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Robust supply chain network design with resilient supplier selection under disruption risks

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Abstract

Supply chain network design and resilient supplier selection play an important role in supply chain risk management to deal with various operational and disruption risks. In this paper, we develop a robust mathematical bi-objective, multi product model to consider resilient supplier and uncertainty in supply chain network design across multi period and multi products simultaneously, and this study offer optimal solutions for resilient supplier selection and order allocation. First we show a mixed-integer linear programming model with two objective functions, The first objective function maximizes the total profit, while the second maximizes the total supplier resilience score, where Fuzzy SECA have been used to obtain the five resiliency criteria weights and obtain the resilience scores for the objective function. we can rank the resilient suppliers using the fuzzy SECA method . we proposed an approach for coordination between production planning, supplier selection, and order allocation. The ε -constraint method was used to obtain optimum amounts of decision variables to maximize the profit for a real case study. Finally, a Pareto solution analysis has been done for the tradeoff between robustness and resilience.

the results show that how uncertainty parameters in the supply chain can affect the objective function. furthermore, this paper finds show that with supplier resilience score 4000, the first objective function of model present highest value, therefore in this point we can have resilient supplier with maximum profitability.

Keywords: resilient supplier selection, robust supply chain network, disruptions, Fuzzy SECA, Pareto solution

1 | Introduction

The supply chain is a group of organizations that exist with financial, material and information flow between them. these organizations include entities that supply services such as wholesaler, distributors and retailers or institutions that produce raw materials and finished products such as suppliers and manufacturers. a robust and efficient supply chain is a competitive advantage for countries and firms, helping them against environmental disturbances and disruptions. Supply chain activities begin with

esponding Author:

TCR_{si} transportation cost of raw material i from supplier s

customer order and finish with the customer payment and deliver commodity or service to the customer [1]

Nowadays, selecting the best suppliers is a critical task for an organization. Raw material activities represents more than half of the total cost and have an impact on the project schedule. Therefore, Suppliers have an impact on supply chain costs and increase resilience and profitability of organization [2]. On the other hand, risk can be minimized by using the best suppliers [3]. Supplier selection and order allocation play a critical role in supply chain management, which can define the best suppliers among set of alternatives while allocating large volume orders to suppliers.

today, managers and shareholders are increasingly interested in improving supply chain resilience to deal efficiently with different types of risks. Supply chain resilience is capacity level of a supply chain to absorb disruptions and maintain basic function and keep structure when faced with risks.(Pettit et al., 2010). The main risks of supply chain network can be divided into two groups as following:

1. Operational risk: these risks affect supply chain operations and are related to the uncertainty of supply chain parameters such as demand, raw material, operation costs, time, etc.

2. functional risk: these risks can occur in any part of the supply chain, and has influences on whole of the network. these risks are disruptions caused by natural and man-made disasters like war, strikes, equipment breakdown and ect [4]

Nowadays, supply chain specialists should know how to consider, mitigate, deal with and model these risks. Different methods have been developed to mitigate risk effects on the entire supply chain network. Scenarios – based robust models for dealing with operational risks are presented. These scenarios can be demonstrated using concepts of uncertainties and probabilistic with using known distribution functions and Fuzzy theory in stochastic model [5]. in this study, a robust supply chain network considering uncertainty parameters was developed to select the desired risk without considering scenarios and their probabilities. the proposed model is according to a robust optimization with interval data uncertainty [6].

to deal with operational risks, supply chain resilience has become one of the interesting research field. Supply chain resilience management is used in various industries, such automotive[7] [8]. airline industry, railroad and shipping [9]. The main objective of this research field is to improve supply chain risk management to design robust supply chain with resilient supplier that can identify and react against random and targeted disruptions.

Researchers have used different criteria to consider supplier resilience [10]. used supplier's capacity as a strategy to improved resilience. they introduced agility and collaboration to consider resilience. In a comprehensive study [11]. presented the criteria of robustness, agility, leanness and flexibility as the main criteria for a resilient supply chain. In this study, we used six criteria (robustness, flexibility, agility, leanness, integration and collaboration) to conduct a comprehensive research on suppliers resilience.

