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Solving a supply chain problem using two approaches of fuzzy goal programming based on TOPSIS and fuzzy preference relations

Bahareh Shafipour-Omrani[1*], Kaveh Khalili-Damghani[1], Peiman Ghasemi[1]

[1]*Department of Industrial Engineering, Faculty of Industrial Engineering, South-Tehran Branch, Islamic Azad University, Tehran, Iran*

bahareh.shafipour@gmail.com, kaveh.khalili@gmail.com, st_p_ghasemi@azad.ac.ir

Abstract

Supply chain problems have many ambiguous parameters, and decisions about these types of problems, which are usually multi-objective, should be made according to the constraints and priorities of the objectives. In this paper, we will examine the integrated model of supply chain network with supply, production and distribution levels, considering the logistics costs and service level simultaneously under uncertainty. In multi-objective Mixed Integer Linear Programming (MILP) model, objectives are considered as fuzzy and with different priorities and to eliminate the ambiguity in membership values of fuzzy objectives, priorities are adjusted with fuzzy relations. The model is solved by two approaches of Fuzzy Goal Programming (FGP) and their results are compared. Presenting a multi-period multi-level multi-product multi-objective model in the field of designing and distribution of supply chains and presenting two methods of fuzzy goal programming and the results are compared to provide a suitable method to convert the proposed model into a fuzzy model are the contributions of this paper. The computational results show that the first method in the criterion of cumulative weight of fuzzy membership values and the second method in determining the cumulative weight of ambiguous preferences of decision-maker have had a good performance. The results of ANOVA and Mann-Whitney tests, show that $p - Value$ of all three criteria is less than acceptable level (0.05) and e first method had a good performance in determining the criterion of membership value of cumulative weight of fuzzy objectives.

Keywords: Supply chain, uncertainty, fuzzy goal programming, fuzzy preference relations

1- Introduction

The growing expansion of the competitive environment and the globalization of the product market have led organizations that in order to survive, make significant efforts regarding supply, procure, produce and distribute goods to meet the diversified needs of customers in the least possible time and with minimum cost (Hardy et al. 2020). This has led to the emergence of the philosophy of Supply Chain Management (SCM). Most researchers use probability distributions for uncertainties in the supply chain, and since past statistical data are not reliable or are not always available, therefore, probabilistic models may not be the best choice (Majumder et al. 2020).

*Corresponding author

The three main methods of dealing with uncertainty are (1) fuzzy programming, (2) random programming, and (3) robust programming, among which the theory of fuzzy sets is one of the most powerful tools to deal with the uncertainty caused by the complexity of markets and the behavior of decision-makers (Khalili-Damghani and Ghasemi). Fuzzy theory and the possibility theory can be more appropriate options than probability theory to deal with supply chain uncertainties (Tirkolaee et al.2020a). Goal Programming (GP) is a technique in the field of multi-criteria decision making (MCDM) and, according to Simon's theory (1955), is a way to reach the closest set of multiple objectives (Zandkarimkhani et al. 2020). The main idea of goal programming is to minimize the unwanted deviations of the objective values determined by the decision-maker in order to reach an acceptable solution (Hanks et al. 2020). The first applied formula of goal programming was introduced by Charnes and Cooper (Colapinto et al. 2020).

Designing a well-structured supply chain network will provide competitive advantage to companies and help them control the growing environmental disturbances (Tirkolaee et al. 2020b). The topic of optimizing the flow of materials in the network is one of the most important and most valuable topics in the supply chain, which can significantly reduce costs and increase customer satisfaction (Ghasemi et al. 2017). The complex and dynamic nature of the supply chain imposes a high degree of uncertainty on the decisions of the supply chain planning and significantly affects the performance of the entire chain (Babaee Tirkolaee et al. 2019). In practice, suppliers deal with a set of criteria, which are expressed as the return on investment or financial ratios. Since their preferences towards these criteria are often descriptive and qualitative and not quantitative, these issues often involve subjective uncertainty (Ghaemi et al. 2019a). Since in supply chain, the decision-making occurs for conflicting objectives, the precise definition of the priority of the objectives is not straightforward, and decision-making for each objective may also affect the definition of the importance relations among other objectives (Ghaemi et al. 2019b). Therefore, the approaches of Fuzzy Goal Programming (FGP), as flexible decision-making tools regarding the uncertainty, are good solutions to supply chain models.

In this paper, a mixed integer models for three-level, multi-commodity supply chain, including supply, manufacturing and distribution centers is provided. The proposed model selects suppliers, manufacturers and distribution centers by evaluating them and tries to minimize the total supply chain costs and maximize the service level by dividing the amount of order and production between them. In the objective function of the proposed model, costs such as raw material and inventory costs, production, product purchase, ordering and maintenance of goods and transportation are considered. In addition to the costs mentioned non-diversion of time and level of pending order is included in the objective function. A case study for the dairy supply chain is presented in which the plan to establish a dairy factory is examined. In the putative chain there are three suppliers, two dairy factories and three distribution centers (see figure 1).

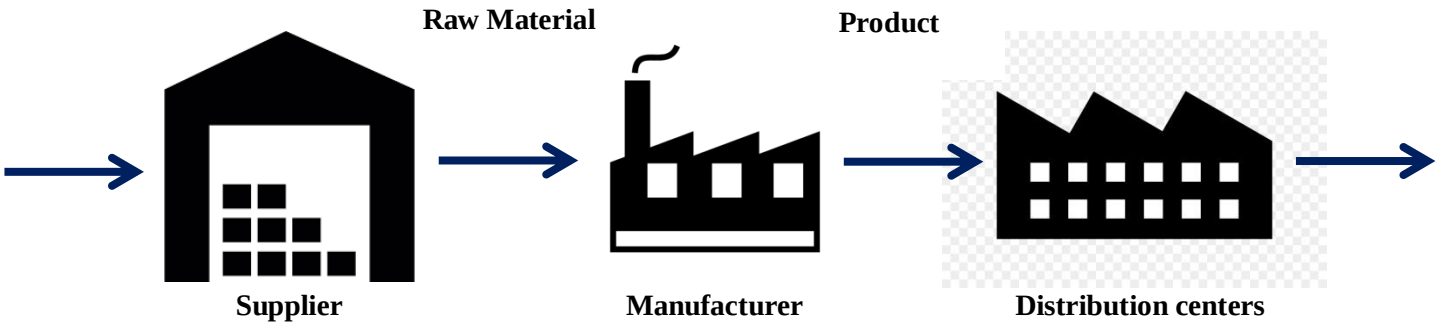


Fig 1. Supply chain framework

The main objective of this paper is to determine the optimal values of logistics costs and service levels of different levels of supply chain in a multi-period horizon, in which the uncertainty of the problem is resolved using two methods of fuzzy goal programming. Levels of significance of the objectives are

unclear in both methods and are defined by fuzzy preference relations. The rest of the article is organized as follows. In Section 2, literature on fuzzy goal programming methods and its applied approaches in the supply chain network is presented. The sets, parameters, decision variables, and the considered problem are expressed in Section 3. In Section 4, we will describe the FGP approaches used in this paper. In Section 5, by presenting a real numerical example, the two mentioned approaches are compared and statistically analyzed. Finally, in Section 6, the conclusion of the research and future proposals will be discussed.

2- Literature review

Since the early 1980s, to show uncertain knowledge about a particular parameter of fuzzy sets in goal programming models, and to show the degree of decision-maker's satisfaction, according to his preference, fuzzy goal programming models were used (Hocine et al. 2020). Kumar et al. (2020) presented an approach to minimize the total allowable weighted variations of variables in FGP models. Their proposed method created a suitable set of possible allocations. Mohtashami et al. (2020) proposed multi-objective programming model for designing a cellular production system and used the fuzzy goal programming approach for converting a multi-objective model to single-objective.

