA-II is a well-known evolutional algorithm used for solving multi-objective problems. It retains the variety of the Pareto front while converging to the global optimal solutions. For more information regarding the NSGA-II method and its implementation steps, please refer to Deb et al. (2002).
The NSGA-II algorithm's pseudo-code is presented in Figure 2.

```
Start
Generate initial solutions as many as the population size (Popsize)
Select the best population members, which produce better objective function values than others (fitness evaluation).
    Iterate the following steps as many as the maximum number of generations (Maxiter)
    Select the parents for crossover and mutation operations.
    Perform the crossover operation and generate the offspring population.
    Perform the mutation operation and generate the mutated population.
    Integrate the populations (the total of the current population and the children obtained from the crossover and mutation
operations.
    Perform the non-dominated sorting method.
    Calculate the crowding distance control parameter.
    Examine the termination conditions and iterate if it is needed.
End of the main loop
Print the non-dominated solution
```

Figure 2. the proposed multi-objective GA's pseudo-code

4.2.1. The chromosome structure

The chromosome structure in the presented NSGA-II algorithm is two-dimensional. The vertical dimension represents the suppliers and vehicles and the horizontal dimension indicates the orders assigned to each supplier and vehicle. To demonstrate, assume that there are 6 orders, 3 suppliers, and 2 vehicles and the assignment of orders to the suppliers and vehicles is shown in Figure 3. The chromosome structure for this assignment is illustrated in Figure 4.

Supplier 1	1
Supplier 2	2-3-5
Supplier 3	4-6
Vehicle 1	2-3-1
Vehicle 2	4-6-5

Figure 3. The assigned orders to the suppliers and vehicles.

Supplier 1	1		
Supplier 2	2	3	5
Supplier 3	4	6	
Vehicle 1	2	3	1
Vehicle 2	4	6	5

Figure 4. The chromosome structure in the proposed multi-objective GA

All assignments in the chromosome structure are random. In the above chromosome, the order of customer 1 in purchased from the first supplier. Similarly, the orders of customers 2, 3, and 5 are provided by the second supplier and the orders of customers 4 and 6 are purchased from the third supplier. First, the orders of customers 2 and 3 are loaded into vehicle 1 by the second supplier, according to its transportation capacity. Once the orders are delivered to customers 2 and 3, the order of customer 1 is loaded into vehicle 1 by the first supplier. A similar procedure is also carried out for vehicle 2.

4.2.2. The crossover and mutation operators

The crossover and mutation operators used in this study are similar to the ones used by Ullrich (2013).

For performing the crossover operator, first, two chromosomes are selected randomly. Then, a random binary array is generated, whose number of arrays is equal to the number of orders. The order to which the number zero is assigned achieves its place in the offspring chromosome from the first parent chromosome, and the order to which the number one is assigned achieves its place from the second parent. If the place has already been filled, the order is allocated to the first empty cell on the right side (Figure 5).

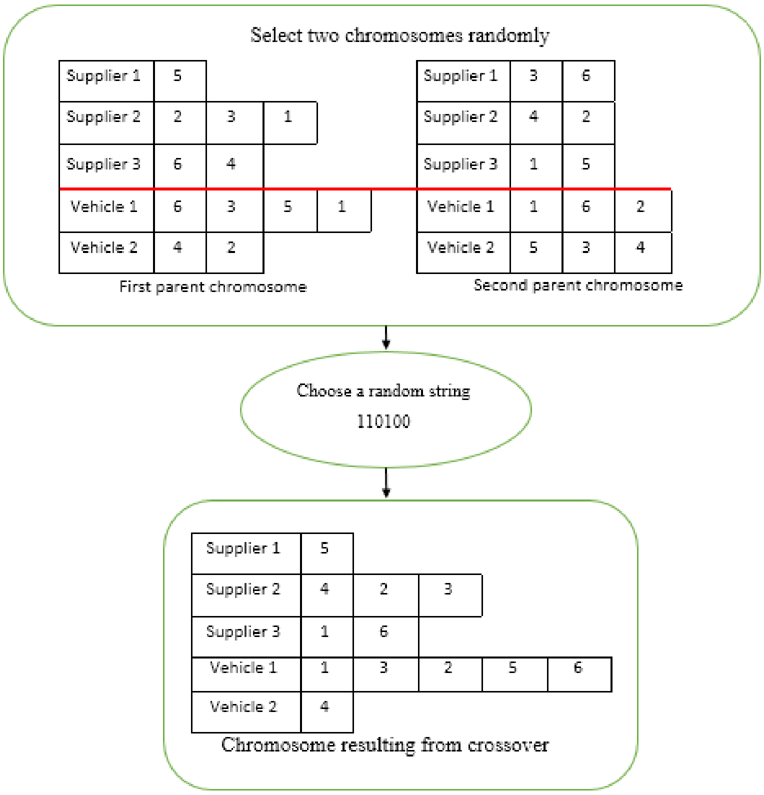


Figure 5. The crossover operator

Figure 6 shows the mutation operator. In this case, the suppliers or the vehicles section is selected with the possibility of 0.5, and two orders are randomly replaced with each are. In the mutation operator used in this study, a random number between 0 and 1 is generated. If the generated number is between 0 and 0.5, two genes are selected from the suppliers section and are replaced with each other. If the number is between 0.5 and 1, two genes are selected from the vehicles section and are replaced with each other. In the new assignment of orders, it should be checked whether the new order can be provided by the supplier or can be transported by the vehicle. If not, a large penalty is considered for the objective function of this chromosome.