Kilic and Yalcin, (2020) presented an integrated approach including the Intuitionistic Fuzzy Technique for Order Preference by Similarity to Ideal Solution (IF-TOPSIS) and a modified two-phase fuzzy goal programming model. The criteria importance weights are determined via IF-TOPSIS which enables the opportunity to handle the vagueness within the evaluation process of decision-makers. The results indicate the proper performance of the proposed model.

Khan et al. (2020) presented goal programming models for multi-objective decision-making, where fuzzy linguistic preference relations are incorporated to model the relative importance of the goals. They formulated fuzzy preference relations as exponential membership functions. The grades or achievement function is described as an exponential membership function and is used for grading levels of preference toward uncertainty.

An FGP approach was proposed for the analysis of the environment, energy, and sustainable goals considering the key economic sections of India by Nomani (2017). Their model analyzed the opportunities for improvement and the implementation of sustainable development programs. The sensitivity analyses show that as demand increases, supply chain costs increase. The results of the solution indicate the proper performance of the proposed model. Pal et al. (2017) implemented the penalty function in the FGP framework in a university resources programming model using the Genetic Algorithm (GA). The first link between the penalty function and the membership of the objectives is defined with the success rate of the fuzzy objectives in different ranges, so that the appropriate values of membership of the objectives are obtained. Then, a set of probabilistic constraints is converted into algebraic equations using the FGP method. In the solution search process, a GA plan evaluates repeatedly the performance of the objective based on specified priorities.

The Multi-Period Multi-Objective Multi-Product Multi-Echelon Model in supply chain was proposed in Subulan et al. (2015). They used an interactive fuzzy goal programming approach to solve the model. In order to obtain the best values for profit and to meet the objectives of environmental indicators, they examined the effects of some parameters on profit performance by an experimental method based on the Taguchi design. Finally, the result of the solution indicates that as the purchase costs increase, the total system costs increase. Fahimnia and Jabbarzade (2016) studied the relationship of sustainability-resilience at the level of supply chain design. The multi-objective model included a sustainable performance assessment method and a random fuzzy goal programming approach that can be used to conduct a dynamic sustainability tradeoff analysis and to design a "resilient sustainable supply chain". The main objective of Rabbani et al. (2016) was to create a multi-objective mixed integer programming model. They optimized several objective functions simultaneously by taking into account the uncertainty in parameters such as demand and budget. Finally, the proposed model is transformed into a deterministic model using the Chance Constraint programming approach. The results of the solution indicate the proper performance of the proposed model. Dalman (2016) presented the GP planning based on Taylor series for

solving the decentralized bi-level multi-objective fractional programming (DBLMOFP) problem. In this approach, all the membership functions are related to fuzzy objectives of each objective function at each level; membership functions are also converted to linear functions using the Taylor series approach.

Razmi et al. (2016) developed a new method for solving multi-objective programming problems. This method is a combination of the concept of intuitionistic fuzzy sets, goal programming and interactive approach, and supports the decision-maker in the process of solving problems with fuzzy and deterministic objectives and constraints. FGP incremental models were formulated for the fuzzy random transportation problem in Giri et al. (2014). In their paper, they summed the membership function of random constraints using deterministic and fuzzy weights, based on the importance of the objectives. Their proposed formula for specific problems (for example, a model with two fuzzy random constraints) can be used. Multi-Period Multi-Objective Multi-Product Aggregate Production Planning Model was presented by Khalili-Damaghani and Shahrokh (2014). Three objectives of minimizing the costs, maximizing the level of customer service and maximizing the quality of the final product were considered simultaneously, and the proposed problem was solved using the FGP approach. Ku et al. (2010) using the fuzzy analytical hierarchy process (FAHP) and fuzzy goal programming, a new approach called the FAHP-FGP for selecting suppliers was presented. Using this method, the ideas of several managers about determining the weight of objectives can be continuously integrated and the order quantities for suppliers can be obtained. Table 1 shows the summary of relevant literature review.

Table 1. Literature review

Authors	Period		Level		Product		Objective		Type of model	
	Single	Multi	Single	Multi	Single	Multi	Single	Multi	Uncertain	Deterministic
Kilic and Yalcin, (2020)	*		*			*	*		*	
Khan et al. (2020)	*			*	*			*	*	
Nomani (2017)	*		*			*		*		*
Pal et al. (2017)		*		*	*		*		*	
Fahimnia and Jabbarzade (2016)	*		*		*			*		*
Rabbani et al. (2016)		*	*		*			*	*	
Dalman (2016)		*	*		*			*	*	
Razmi et al. (2016)		*	*			*		*	*	
Giri et al. (2014)		*		*	*		*		*	
This paper		*		*		*		*	*	

The mentioned researches include a wide range of SC networks, from single-stage to multi-stage. Decision-making at supply chain levels in uncertain conditions is one of the problems of the real world and is also the major concern in this study. According to our information, the uncertainty conditions in a comprehensive multi-period multi-level multi-product multi-objective model in the field of designing and distribution of supply chains has not been considered in any of the previous researches. In this paper, the proposed model is considered under uncertainty. Then, logistics costs and service level of the model are solved by two methods of fuzzy goal programming and the results are compared to provide a suitable method to convert the proposed model into a fuzzy model. The entire process of solving the model is coded and implemented using Lingo software.

3- Mathematical model

Indices:

i	Index of suppliers ($i = 1, \ldots, I$)
j	Index of producers ($j = 1, \ldots, J$)
k	Index of distribution centers (warehouse) ($k = 1, \ldots, K$)
l	Index of final product ($l = 1, \ldots, L$)
n	Index of raw material ($n = 1, \ldots, N$)
t	Index of periods ($t = 1, \ldots, T$)

Parameters:

D_{lkt}	The demand for product l at the distribution center k during period t
Ur_{nl}	The amount of raw material n needed to produce one unit of product l
Cap_{ljt}	The production capacity of product l in factory j during period t
Vmr_j	The volume of raw materials warehouse of the factory j
Vmp_j	The volume of the final product warehouse of the factory j
Vdc_k	The volume of the final product warehouse of the distribution center k
Pc_{lj}	Production costs of a unit of product l (except raw material) at the factory j
Pr_{ni}	Selling price of raw material n by supplier i
Hmr_{nj}	Holding costs of one unit of raw material n at the factory j
Pp_{lj}	Selling price of the product l by producer j
$Trmax_{nijt}$	Maximum time allowed to receive the batch unit of raw material n from supplier i by factory j during period t
Bsm_{ni}	Batch size of the raw material n in supplier i
Bsm_{lj}	Batch size of the product l in factory j
SSm_{njt}	Safety stock of raw material n in factory j during period t
SSp_{lkt}	Safety stock of the final product l in distribution center k during period$t$
Cbl_{lk}	The unit shortage cost of the product l in distribution center k
$Tpmax_{ljkt}$	Maximum time allowed to receive the batch unit of final product l from factory j by distribution center k during period t
Hmp_{lj}	Holding costs of one unit of product l at the factory j
Hdc_{lk}	Holding costs of one unit of product l at the distribution center k
Qp_l	Required space of each unit of product l
Qr_n	Required space of each unit of raw material n
Fcr_{nij}	Fixed costs of transportation of raw material n from supplier i to the factory j
Vcr_{nij}	Transportation costs of raw material n from supplier i to the factory j
Vcp_{ljk}	Variable costs of transportation of one unit of product l from factory j to the distribution center k
Fcp_{ljk}	Fixed costs of transportation of the product l from factory j to the distribution center k
Tdp_{ljkt}	Delivery time of the batch unit of final product l from factory j to the distribution center k during period t
Tdr_{nijt}	Delivery time of the batch unit of raw material n from supplier i to the factory j during period t
M_2, M_1	Positive and large numbers
α_{lkt}	The maximum quantity allowed for backorder of product l at the distribution center k during period t, which is defined as a percentage of the demand for that period.

Variables:

X_{nijt}	Purchase quantity of raw material n from supplier i by factory j during period t
Y_{ljt}	Production quantity of product l by producer j during period t
Z_{ljkt}	Transportation quantity of final product l from factory j to the distribution center k during period t
IRm_{njt}	Ending inventory level of raw material n at the factory j during period t
Ipm_{ljt}	Ending inventory level of final product l at the factory$j$ during period t
Ip_{lkt}	Ending inventory level of final product l at the distribution center k during period t
TR_{nijt}	Delivery time of raw material n from supplier i to the factory j during period t
TP_{ljkt}	Delivery time of final product l from the factory j to the distribution center k during period t
W_{nijt}	1 If factory j orders the raw material n to supplier i during period t , otherwise 0
U_{ljkt}	1 If distribution center k orders the product l to factory j during period t , otherwise 0
Blg_{lkt}	The lag level of product l at the distribution center k at the end of period t
Q_{lkt}	Sales volume of product l at the distribution center k during period t

$$\begin{aligned} Min \quad TCs = & \sum_t \sum_n \sum_i \sum_j X_{nijt}\, Vcr_{nij} + \sum_t \sum_n \sum_i \sum_j X_{nijt}\, Pr_{ni} \\ & + \sum_t \sum_n \sum_i \sum_j W_{nijt}\, Fcr_{nij} + \sum_t \sum_n \sum_j Hmr_{nj} IRm_{njt} + \sum_t \sum_l \sum_j Y_{ljt} Pc_{lj} \\ & + \sum_t \sum_n \sum_i \sum_j Hmp_{lj}\, IP_{ljt} + \sum_t \sum_l \sum_j \sum_k Z_{ljkt}\, Pp_{lj} \\ & + \sum_t \sum_l \sum_j \sum_k Z_{ljkt}\, Vcp_{ljk} + \sum_t \sum_l \sum_j \sum_k U_{ljkt}\, Fcp_{ljk} \\ & + \sum_t \sum_l \sum_k Hdc_{lk} Ip_{lkt} + \sum_t \sum_l \sum_k Cbl_{lk} Blg_{lkt} \end{aligned} \tag{1}$$

$$Max \quad SL_1 = \sum_t \sum_n \sum_i \sum_j (Trmax_{nijt} - TR_{nijt}) + \sum_t \sum_l \sum_j \sum_k (Tpmax_{ljkt} - Tp_{ljkt}) \tag{2}$$

$$Min \quad SL_2 = \sum_t \sum_l \sum_k Blg_{lkt} \tag{3}$$

$$IRm_{njt} = IRm_{nj,t-1} + \sum_i X_{nijt} - \sum_l Ur_{nl}\, Y_{ljt} \qquad \forall t, n, j \tag{4}$$

$$IPm_{ljt} = IPm_{lj,t-1} + Y_{ljt} - \sum_k Z_{ljkt} \qquad \forall t, l, j \tag{5}$$

$$IP_{lkt} = IP_{lk,t-1} + \sum_j Z_{ljkt} - Q_{lkt} \qquad \forall t, l, k \tag{6}$$

$$IRm_{njt} \geq SSm_{njt} \qquad \forall t, n, j \tag{7}$$

$$IP_{lkt} \geq SSp_{lkt} \qquad \forall t, l, k \tag{8}$$

$$\sum_n Q_n\ IRm_{njt} \leq Vmr_j \qquad \forall t, j \tag{9}$$

$$\sum_{l} Qp_l \; IPm_{ljt} \leq Vmp_j \qquad \forall t, j \qquad (10)$$

$$\sum_{l} Qp_l \; IP_{lkt} \leq Vdc_k \qquad \forall t, k \qquad (11)$$

$$Y_{ljt} \leq Cap_{ljt} \qquad \forall l, j, t \qquad (12)$$

$$Tdr_{nijt} \times (X_{nijt}/Bsm_{ni}) \leq Trmax_{nijt} \qquad \forall n, i, j, t \qquad (13)$$

$$Tdp_{ljkt} \times (Z_{ljkt}/Bsp_{lj}) \leq Tpmax_{ljkt} \qquad \forall l, j, k, t \qquad (14)$$

$$Tdr_{nijt} \times X_{nijt}/Bsm_{ni} = TR_{nijt} \qquad \forall n, i, j, t \qquad (15)$$

$$Tdp_{ljkt} \times Z_{ljkt}/Bsp_{lj} = TP_{ljkt} \qquad \forall l, j, k, t \qquad (16)$$

$$Blg_{lkt} = Blg_{lk,t-1} + D_{lkt} - Q_{lkt} \qquad \forall l, k, t \qquad (17)$$

$$Blg_{lkt} \leq \alpha_{lkt} D_{lkt} \qquad \forall t, l, k \qquad (18)$$

$$D_{lkt} - Q_{lkt} \leq Blg_{lkt} \qquad \forall t, l, k \qquad (19)$$

$$W_{nijt} M_1 \geq X_{nijt} \qquad \forall n, i, j, t \qquad (20)$$

$$U_{ljkt} M_2 \geq Z_{ljkt} \qquad \forall l, j, k, t \qquad (21)$$

$$U_{ljkt}, W_{nijt} \in \{0,1\} \qquad \forall n, l, i, j, k, t \qquad (22)$$

$$X_{nijt},\ Y_{ljt},\ Z_{ljkt},\ IRm_{njt}, Ipm_{ljt},\ Ip_{lkt},\ TR_{nijt},\ TP_{ljkt},\ Blg_{lkt},\ Q_{lkt} \geq 0 \qquad \forall n, l, i, j, k, t \qquad (23)$$

The first objective function minimize the supply costs (including supply, purchase, transportation of raw materials to factories and holding cost of raw materials inventory at the factory in each period), (2) production costs (including production and holding of final product inventory at the factory in each period); and (3) distribution costs (including purchase, transportation, holding product inventory, and shortage costs in each period at distribution centers). The second objective function maximize the amount of deviation of the delivery time of the raw material from the supplier and the final product from the factory compared to the time that was determined by the customer in period t. The third objective function minimizes the level of backorders in distribution centers.

Constraint (4) shows the amount of raw materials inventory in the warehouse of the factories, constraint (5) shows the amount of product inventory in the warehouse of the factories, and constraint (6) shows the inventory balance of the product at the distribution centers, considering the backorders. In addition, Constraints (7) and (8) represent the balance of the safety stock of raw material in the factory warehouse and the final product at the distribution centers in each period. Constraints (9) and (10) apply the constraint of the warehouse space of raw materials and products in the factories, for raw materials and products separately, and constraint (11) applies the constraint of the product warehouse space at the distribution centers. Constraint (12) shows that the production quantity of each product should not exceed the maximum capacity of the factory. Constraints (13) and (14) determine the delivery time of the raw materials by the suppliers and the products by the factories, and accordingly we will have (15) and (16). Constraint (17) indicates the amount of backorders for each product at the distribution center. Constraints (18) and (19) determine the amount of lost sales relative to the amount of demand for the product at distribution centers. Constraints (20) and (21) are logical constraints of the model and (21) and (23) represent the type of variables.

The output of the solution of this problem determines the purchase quantity of each raw material from each supplier by each producer, the production quantity of each product by the producer, the quantity of product transported from the producer to the distribution center, the ending inventory level of the raw material in the factory, the ending inventory level of each product in the factory and distribution center, the delivery time of the raw material from the supplier to the factory, the delivery time of the product from the factory to the distribution center, the sales volume of the product at the distribution center, and the level of ending lag at the distribution center.