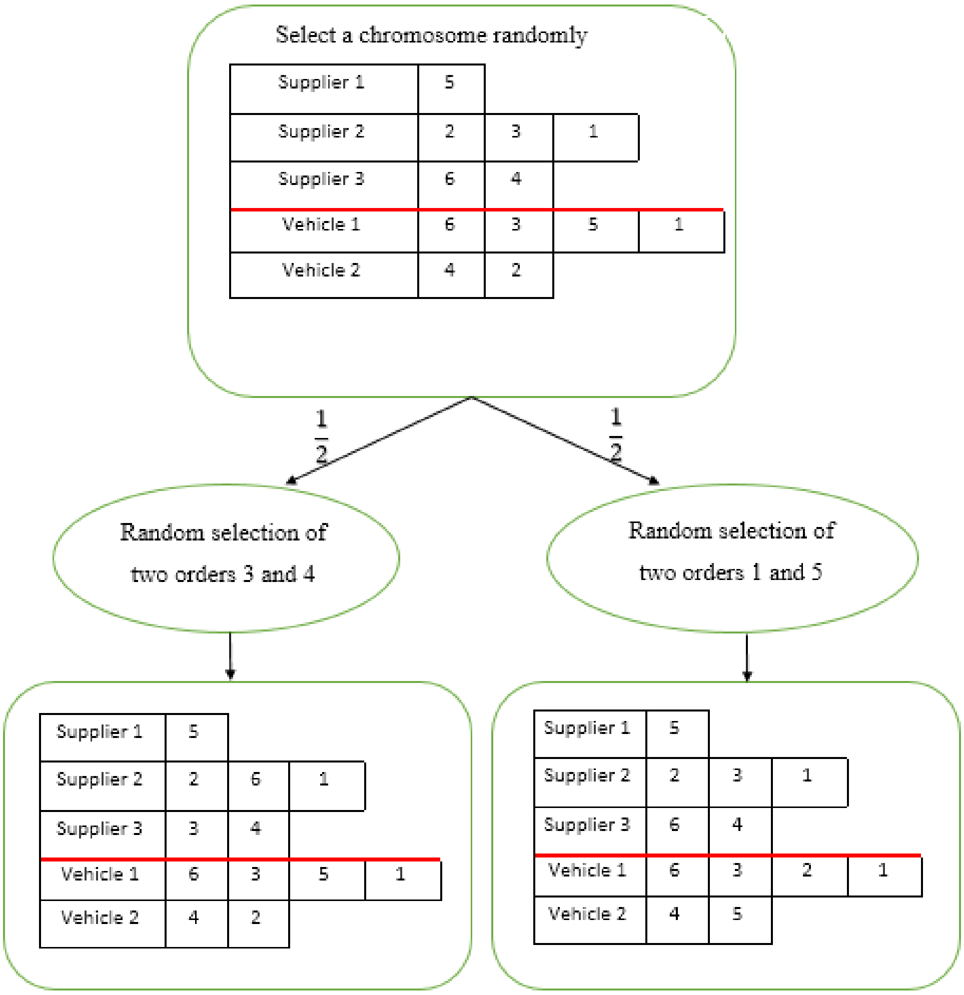


Figure 6. The mutation operator

4.3. The MOTTH metaheuristic algorithm

Taheri and Beheshti Nia (2019) presented a new extension of GA inspired by human's ultimate fantasy of time travel. In this algorithm, the worst solutions in R generations earlier are replaced by the best solutions in the present generation. This allows for searching more parts of the solution area, which eventually delays convergence (Taheri and Beheshti Nia, 2019). The TTH used in their study was single-objective whereas in this study, a new extension of TTH, namely MOTTH, is presented for solving multi-objective problems. In the MOTTH algorithm, one condition and two parameters are added to the NSGA-II algorithm, which are described in the following:

The reverse condition: once this condition is satisfied, the reverse movement in history begins. In this study, the reverse condition is that the generation counter variable reaches a certain number, indicated by *GB*.

R: this parameter determines the number of the previous generation to which the chromosomes are transferred. If *current* indicates the current generation's number, then the chromosomes are transferred to generation *current-R*.

Transrate: this parameter specifies the number of the chromosomes in the current generations that should be transferred in history. In other words, as many as *Transtrate* chromosomes in the current generations' first non-dominated front that do not exist in the *current-R*th generation are selected and transferred to generation *current-R*. On the other hand, as many as *Transtrate* chromosomes in generation *current-R* that exist in the last non-dominated front (worst chromosomes) are eliminated.