4- Proposed approach

One of the main features of multi-objective decision-making methods is their ability to adjust decision-makers' preferences according to priority of the objectives (Caramia and Dell'Olmo, 2020). The decision-makers' preferences for determining the priority of membership values of fuzzy objectives can be determined through fuzzy relations (Loetamonphong et al. 2002). The level of achievement of fuzzy objectives due to the involvement of the decision maker's preference in determining the priority of objectives should follow a hierarchical structure (Chakraborty et al. 2016). Since the level of success of objectives is ambiguous, deterministic relations can't be used to draw a hierarchical structure. Therefore, fuzzy relations are the appropriate approach to demonstrate the preferences of decision-makers regarding the priority of fuzzy objectives. Khalili Damghani and Sadi-Nezhad (2013) used fuzzy preference relations to show decision makers' preferences in determining the priority of fuzzy objectives.

Definition 1: $G = \{\tilde{g}_1, \dots, \tilde{g}_u\}$ is a finite set of fuzzy objectives and $G = B \cup C$ in which B represents the maximizing objectives and C represents the minimizing objectives, $X = \{x_1, \dots, x_m\}$ is the set of decision variables of the model (1) - (23) and $F = \{\mu_1(X), \dots, \mu_u(X)\}$ is a finite set of the membership values of the fuzzy objectives of$G$. The preferences of decision-makers for F are shown with the fuzzy preference relations, $R \subset F \times F$ with the degree of membership of$\mu_R: F \times F \to [0,1]$, which $\mu_R(\mu_s(X), \mu_d(X))$ shows the degree of membership of the fuzzy objective s on the degree of membership of the fuzzy objective d.

It can be concluded that R is a function of the membership value of fuzzy objectives, while the membership values of fuzzy objectives are a function of its own decision-making variable X. A hierarchical structure is modeled for decision preferences of the membership value of fuzzy objectives using fuzzy relations R. To simplify, we use μ_s instead of$\mu_s(X)$. μ_R represents the approximation priority of $\mu_s$over μ_d. R_h, $h = 1, 2, \dots, 10$ is a function of $\mu_s - \mu_d$, which here we use four different linguistic terms to represent decision-makers' preferences at the improvement level of fuzzy objectives, as presented in Table 2 and figure 2.

Table 2. Linguistic terms and fuzzy relations

linguistic terms	fuzzy relations
Exactly equal	$\tilde{R}_1$
Almost equal	$\tilde{R}_2$
Somewhat more important	$\tilde{R}_3$
Incomparable	$\tilde{R}_4$

Linear membership functions are used to show fuzzy preference relations. The membership function of fuzzy relations between fuzzy objectives can be expressed as equations (24) - (27).

$$\mu_{\tilde{R}_1} \begin{cases} 0 & if \quad -1 \le \mu_s - \mu_d < 0 \\ 1 & if \quad \mu_s - \mu_d = 0 \\ 0 & if \quad 0 \le \mu_s - \mu_d < +1 \end{cases} \tag{24}$$

$$\mu_{\tilde{R}_2} \begin{cases} 0 & if \quad -1 \le \mu_s - \mu_d \le -0.5 \\ 2(\mu_s - \mu_d + 0.5) & if \quad -0.5 \le \mu_s - \mu_d \le 0 \\ -2(\mu_s - \mu_d - 0.5) & if \quad 0 \le \mu_s - \mu_d < 0.5 \\ 0 & if \quad 0.5 \le \mu_s - \mu_d < +1 \end{cases} \tag{25}$$

$$\mu_{\tilde{R}_3}\begin{cases}2(\mu_s-\mu_d+1) & if \quad -1\le\mu_s-\mu_d\le-0.5\\ 1 & if \quad -0.5\le\mu_s-\mu_d<+1\end{cases} \tag{26}$$

$$\mu_{\tilde{R}_4}\begin{cases}0 & if \quad -1\le\mu_s-\mu_d\le+1\\ 1 & if \quad \mu_s-\mu_d=+1\end{cases} \tag{27}$$

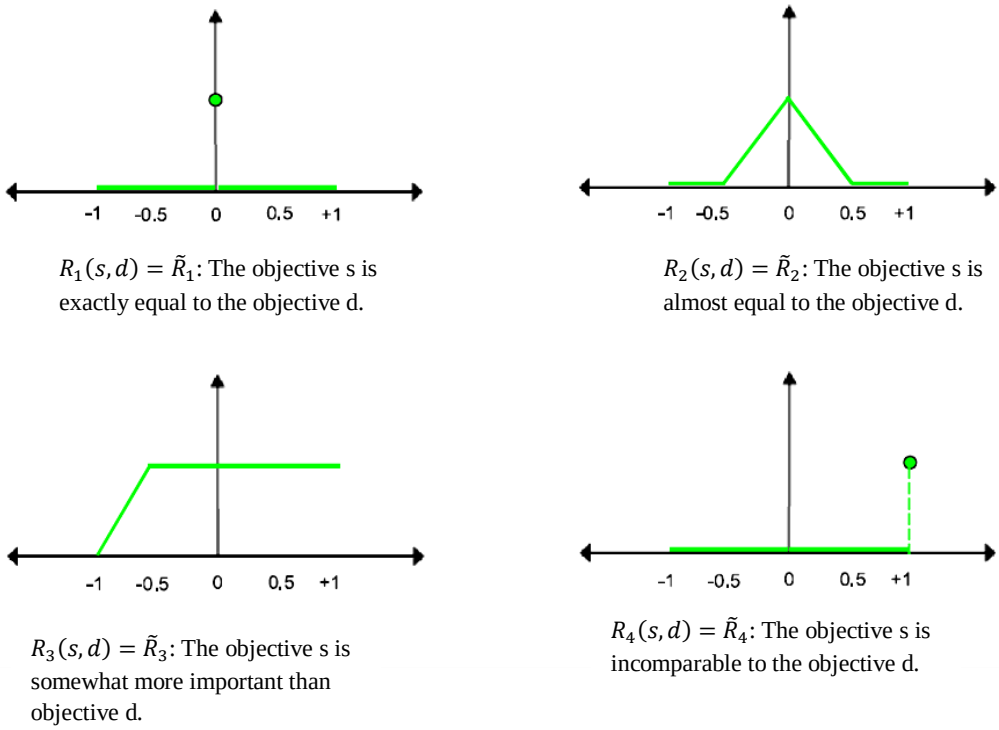


Fig 2. Membership functions of linear fuzzy relations

In the following, in order to resolve the uncertainty of the parameters of supply chain problem presented in section 3, two different techniques based on fuzzy goal programming are proposed.

4-1- The first method (the approach of Akoz and Petrovich (2007))

The uncertainty regarding the priority of the objectives affects not only on the main relations, but also on the determined fuzzy objectives and as a result on the decision space. In this approach, the significance levels of objectives are undetermined and they determine it using fuzzy relations. They defined the achievement function as a set of improvement degree of objectives and degree of satisfaction from the relative importance relations between objectives. The proposed FGP method is a resilient support tool that uses relative importance relations to resolve the ambiguity. According to Akoz and Petrovich (2007), the goal programming model using fuzzy preference relations is used to solve the multi-objective supply chain model (1) - (23) in the following.

Added parameters:

$0\le\lambda\le1$, λ : Relative importance of relations

z_h^+: The level of satisfaction from the hth objective function in the model (1) - (23) in ideal state

z_h^-: The level of satisfaction from the hth objective function in the model (1) - (23) in anti-ideal state

z_h: The value of the hth objective function in the model (1) - (23)

$s \neq d$, l_{sd}: If the importance relations between the objectives of $g_s$and g_d exists, it is equal to 1; otherwise 0

$q = 1, 2, \dots, 10$, $\tilde{R}_h(s, d) = \tilde{R}_q$: The hth-type fuzzy relation that is defined between the satisfaction level of fuzzy objectives from the existing objective functions in model (1) - (23). In this paper, $q = 3$is assumed.

Added variables:

μ_h: Degree of achievement to the hth objective

$q = 1, 2, \dots, 10$, $\mu_{\tilde{R}_q(s,d)}$: The satisfaction level from the hth-type fuzzy relations

X: The vector of decision variable for the main multi-objective model (1) - (23)

S: Possible space for the main multi-objective model (1) - (23)

Model:

$$Max \quad \lambda \times \left(\sum_{h=1}^{H} \mu_h \right) + (1 - \lambda) \times \sum_{s=1}^{h} \sum_{\substack{d=1 \\ d \neq s}}^{h} l_{sd}\, \mu_{\tilde{R}(s,d)} \tag{28}$$

$$\mu_h = \frac{z_h^+ - z_h(X)}{z_h^+ - z_h} \qquad \forall\, z_h \in C \tag{29}$$

$$\mu_h = \frac{z_h(X) - z_h^-}{z_h - z_h^-} \qquad \forall\, z_h \in B \tag{30}$$

$$2\left(\mu_P^{PIS} - \mu_P^{NIS} + 1\right) \geq \mu_{\tilde{R}_3(s,d)} \qquad \forall\, l_{sd} = 1, \quad \tilde{R}(s,d) = \tilde{R}_3 \tag{31}$$

$$\mu_h \leq 1 \qquad \forall\, h = 1, \dots, H \tag{32}$$

$$0 \leq \mu_{\tilde{R}(s,d)} \leq 1 \qquad \forall\, l_{sd} = 1, \quad s \neq d \tag{33}$$

$$l_{sd} \in \{0, 1\} \qquad \forall\, s, d = 1, 2, \quad s \neq d \tag{34}$$

$$0 \leq \lambda \leq 1 \tag{35}$$

$$X \in S \tag{36}$$

The objective function (28) maximizes the improvement degree of objectives and the degree of satisfaction of the relative importance relations between the objectives. Constraints (29) and (30) should be written for the ideal and anti-ideal states for fuzzy objectives. Constraint (31) reduces the overall complexity of the process of the problem, and only one judgment about the decision maker's preferences is needed for determining membership values. Constraints (32) - (35) are to determine the sign and type of variable. Constraint (36) illustrates the constraints of the main multi-objective problem.

4-2- The second method (the approach of Khalili-Damghani et al. (2013))

In their proposed method, fuzzy objectives are defined with a predetermined membership function and are modeled using fuzzy relations to resolve the ambiguity in the priority of the membership values of fuzzy objectives, and ultimately solve it by fuzzy goal programming. They also use the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and fuzzy preference

relations. The application of TOPSIS is converting the multi-objective problem into a bi-objective problem, and fuzzy preference relations are also used to help decision-makers to express their preferences according to the membership values of fuzzy objectives. In the following, the goal programming model using fuzzy preference relations is proposed to solve the multi-objective supply chain model (1) - (23).

Added parameters:

$0 \leq \lambda \leq 1$, λ: Convex linear combination parameter is for incremental weight of improvement degree of fuzzy objectives and cumulative weight of the priority of decision-makers is for the membership values of fuzzy objectives.

w_P^{PIS}: The relative importance of the satisfaction level of the model (1) - (23) in the ideal state

w_P^{NIS}: The relative importance of the satisfaction level of the model (1) - (23) in anti-ideal state

$s \neq d$, $s, d \in \{1, 2\}$, l_{sd}: If there are importance relations between the membership values of $d_P^{PIS}(x)$and $d_P^{NIS}(x)$,it is equal to 1, otherwise 0

$0 \leq w_{sd} \leq 1$, w_{sd}: The relative importance of the decision maker's priority from satisfaction level of the fuzzy objectives s and d

$q = 1, 2, \dots, 10$, $\tilde{R}_h(s, t) = \tilde{R}_q$: The hth-type fuzzy relation that is defined between the satisfaction level of fuzzy objectives from the existing objective functions in model (1) - (23) (for each $d_P^{PIS}(x)$ and $d_P^{NIS}(x)$). In this paper, $q = 3$is assumed.

d_p^{PIS+}: The minimum PIS distance for the compromise rate p when the model (1) - (23) is solved as single-objective.

d_p^{PIS-}: The maximum PIS distance for the compromise rate p when the model (1) - (23) is solved as single-objective.

d_p^{NIS-}: The minimum NIS distance for the compromise rate p when the model (1) - (23) is solved as single-objective.

d_p^{NIS+}: The maximum NIS distance for the compromise rate p when the model (1) - (23) is solved as single-objective.

Added variables:

μ_P^{PIS}: The membership value of the objective for the model (1) - (23) in the ideal state

μ_P^{NIS}: The membership value of the objective for the model (1) - (23) in the anti-ideal state

$d = 1, 2, \dots, 10$, $\mu_{\tilde{R}_h(s,d)}$: The membership value of the dth-type fuzzy relations is defined between the membership value of$d_P^{PIS}(x)$ and$d_P^{NIS}(x)$.

X: The vector of decision variable for the main multi-objective model (1) - (23)

S: Possible space for the main multi-objective model (1) - (23)

Model:

$$Max \quad \lambda \times \left(w_P^{PIS} \times \mu_P^{PIS} + w_P^{NIS} \times \mu_P^{NIS}\right) + (1-\lambda) \times \sum_{s=1}^{2} \sum_{\substack{d=1 \\ d \neq s}}^{2} w_{sd}\, l_{sd}\, \mu_{\tilde{R}(s,d)} \tag{37}$$

$$\mu_P^{PIS} \leq \frac{d_p^{PIS+} - d_p^{PIS}(X)}{d_p^{PIS+} - d_p^{PIS-}} \tag{38}$$

$$\mu_P^{NIS} \leq \frac{d_p^{NIS}(X) - d_p^{NIS-}}{d_p^{NIS-} - d_p^{NIS+}} \qquad \forall\, l_{sd} = 1, \qquad \tilde{R}(s,d) = \tilde{R}_3 \tag{39}$$

$$2\left(\mu_P^{PIS} - \mu_P^{NIS} + 1\right) \geq \mu_{\tilde{R}_3(s,t)} \tag{40}$$

$$0 \leq \mu_P^{PIS} \leq 1 \tag{41}$$

$$0 \leq \mu_P^{NIS} \leq 1 \tag{42}$$

$$0 \leq \mu_{\tilde{R}(s,d)} \leq 1 \qquad \forall\, l_{sd} = 1, \qquad s,d = 1,2, \qquad s \neq d \tag{43}$$

$$l_{sd} \in \{0,1\} \qquad s,d = 1,2, \qquad s \neq d \tag{44}$$

$$0 \leq \lambda \leq 1 \tag{45}$$

$$w_P^{PIS} + w_P^{NIS} = 1 \tag{46}$$

$$X \in S \tag{47}$$

The objective function (37) simultaneously combines the convex composition of the incremental weight of membership values of the fuzzy objectives and the cumulative weight of the decision-makers' preferences for the membership values of the fuzzy objectives. Constraints (38) and (39) should be written for ideal fuzzy objectives in ideal and anti-ideal states. Constraint (40) reduces the overall complexity of the problem, and only one judgment is required about the preferences of decision-makers to determine membership values. Constraints (41) - (43) determine the low and high membership values for fuzzy objectives using fuzzy relations. Constraint (44) determines the binary properties of the variable and constraint (45) determines the values of the parameter λ. Constraint (46) is for controlling the cumulative weight of t $w_P^{PIS}$and w_P^{NIS}. Constraint (47) illustrates the constraints of the main multi-objective problem.