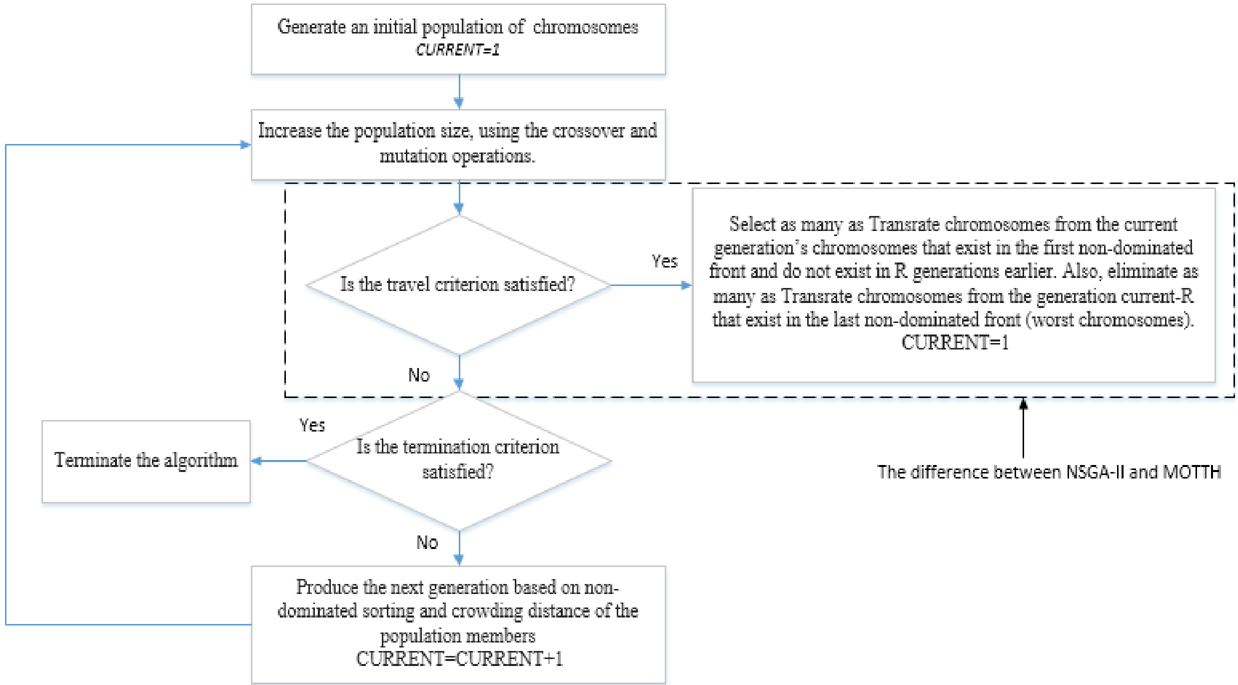


Figure 7. The flowchart of MOTTH algorithm.

Figure 7 shows the MOTTH algorithm's flowchart, in which the difference between MOTTH and NSGA-II is illustrated. Therefore, the steps of the MOTTH algorithm are as follows:

Step 1: generate some random chromosomes as the initial generation and let *CURRENT=1* (*CURRENT* indicates the generation number)

Step 2: increase the current generation's population by performing crossover and mutation operations.

Step 3: if the reverse condition is satisfied (*CURRENT>GB*), go to step 6; otherwise, proceed to step 4

Step 4: if the termination condition is satisfied, then terminate the algorithm; otherwise, proceed to step 5.

Step 5: produce the next generation based on non-dominated sorting and crowding distance of the population members and let *CURRENT=CURRENT+1* and go to step 2.

Step 6: select as many as *Transrate* chromosomes from the current generation's chromosomes that exist in the first non-dominated front and do not exist in R generations earlier. Also, eliminate as many as *Transrate* chromosomes from the generation *current-R* that exist in the last non-dominated front (worst chromosomes). Let *CURRENT=1* and go to step 2.

In order to determine the MOTTH algorithm's control parameters, the Taguchi method is employed. The MOTTH metaheuristic has six control parameters, namely the initial population, the termination criteria which is a certain number of populations, the crossover rate, the mutation rate, GB, and R. Three levels are considered for each parameter, as shown in Table 5.

Table 5. Levels related to the control parameters of the MOTTH algorithm

Levels	Parameters					
	Initial population size	Crossover rate	Mutation rate	GB	R	Algorithm termination
Level 1	50	0.20	0.15	20	5	150
Level 2	100	0.50	0.30	25	10	200
Level 3	150	0.70	0.45	30	15	250

By using the Taguchi method in the design of experiments, the experiment design L27 was formed for investigating the impact of parameters on the algorithm's solution. The results obtained from the design of experiments by the Minitab software are shown in Figure 8.