5- Computational results

To test the effectiveness and applicability of proposed approaches of chapter 4, a case study of the dairy industry supply chain is examined. There are three suppliers, two dairy factories and three distribution centers in the assumed chain. Its products are milk, yogurt and flavored yogurt. The raw materials used by the factories include milk, milk packaging bottles, sharing nylon, starter, stabilizer, flavoring, disposable container of 311g (yogurt), disposable container of 111g (flavored yogurt), aluminum foil (container lid) and dry milk. The raw material requirements of these products are estimated from the real example and transportation costs are estimated for product and raw material separately, according to the assumed distances of these resources from each other. Prices and values are estimated using a pattern of real examples. In this section, the performances of the two proposed approaches of FGP are compared for the supply chain of dairy industry. Both methods are coded in 17Lingo and run on a computer with operating system of Windows 7, 4Pentium with a 2-core processor, 2 GHz, and 1 GB of memory. The amounts of raw material needed to produce one unit of product l are as table 3.

Table 3. The amount of raw material n needed to produce one unit of product l

Raw material/ Product	$l1$	$l2$	$l3$	$l4$
$n1$	2	0.5	0.7	3
$n2$	1	1.8	2	0.2
$n3$	-	2	3	0.7
$n4$	2	-	-	0.25
$n5$	1	2	-	1
$n6$	0.5	0.5	2	3

5-1- Implementing the proposed approaches

Table 4 presents the optimization results of the main multi-objective problem (1) to (23) in a single-objective form and in ideal and anti-ideal states. These values are used to form a bi-objective function to determine the distance function based on TOPSIS. Using the single-objective optimization results from table 4, the main problem can be converted into a bi-objective problem based on TOPSIS which its results are given in table 5. It should be noted that in table 3, the values of w_h and p are respectively equal to 0.2 and 1. In fact, using table 3, the conflicting objectives can be compared with each other in a limited distance.

The decision-makers' preferences for membership values of fuzzy objectives in the main problem and the bi-objective problem (based on TOPSIS) are presented in Tables 6 and 7, respectively. Decision-makers prioritize the membership values of fuzzy objectives independently. The values of table 4 were used in the first method and the values of Table 7 were used in the second method.

Table 4. Single-objective optimization results for the main problem

	Z_1	Z_2	Z_3
Ideal calculations			
Min Z_1	6177782000	1078.184	22800
Max Z_2	6382138000	1122.222	32950
Min Z_3	6363940000	1058.820	10575
Anti-ideal calculations			
Max Z_1	27513540000	145.9041	42850
Min Z_2	27494600000	100.3713	19375
Max Z_3	6359678000	1063.829	42850

Table 5. Bi-objective problem based on TOPSIS

	d_p^{PIS}	d_p^{NIS}
Ideal calculations		
Min d_p^{PIS}	0.00000001	1
Max d_p^{NIS}	0	1
Anti-ideal calculations		
Max d_p^{PIS}	0.9732210	0.2677899
Min d_p^{NIS}	0.9732210	0.2677899

Table 6. Fuzzy priority of improvement level of objectives in the main problem

	Z_1	Z_2	Z_3
Z_1		R_3	R_3
Z_2	-		R_3
Z_3	-	-	

Table 7. Fuzzy priority for the achievement level of the bi-objective problem based on TOPSIS

	d_p^{PIS}	d_p^{NIS}
d_p^{PIS}		R_3
d_p^{NIS}	-	-

The results of the first and second FGP procedures are presented in tables 8 and 9, respectively. The step size of the parameter λ is equal to 0.1 in both methods. The weights of all objectives are assumed equal and deterministic in order for objective functions of both methods to be compared with each other. According to Tables 8 and 9, it can be concluded that the mean of cumulative weight of membership value of fuzzy objectives in the first method is higher than the mean of the proposed FGP method in the second method, which means that the method of Akoz and Petrovich (2007) performs better in cases where the satisfaction level of objective function is maximized alone. Also, the mean of incremental weight of membership value according to the decision makers' preferences for fuzzy objectives in the second method is much higher than the mean of the first method, which means that if the satisfaction of the relationship between the objectives is maximized, Khalili-Damghani et al. (2013) proposed method will work better.

Table 8. Results of Akoz and Petrovich (2007) method for supply chain model of dairy products

λ	μ_1	μ_2	μ_3	$\sum_h w_h \mu_h$	$\sum_s \sum_d w_{sd} l_{sd} \tilde{\mu}_R(s,d)$	**O.F.V.**
0	0.9991123	0.02570092	0	0.4323674	0.5919924	0.5919924
0.1	0.9991123	0.01376419	0	0.5083878	0.5859971	0.5782362
0.2	0.9991123	0.01147752	0	0.5629347	0.5777578	0.5747931
0.3	0.9991123	0.01149066	0	0.5629396	0.5777563	0.5733113
0.4	0.9991123	0.01149066	0	0.5629396	0.5777563	0.5718296
0.5	0.9991123	0.01491563	0	0.5637553	0.5771366	0.5704460
0.6	0.9785858	0.2622263	0	0.6088641	0.5193399	0.5730544
0.7	0.9155389	0.5073670	0.5073670	0.7492538	0.2433950	0.5974962
0.8	0.9020625	0.5477769	0.5477769	0.7603483	0.2125713	0.6507929
0.9	0.8501929	0.6704871	0.6704871	0.7783106	0.1078235	0.7112619
1	0.8058474	0.7404676	0.7404676	0.7796955	0	0.7796955
Mean	0.9497183	0.2561059	0.2561059	0.6245270	0.4155933	0.6157190

Table 9. Results of Khalili-Damghani et al. (2013) method for supply chain model of dairy products

λ	μ_p^{PIS}	μ_p^{NIS}	$\sum_h w_h \mu_h$	$\sum_s \sum_d w_{sd} l_{sd} \tilde{\mu}_R(s,d)$	**O.F.V.**
0	0.0000000	0.0000000	0.0000000	1.0000000	1.0000000
0.1	0.2973635	0.7026364	0.5000000	1.0000000	0.9500000
0.2	0.2500000	0.7500000	0.5000000	1.0000000	0.9000000
0.3	0.2507763	0.7492237	0.5000000	1.0000000	0.8500000
0.4	0.5062594	0.4937405	0.5000000	1.0000000	0.8000000
0.5	0.2500000	0.7500000	0.5000000	1.0000000	0.7500000
0.6	0.7176455	0.2823545	0.5000000	1.0000000	0.7000000
0.7	0.6404262	0.3595737	0.5000000	1.0000000	0.6500000
0.8	0.5518436	0.4481564	0.5000000	1.0000000	0.6000000
0.9	0.8470471	0.1529529	0.5000000	1.0000000	0.5500000
1	0.4314684	0.5685315	0.5000000	0.0000000	0.5000000
Mean	0.4316640	0.4779241	0.4500000	0.9090900	0.7500000

Table 10 shows transportation quantity of final product l from factory j to the distribution center k during period t. For example according to table 2 the quantity of final product 2 from factory 2 to the distribution center 2 during period 3 is 6843 unit.