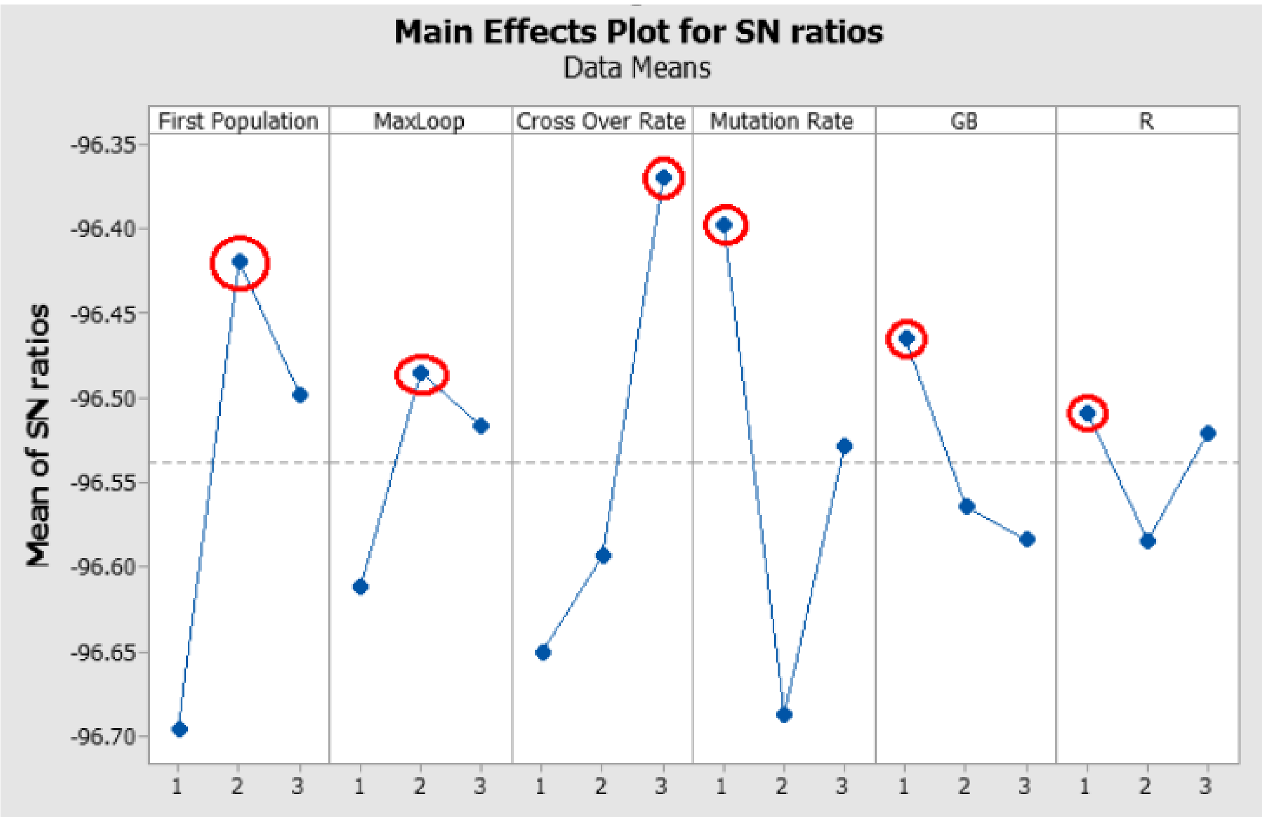


Figure 8. The SN Ratio for setting MOTTH parameters

The SN Ratio (Figure 8) is known as the solutions' robustness. Therefore, the more the solution's robustness, the better is the solution. For this reason, according to Figure 8, the MOTTH algorithm's control parameters' values, obtained by the Taguchi experiment, are depicted in Table 6. For having equal conditions in comparing the results of MOTTH and NSGA-II, the values for the NSGA-II algorithm's parameters are considered the same as the ones for MOTTH.

Table 6. The values specified for the parameters of NSGA-II and MOTTH

Parameter	Value
Initial population size	100
Crossover rate	0.7
Mutation rate	0.15
GB	20
R	5
Algorithm termination	Examining 200 generations

5. Validating the algorithms

In order to evaluate the algorithms' performance, first, their performance in solving small problems are compared with exact solving methods. Thereafter, 27 random problems were generated in different sizes and the two algorithms' performances are compared with each other. All required computer programming was performed on MATLAB software and run on a computer with Intel Corei5 2.5 GHz CPU.

5.1. Comparing with the exact method

In this section, six random problems were generated in different sizes and solved using the augmented ε-constraint method and the NSGA-II and MOTTH algorithms. Each random problem is indicated by the three parameters of the number of customers, suppliers, and vehicles. Other parameters for each problem are shown in table 2.

The comparison results are shown in Table 7. In this table, the first four columns indicate the problem specifications. The best solutions found for the first and second objective functions among the Pareto points using the augmented ε-constraint method and the problem-solving time are shown in the next three columns. The results regarding NSGA-II are shown in columns eight to ten and the results of MOTTH are depicted in columns 11 to 13. In the last four columns, the errors of NSGA-II and MOTH are shown for each objective function and are calculated using the following equation.

$$\text{The solution difference rate} = \left|\frac{\text{The heuristic algorithm solution} - \text{The exact method solution}}{\text{The exact method solution}}\right| \times 100 \tag{46}$$

Table 7. Comparing NSGA-II and MOTTH with the exact solutions

Row	Number of customers (*NC*)	Number of Suppliers (*NS*)	Number of vehicles (*NV*)	Augmented ε-constraint			NSGA-II			MOTTH			NSGA-II error (%)		MOTTH error (%)	
				First objective	Second objective	Solving time	First objective	Second objective	Solving time	First objective	Second objective	Solving time	First objective	Second objective	First objective	Second objective
1	3	3	3	814.3	1925	2.7	814.3	1925	13.3	814.3	1925	15.1	0	0	0	0
2	6	3	3	1406.2	6868	5.9	1404.9	6938	20.8	1406.2	6868	20.8	0.09	1.01	0	0
3	6	4	5	1350.6	6311	47.7	1330.1	6743	22.5	1331.4	6527	22.4	1.5	6.8	1.4	3.4
4	10	6	6	2421.9	12991	1153.4	2417	13440	32.6	2418.7	13301	33.4	0.2	3.4	0.1	2.4
5	10	7	9	2325.5	13711	4092.7	2301.9	13944	36.4	2301.7	13721	36.2	1.01	1.7	1.02	0.07
6	25	8	9	-	-	-	6098.8	40600	90.8	6102.3	40301	93.1	-	-	-	-
Average (except problem 6)				1663.7	8361.2	1060.48	1653.64	8598	25.12	1654.46	8468.4	25.58	0.56	2.58	0.5	1.17

The above table suggests that the MOTTH algorithm produced solutions that are closer to the exact solution than the ones produced by NSGA-II, in terms of the best solution for each objective function. Moreover, by investigating the solving times it was found that the augmented ε-constraint method's solving time increases exponentially whereas the increase in the NSGA-II and MOTTH algorithms' solving times are linear and insignificant (Figure 9). This shows the perfectly reasonable solving time of metaheuristics. On the other hand, the exact solving method is not capable of solving problem 6, due to being NP-Hard.

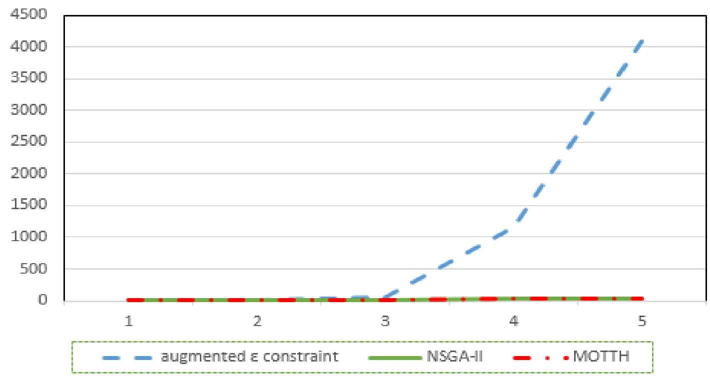


Figure 9. comparing problem-solving times of the exact solving method and the metaheuristics

5.2. Comparing the algorithms

In order to compare the NSGA-II and MOTTH algorithms, first, 27 random problems in different sizes are generated and then solved by both algorithms.

5.2.1. Generating random problems

This problem has three main parameters, namely the number of customers, the number of suppliers, and the number of vehicles. three levels of high, medium, and low are considered for each parameter, as shown in the following table. Other parameters are shown in Table 2.

Table 8. different values for the three main parameters

	High	Medium	Low
Number of customers	100	50	10
Number of suppliers	25	15	3
Number of vehicles	25	15	3

By combining the above parameters (3*3*3), 27 random problems are generated.

5.2.2. Comparison results

All 27 random problems were solved by both algorithms and the results are shown in Table 9. The multi-objective algorithms' performance is far more complicated than that of single-objective algorithms. Thus, one evaluation criterion is not enough to examine the solutions obtained from the presented algorithms. For this reason, the two comparison criteria of Q metric (the number of non-dominated solutions found) and S metric (the scatter criterion) are used in this study in order to evaluate the solutions' quality obtained from the two algorithms. The higher the Q metric and the lower the S metric, the better is the quality of the presented solution.

A low value for the scatter criterion shows that generated solutions are homogeneous.

S metric is obtained using the following equation.

$$S = \sqrt{\frac{\sum_{i=1}^{N-1}(d_i - d_{mean})^2}{(N-1)d_{mean}}} \qquad (47)$$

In the above equation, d_i indicates the Euclidean distance between two neighbor non-dominated solutions, and d_{mean} indicates the average of d_i values.

Therefore, table 9 consists of 5 criteria:

1. The best solution found for the first objective function and its corresponding solution for the second objective function;
2. The best solution found for the second objective function and its corresponding solution for the first objective function;
3. Q metric;
4. S metric;
5. Solving time.