Table 10. Transportation quantity of final product

Z_{ljkt}	Quantity	Z_{ljkt}	Quantity	Z_{ljkt}	Quantity
$z(1,1,1,1)$	1532	$z(1,2,3,1)$	6532	$z(2,2,2,2)$	10762
$z(1,1,1,2)$	20165	$z(1,2,3,2)$	7152	$z(2,2,2,3)$	6843
$z(1,1,1,4)$	15890	$z(2,1,1,1)$	6841	$z(2,2,2,4)$	11640
$z(1,1,3,1)$	20762	$z(2,1,1,2)$	11264	$z(2,2,3,1)$	16520
$z(1,1,3,2)$	21910	$z(2,1,1,3)$	10974	$z(3,1,1,1)$	16404
$z(1,1,3,3)$	14650	$z(2,1,1,4)$	8628	$z(3,1,1,2)$	6982
$z(1,1,3,4)$	15220	$z(2,1,3,1)$	10654	$z(3,1,2,1)$	13264
$z(1,2,2,1)$	16970	$z(2,1,3,2)$	9481	$z(3,1,2,2)$	11364
$z(1,2,2,2)$	13852	$z(2,1,3,3)$	13226	$z(3,1,2,4)$	12681
$z(1,2,2,3)$	16512	$z(2,1,3,4)$	11641	$z(3,1,3,1)$	10236
$z(1,2,2,4)$	17889	$z(2,2,2,1)$	9823	$z(3,1,3,3)$	15531

Figure 3 shows the sensitivity analysis of the proposed model in terms of demand changes. As can be seen, with increasing demand, the amount of the first objective function increases. For example, a 10% increase in demand in Khalili-Damghani et al. (2013) increases the value of the objective function to 16793 units and 20% increase in demand in this model, increases the value of the objective function to 17208 units. Also 10% increase in demand in Akoz and Petrovic (2007) increases the value of the objective function to 16219 units and 20% increase in demand in this model, increases the value of the objective function to 16970 units. The slope of the chart also indicates that the changes in Khalili-Damghani et al. (2013) method have been less than the change in demand. In addition, the value of the objective function in Khalili-Damghani et al. (2013) method is less than in Akoz and Petrovic (2007). Therefore, according to the results of sensitivity analysis, Khalili-Damghani et al. (2013) method has performed better than Akoz and Petrovic (2007).

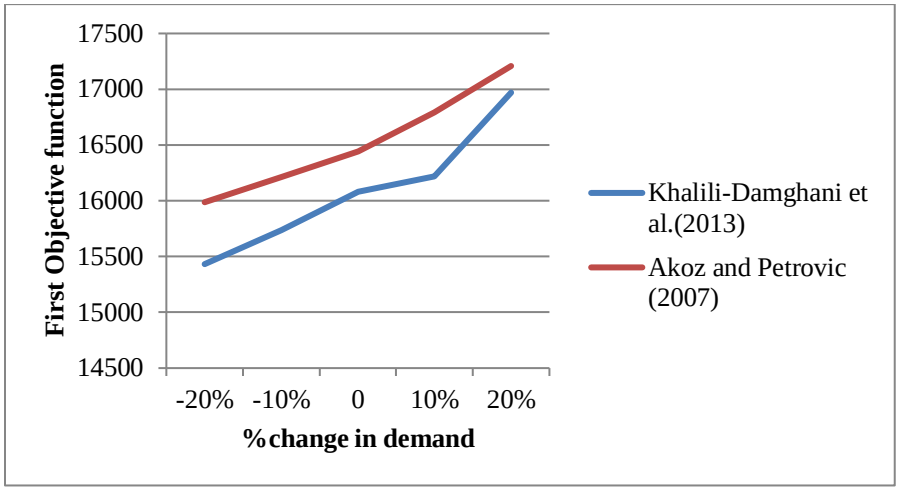


Fig 3. The influence of demand change on first objective function

5-2- Comparison index

In this paper, to compare the performance of two FGP methods, the following are used: (1) the membership value of the cumulative weight of the fuzzy objectives, (2) the cumulative weight of the decision-maker's ambiguous preferences to determine the priority of the membership values of the objectives, and (3) the closeness coefficient (CC) which the results of these three issues will be reported in section 5.3. To calculate CC we perform as following:

$$CC_{\lambda i} = \frac{d_p^{NIS_{\lambda i}}}{d_p^{NIS_{\lambda i}} + d_p^{PIS_{\lambda i}}} \qquad i \in \{1,2\}, \quad \lambda \in [0,1] \qquad (50)$$

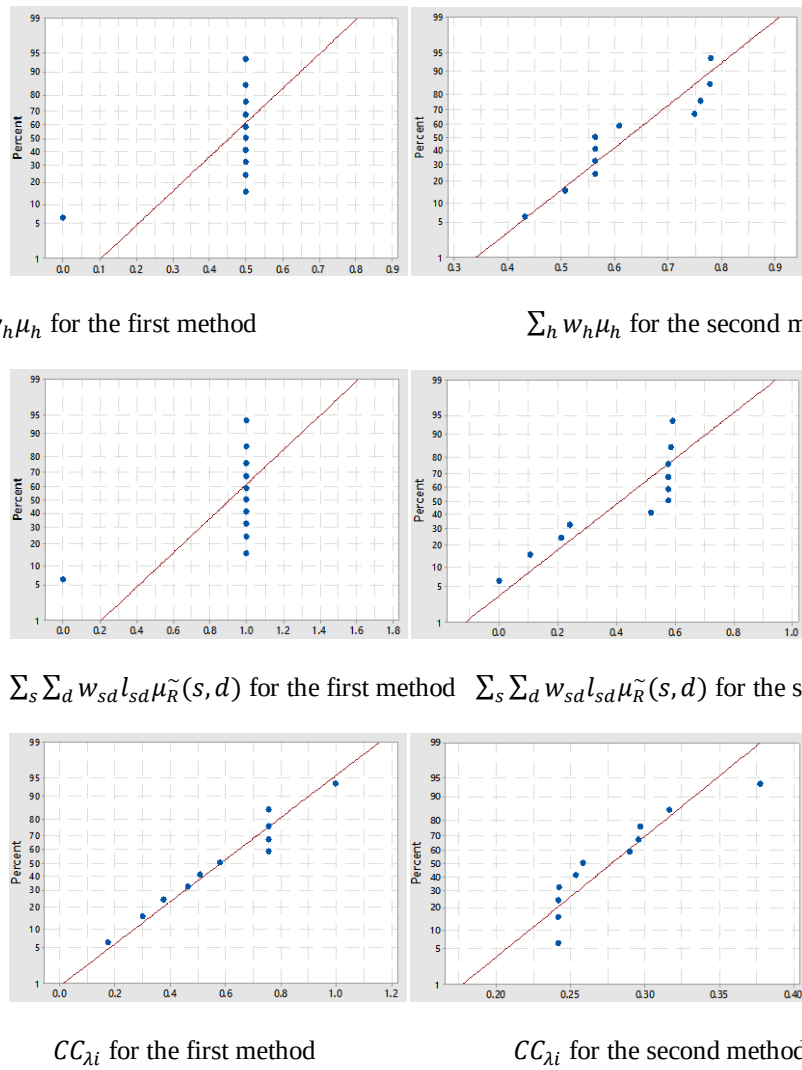
In the formula (50), $d_p^{NIS_{\lambda i}}$and $d_p^{PIS_{\lambda i}}$respectively represent the distance from NIS and PIS for the method i according to the parameterλ. The greater the value of fraction, the closer it is to the ideal (PIS) and the farther it is from the anti-ideal (NIS). Table 11 provides the value of $CC_{\lambda i}$for both proposed methods. According to the results of the table, it is shown that the performance of the second method is better than the first proposed method.