Table 9. The comparison between MOTTH and NSGA-II

Row	*NC*	*NS*	*NV*	NSGA-II							MOTTH						
				The best Z_1 value	**The corresponding Z_2 value**	**The best Z_2 value**	**The corresponding Z_1 value**	**S metric**	**Q metric**	**CPU time (Second)**	**The best Z_1 value**	**The corresponding Z_2 value**	**The best Z_2 value**	**The corresponding Z_1 value**	**S metric**	**Q metric**	**CPU time (Second)**
1	10	3	3	2320	18586	18174	2317.2	4.3	3	29.5	2321.8	18499	18151	2316.9	4.6	3	31.9
2	10	3	15	2282.9	17594	12086	1647.9	14.6	15	29.3	2282.9	18315	12144	1781.1	17.6	16	30.2
3	10	3	25	2356.3	19005	17049	2068	24.4	7	30.3	2388.3	25771	16454	2169.4	16.9	11	29.9
4	10	15	3	2377.6	14701	13242	2368.2	15.1	8	119.3	2379.8	14168	11995	2361.1	22	7	117.4
5	10	15	15	2384	15729	11270	2147.3	35.5	10	107.9	2397	18974	10935	2150.3	25.5	12	153.1
6	10	15	25	2435.5	15192	10489	2362.6	34.6	10	116.8	2439.3	13132	10163	2395.7	11.8	6	110.9
7	10	25	3	2434.6	11942	11178	2434.2	0.9	3	176.8	2432.3	11243	11085	2432	1.5	3	177.6
8	10	25	15	2432.6	9840	9095	2413.1	36.4	3	166.7	2440.3	11990	8589	2357.1	18.6	6	169.5
9	10	25	25	2481.1	17345	11177	2356.6	48.9	7	174.1	2472.2	15400	11409	2269.3	38.9	13	164.9
10	50	3	3	9535.5	98707	97632	9485.2	20.6	3	188.8	9436.3	98111	95404	9228.7	36.5	3	189.4
11	50	3	15	10997	121022	93977	10331	37.9	8	159.8	11171	137293	93201	10535	209.3	10	159.2
12	50	3	25	11008	129886	95529	10049	53.3	11	195.3	10893	121402	94991	9851	45.9	17	195.4
13	50	15	3	11722	71755	71555	11707	0.4	3	1587.9	11766	69941	69063	11746	4.8	3	1631.1
14	50	15	15	10562	99775	79108	9979	70.2	9	1499.1	10610	99690	75515	9796	38.9	12	1501.4
15	50	15	25	10956	101019	84931	10556	34.8	7	1470.9	11061	93112	81346	10546	26.8	11	1466.4

Table 9. Continued

Row	*NC*	*NS*	*NV*	NSGA-II: The best Z_1 value	NSGA-II: The corresponding Z_2 value	NSGA-II: The best Z_2 value	NSGA-II: The corresponding Z_1 value	NSGA-II: S metric	NSGA-II: Q metric	NSGA-II: CPU time (Second)	MOTTH: The best Z_1 value	MOTTH: The corresponding Z_2 value	MOTTH: The best Z_2 value	MOTTH: The corresponding Z_1 value	MOTTH: S metric	MOTTH: Q metric	MOTTH: CPU time (Second)
16	50	25	3	10342	74494	73214	10299	6.9	14	2790.8	10336	78972	73122	10277	47.2	8	2776.6
17	50	25	15	11296	79130	71294	11025	35.9	9	2428.3	11325	82278	70036	11098	21.3	10	2478.6
18	50	25	25	10866	111741	86328	10575	46.3	7	2160.5	10878	98849	82233	10635	18.1	4	2147.7
19	100	3	3	22129	210556	195913	21308	50.4	9	685.6	22097	206248	206113	22091	0	2	688.3
20	100	3	15	20899	259208	225554	19307	67.3	8	698.1	20880	256494	221120	18897	50.9	15	695.8
21	100	3	25	22061	224091	197996	21428	42.8	10	716.6	22125	223103	197250	21625	43.2	9	721.4
22	100	15	3	20085	137498	135888	20045	21.8	9	4845.4	20197	130902	129719	20151	5.7	8	5053.7
23	100	15	15	19799	233321	168671	17689	149.8	17	4292.7	20175	202829	180975	16345	63.8	8	4520.5
24	100	15	25	21448	197224	183201	18515	62.5	5	4465.6	21438	215658	180010	20230	41.3	8	4864.8
25	100	25	3	23299	226477	225510	23280	11.7	7	7341.5	23389	219529	219112	23381	3.1	5	7988.5
26	100	25	15	22440	221021	182725	21550	62.8	12	7006.5	22572	220844	179462	21424	57.5	12	7742.3
27	100	25	25	22461	206002	171135	22203	77.3	7	7287.5	22448	193131	164009	22194	57.3	12	7864.8
Average				11607.78	108994.9	94589.67	11090.6	39.53	8.18	1880.43	11642.64	107254.7	93466.89	11121.61	34.40	8.66	1987.82

Among the above 27 problems, the MOTTH algorithm produced better solutions than NSGA-II in 5 problems (6-13-18-22-25) for both objective functions (customer satisfaction and costs). The Q metric and S metric evaluation for the remaining problems also suggests the better performance of MOTTH.

Because the MOTTH algorithm managed to find more solutions than NSGA-II in the first non-dominated front which has a lower scatter criterion. For this reason, the decision-maker has more alternatives that are more homogeneous and they can choose any solution based on the importance of each objective function.

In NSGA-II, the algorithm converges to one solution after a few generations and the chromosomes' structures in the last generation are similar. When two chromosomes are similar, their crossover offspring will also be similar to them and the chance for searching and finding new solutions will be jeopardized. As a result, producing new generations will not lead to an improvement in the current best solution. However, as mentioned in the TTH introduction, the reverse movement in history increases the chance to search more parts of the solution area by replacing the current generation's best solutions with the worst solutions of R generations earlier. Therefore, convergence is delayed (Taheri & Beheshti nia, 2019).