Table 11. Closeness coefficient for both methods

	Akoz and Petrovic (2007)			Khalili-Damghani et al.(2013)		
λ	$d_p^{PIS_{\lambda 1}}$	$d_p^{NIS_{\lambda 1}}$	$CC_{\lambda 1}$	$d_p^{PIS_{\lambda 1}}$	$d_p^{NIS_{\lambda 1}}$	$CC_{\lambda 1}$
0	0.6220870	0.3779130	0.3779130	0.0012320	0.9987680	0.9987680
0.1	0.7028820	0.2971179	0.2971179	0.2433052	0.7566947	0.7566948
0.2	0.7583436	0.2416563	0.2416563	0.2433052	0.7566947	0.7566948
0.3	0.7583433	0.2416567	0.2416567	0.2440607	0.7559392	0.7559392
0.4	0.7583433	0.2416567	0.2416567	0.4927023	0.5072977	0.5072977
0.5	0.7577890	0.2422110	0.2422110	0.2433052	0.7566947	0.7566948
0.6	0.7039735	0.2960265	0.2960265	0.6984277	0.3015723	0.3015723
0.7	0.7463070	0.2536929	0.2536930	0.6232763	0.3767237	0.3767237
0.8	0.7412375	0.2587625	0.2587625	0.5370658	0.4629342	0.4629342
0.9	0.7101157	0.2898842	0.2898842	0.8243640	0.1756359	0.1756359
1	0.6835085	0.3164915	0.3164915	0.4199141	0.5800858	0.5800858
Mean	0.7220850	0.2779150	0.2779150	0.4160000	0.5844583	0.5844583

5-3- Statistical comparison and the results of the ANOVA and Mann-Whitney tests

Kolmogorov-Smirnov test was performed for 11 different samples from the results of tables 6, 7 and 8 at 95% confidence level by MINITAB 19 software to examine the normality of the samples. Figure 4 shows the results of the Kolmogorov-Smirnov test. According to Fig. 2, the statistical distribution of the first and second methods is not normal for the criteria of $\sum_h w_h \mu_h$ and $\sum_s \sum_d w_{sd} l_{sd} \mu_{\tilde{R}}(s,d)$. Therefore, a non-parametric Mann-Whitney test should be used to compare them. Also, the results obtained from the Kolmogorov-Smirnov method show that the$CC_{\lambda i}$criterion has a normal distribution in both methods, so an ANOVA test should be used. The results of Mann-Whitney and ANOVA tests are presented in tables 9 and 10, respectively.



$\sum_h w_h \mu_h$ for the first method

$\sum_h w_h \mu_h$ for the second method

$\sum_s \sum_d w_{sd} l_{sd} \mu_{\tilde{R}}(s,d)$ for the first method

$\sum_s \sum_d w_{sd} l_{sd} \mu_{\tilde{R}}(s,d)$ for the second method

$CC_{\lambda i}$ for the first method

$CC_{\lambda i}$ for the second method

Fig 4. Results of Kolmogorov-Smirnov test for the criteria of both methods

The results of tables 12 and 13 show that $p - Value$ of all three criteria is less than acceptable level (0.05). Therefore, the assumption of the equality of criteria is rejected, which means that there is a significant difference between the criteria of the two methods. According to the above, there is enough evidence to reject the assumption of equality of three criteria. The results of ANOVA and Mann-Whitney tests, as well as the values of tables 6, 7 and 8, show that the first method had a good performance in determining the criterion of membership value of cumulative weight of fuzzy objectives and the second

method in determining the cumulative weight of the decision-maker's ambiguous preferences for the priority of membership values of the objectives.

Table 12.The results of Mann-Whitney test

Input	N	Mean	*p -Value*
1.The first criterion$\sum_h w_h \mu_h$			
The second method	11	0.5000	
			0.0010
The first method	11	0.5638	
2.The second criterion $\sum_s \sum_d w_{sd} l_{sd} \mu_{\tilde{R}}(s,d)$			
The second method	11	1.0000	
			0.0012
The first method	11	0.5771	

Table 13. The results of analysis of variance test

Input	Degrees of freedom	sum of squares	average of squares	*F*	*p-Value*
The third criterion$CC_{\lambda i}$					
The first method	8	0.016470	0.002059	0.303	0.042
Error	2	0.002030	0.001015		
Sum	10	0.018500			
R-sq (adj)=45.13% R-sq=89.03% S=0.0318618					

The superiorities of the proposed method are as follows:

1- The first method in the criterion of cumulative weight of fuzzy membership values and the second method in determining the cumulative weight of ambiguous preferences of decision-maker have had a good performance.
2- The solution time of Khalili-Damghani et al. (2013) is less Akoz and Petrovich (2007) approach. Therefore, one of the superiorities of Khalili-Damghani et al. (2013) is its low solution time.

Figure 5 shows the solution time results of the two proposed approaches. As the scale of the problem increases, the problem solving time increases. As shown in this figure the solution time of Khalili-Damghani et al. (2013) is less Akoz and Petrovich (2007) approach.

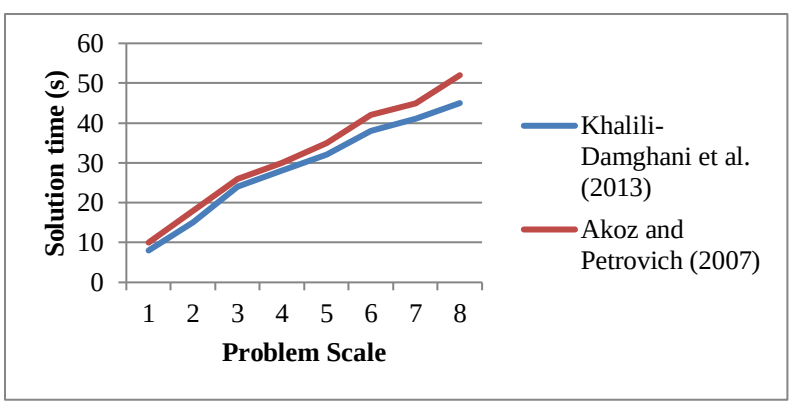


Fig 5. Solution time

6- Conclusion

Network design is one of the most recognized issues of SC management. Although many studies have been done to optimize SC network design problems, most of them are based on deterministic approaches. To bring the supply chain problems closer to the real world, the parameters and objective functions should be expressed as ambiguous. We developed a multi-objective multi-level aggregate model in the supply chain with fuzzy approach. This model selects suppliers, manufacturers, and distribution centers, and also divides both order and production quantities between them, so that chain costs will be minimized and service levels will be maximized according to decision makers' preferences. According to our data, the uncertainty conditions in a comprehensive multi-period multi-level multi-product multi-objective model in the field of designing and distribution of supply chains has not been considered in any of the previous researches. In this paper, the proposed model is considered under uncertainty. Then, logistic costs and service level of the model were solved by two methods of fuzzy goal programming and their results were compared. By comparing the performance of both methods and according to statistical analysis, it was determined that the first method is effective in determining the criterion of membership value of cumulative weight of fuzzy objectives and the second proposed method in determining the cumulative weight of the decision-maker's ambiguous preferences for the priority of the membership values of the objectives.

According to our knowledge, the uncertainty conditions in a comprehensive multi-period multi-level multi-product multi-objective model in the field of designing and distribution of supply chains has not been considered in any of the previous researches. Therefore the contributions of this research are as follows:

1- Presenting a multi-period multi-level multi-product multi-objective model in the field of designing and distribution of supply chains
2- Presenting two methods of fuzzy goal programming and the results are compared to provide a suitable method to convert the proposed model into a fuzzy model
3- The proposed model has been utilized in a real case study in Tehran, Iran.

The main bounds and limitations of this study are summarized as follows:

1- Lack of accurate information about parameters of case study
2- Too much time for data gathering about the case study parameters

For future research, the model can be expanded into five levels of supply chain in order to include retailers. Another of the most important suggestions for future research is using the heuristic or meta-heuristic algorithms to constantly review the performance of the objectives based on determined priorities. In addition, adding discount models to the model is also suggested.

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