The average solving time of NSGA-II is less than that of MOTTH. The reason is that MOTTH uses the reverse movement mechanism. However, the problem-solving time is directly related to the computer's processor speed and using computers with higher processor speed will improve the solving time.

6. Conclusion and future research

In this paper, the integration of decisions regarding food supply and distribution is investigated in conditions of uncertainty. The objectives considered in this study were maximizing customer satisfaction, which depends on the quality of the delivered products to them and minimizing the purchase costs, and the vehicles' fixed and variable costs. First, the mathematical model of the problem was presented and solved using the augmented epsilon-constraint method. By using this method, the relationship between the two objective functions was identified and it was demonstrated that by increasing the quality of delivered products to customers, the costs will also increase. Because according to constraints 15 and 16, quality improvement occurs when the number of cargos with one delivery priority is increased. In that case, each vehicle only services one customer and no other products are left in the refrigerated vehicle to endure temperature fluctuations and quality reduction. On the other hand, increasing the number of cargos with one delivery priority causes the vehicles' fixed and even variable costs to increase. For this reason, managers choose a solution based on the importance of each objective function and their company's circumstances.

Moreover, it was shown in Table 7 that an exact solving method is not capable of solving large problems in a reasonable time. Therefore, metaheuristics must be used for solving them, and the MOTTH algorithm is presented in this study, which is a new extension of the genetic algorithm is inspired from human's ultimate fantasy of time travel. In this algorithm, by replacing the best solutions of the current generation with the worst solutions of R generations before, the algorithm's premature convergence is prevented and more solutions are searched in the solution area.

In order to evaluate the proposed algorithm, its performance is first compared with the exact solution, and then with the performance of the NSGA-II algorithm. According to the results of this research, a practical suggestion for cold supply chain managers is to use MOTTH for determining which orders should be purchased from which suppliers and which refrigerated vehicles should deliver them in which cargo and which priority. The reason is that this algorithm produces better solutions compared to NSGA-II, that is the quality of the delivered products is better and purchase costs and the vehicles' fixed and variable costs are less. Furthermore, another practical suggestion is use partitioned refrigerated vehicles with separate doors and separate refrigeration systems for delivering food products because by repeatedly opening and closing the one partition's door and unloading its containing products, the remaining products in other partitions will not endure any temperature fluctuation and as the result, not any quality loss. In this study, a mathematical model was presented to minimize the purchase costs, and the vehicles' fixed and variable costs and maximize the quality of the delivered products and the MOTTH metaheuristic algorithm was proposed to solve the problem, which is the main difference of this research form the previous studies. Also, based on the results of this research, the following suggestions may be considered in conducting future studies:

- In this study, only the product travel time was considered probabilistic. Other parameters, such as the loading time and the amount of time the refrigerator's door is open may also be considered probabilistic in future studies.
- Only the two objective functions of costs and products' quality were considered in this research. In future studies, other related variables may be investigated, such as the delivery duration and pollution reduction.
- In this study, only the delivery of products to customers was considered. The return of rejected or expired products may be examined in future research.
- The combination of MOTTH with other metaheuristics such as the simulated annealing and the bee colony algorithms may also be examined in future studies.

References

Brito J., Martinez F.J., Moreno J.A. and Verdegay J. L. (2012). Fuzzy optimization for distribution of frozen food with imprecise times. *Fuzzy Optimization and Decision Making*, Vol. 11(3), pp. 337-349.

Carson J.K. and East A.R. (2018). The cold chain in New Zealand–A review. *International Journal of Refrigeration*, Vol. 87, pp. 185-192.

Chankong V. and Haimes Y.Y. (1983). *Multiobjective decision making theory and methodology*, New York: Noth-Holland.

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

Derens E., Palagos B. and Guilpart J. (2006). The cold chain of chilled products under supervision in France. *In 13th World Congress of Food Science & Technology 2006*, pp. 823-823.

Ghare P.M. and Schrader G.F. (1963). An inventory model for exponentially deteriorating items. *Journal of Industrial Engineering*, Vol. 14(2), pp. 238-243.

Ghomi-Avili M., Khosrojerdi A. and Tavakkoli-Moghaddam R. (2019). A multi-objective model for the closed-loop supply chain network design with a price-dependent demand, shortage and disruption. *Journal of Intelligent & Fuzzy Systems*, Vol. 36(6), pp. 5261-5272.

Gustavsson J., Cederberg C., Sonesson U., Van Otterdijk R. and Meybeck A. (2011). Global food losses and food waste. *Save Food Congress, Düsseldorf 16 May 2011*.

Hsiao Y.H., Chen M.C. and Chin C.L. (2017). Distribution planning for perishable foods in cold chains with quality concerns: Formulation and solution procedure. *Trends in food science & technology*, Vol. 61, pp. 80-93.

Hsu C.I., Hung S.F. and Li H.C. (2007). Vehicle routing problem with time-windows for perishable food delivery. *Journal of food engineering*, Vol. 80(2), pp. 465-475.

Jiménez M., Arenas M., Bilbao A. and Rodrı M.V. (2007). Linear programming with fuzzy parameters: an interactive method resolution. *European Journal of Operational Research*, Vol. 177(3), pp. 1599-1609.

Joshi K., Warby J., Valverde J., Tiwari B., Cullen P.J. and Frias J.M. (2018). Impact of cold chain and product variability on quality attributes of modified atmosphere packed mushrooms (Agaricus bisporus) throughout distribution. *Journal of Food Engineering*, Vol. 232, pp. 44-55.

Koseki S. and Isobe S. (2005). Prediction of pathogen growth on iceberg lettuce under real temperature history during distribution from farm to table. *International Journal of Food Microbiology*, Vol. 104(3), pp. 239-248.

Koutsoumanis K., Pavlis A., Nychas G.J.E. and Xanthiakos K. (2010). Probabilistic model for Listeria monocytogenes growth during distribution, retail storage, and domestic storage of pasteurized milk. *Appl. Environ. Microbiol.*, Vol. 76(7), pp. 2181-2191.

Lesmawati W., Rahmi A. and Mahmudy W.F. (2016). Optimization of frozen food distribution using genetic algorithms. *Journal of Environmental Engineering and Sustainable Technology*, Vol. 3(1), pp. 51-58.

Likar K. and Jevšnik M. (2006). Cold chain maintaining in food trade. *Food control*, Vol. 17(2), pp. 108-113.

Lundén J., Vanhanen V., Kotilainen K. and Hemminki K. (2014). Retail food stores' internet-based own-check databank records and health officers' on-site inspection results for cleanliness and food holding temperatures reveal inconsistencies. *Food control*, Vol. 35(1), pp. 79-84.

Mai N.T.T., Margeirsson S., Bogason S.G., Sigurgisladottir S. and Arason S. (2012). Temperature mapping of fresh fish supply chains–air and sea transport. *Journal of food process engineering*, Vol. 35(4), pp. 622-656.

Martinsdóttir E., Lauzon H.L., Margeirsson B., Sveinsdóttir K., Þorvaldsson L., Magnússon H. and Eden M. (2010). The effect of cooling methods at processing and use of gel packs on storage life of cod (Gadus morhua) loins. Effect of transport via air and sea on temperature control and retail-packaging on cod deterioration. *Report/Skýrsla Matís*.

Mavrotas G. (2009). Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. *Applied mathematics and computation*, Vol. 213(2), pp. 455-465.

Mohebalizadehgashti F., Zolfagharinia H. and Amin S.H. (2020). Designing a green meat supply chain network: A multi-objective approach. *International Journal of Production Economics*, Vol. 219, pp. 312-327.

Ndraha N., Sung W.C. and Hsiao H.I. (2019). Evaluation of the cold chain management options to preserve the shelf life of frozen shrimps: A case study in the home delivery services in Taiwan. *Journal of food engineering*, Vol. 242, pp. 21-30.

Nedović V., Raspor P., Lević J., Šaponjac V.T. and Barbosa-Cánovas G.V. (2016). *Emerging and traditional technologies for safe, healthy and quality food*, pp. 257-268.

Osvald A. and Stirn L.Z. (2008). A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. *Journal of food engineering*, Vol. 85(2), pp. 285-295.

Pelletier W., Brecht J K., Nunes, M.C. and Emond J.P. (2011). Quality of strawberries shipped by truck from California to Florida as influenced by postharvest temperature management practices. *HortTechnology*, Vol. 21(4), pp. 482-493.

Rediers H., Claes M., Peeters L. and Willems K.A. (2009). Evaluation of the cold chain of fresh-cut endive from farmer to plate. *Postharvest Biology and Technology*, Vol. 51(2), pp. 257-262.

Rong A., Akkerman R. and Grunow M. (2011). An optimization approach for managing fresh food quality throughout the supply chain. *International Journal of Production Economics*, Vol. 131(1), pp. 421-429.

Song B.D. and Ko Y.D. (2016). A vehicle routing problem of both refrigerated-and general-type vehicles for perishable food products delivery. *Journal of food engineering*, Vol. 169, pp. 61-71.

Srinivas N. and Deb K. (1994). Muiltiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary computation*, Vol. 2(3), pp. 221-248.

Taheri S.M.R. and Beheshtinia M.A. (2019). A Genetic Algorithm Developed for a Supply Chain Scheduling Problem. *Iranian Journal of Management Studies*, Vol. 12(2), pp. 107-132.

Tarantilis C.D. and Kiranoudis C.T. (2001). A meta-heuristic algorithm for the efficient distribution of perishable foods. *Journal of food Engineering*, Vol. 50(1), pp. 1-9.

Ullrich C.A. (2013). Integrated machine scheduling and vehicle routing with time windows. *European Journal of Operational Research*, Vol. 227(1), pp. 152-165.

Zubeldia B.B., Jiménez M.N., Claros M.T.V., Andrés J.L.M. and Martin-Olmedo P. (2016). Effectiveness of the cold chain control procedure in the retail sector in Southern Spain. *Food Control*, Vol. 59, pp. 614-618.