The objective of this paper is to develop a hybrid robust mathematical multi-objective model that can work under uncertainty conditions with ranking and selecting the suppliers considering the resilience criteria and their important weights. This study aims to define, how the fuzzy MCDM method in terms of resilience criteria can assist the managers to form a robust supply chain considering uncertainty conditions while meeting the resilience requirements of suppliers.

The selection of resilient suppliers in supply chains under the MCDM perspective has been the subject of several studies such as [12] and [13] and many research papers developed a multi - objective model to maximize supply chain resilience such as [14] and [15], but most of the researches paid little attentions to suppliers resilience with their weight importance and their role in achieving a robust supply chain under uncertainty.

The main contribution of this study is to consider supplier resilience in a robust supply chain network , deviating from previous studies that used MCDM to identify resilient suppliers and implement scenarios in a robust mathematical model. unlike previous studies on supplier resilience, we used the fuzzy SECA model introduced in 2018. This method uses a non- linear optimization model to represent criteria weights and supplier performance based on the weights. This is one of the contributions of the paper. A complementary contribution of this paper is the use of fuzzy theory in robust supply chain networks under uncertainty parameters. These contribute to development of hybrid methods that aim to obtain more accurate results than the use of single technique.

This paper is divided into eight remained sections as follows. section 2, discuss the background of the robust supply chain network and resilient supply chain network. The used proposed approach in this paper described in section 3. Problem definition that include mathematical modelling and robust formulation is represented in section 4. In section 5, we describe the computational experiments. In section 6, we present the results of the multi objective analysis. In section 7 and 8 we describe the sensitivity analysis of the robust model and the resilience values, respectively. Finally, in section 9, we address conclusions and opportunities for future work.

2 | Literature review

As the body of literature about robust supply chain network design with resilient suppliers present, mixed- integer programing models with various uncertainties such as demand, transportation cost, holding cost in the supply chain management are the common models used in this area. these models range from simple facility location model to complex multi period or multi objective models. generally objective of these models are determine the minimum cost design that is involves fixed costs and transportation costs. Several methods have been developed in mathematical model under uncertainty such as stochastic optimization, possibility method, interval optimization, simulation, fuzzy sets and robust optimization [16]. Our proposed model is classified as robust and resilient supply chain network and we review three research aspect in the literature review: Ⅰ) robust supply chain network Ⅱ)resilience supply chain and Ⅲ) robust and resilient supply chain network.

2.1 | Robust supply chain network

Aras and Bilge [17] presented multi product model of supply chain network with multi-period, their MILP model solved in two phase: deterministic and uncertainty then the results suggested the robust solution for suitable place to opening the new plant. Polo et al [18] proposed MINLP model to integrate financial risk in the robust design of closed-loop supply chain. They presented multi period – multi product model to solve the supply chain network under uncertainty condition of the demand. Maximize the economic value-added(EVA) was the objective of this paper , therefore the most robust configuration is identified. Yaghoubi et al [19] suggested bi objective model to tradeoff relationship between the costs and platelets' freshness. The network robustness under uncertainty condition investigated by using robust method and Pareto solution. This research result shows demand uncertainty and disruption increase logistic cost and delivery time. Nayeri et al [20] Presented multi objective mixed integer programming model to design the sustainable supply chain network. This model objective was minimizing the cost and maximizing the social impacts. The fuzzy robust approach proposed for uncertain data and meta-goal programming developed to solve the model, as a result, interactions between responsiveness, sustainability, and resilience dimensions been investigated. Wang and Wan [21] have introduces a bi-objective mixed integer mathematical model with aim maximize profit and minimize carbon emission. Production process in this model was uncertain. the Mont Carlo method used to produce the initial scenarios then they develop hybrid metaheuristic algorithm t to solve the model and investigate the efficiency and effectiveness of the proposed approach.

2.2 | Resilient Supplier selection

Resilient suppliers are capable to respond to unexpected events such as natural disaster and resume normal operations. Hosseini and Al Khaled [22] determined a resilient supplier index by using AHL approach. They used eight criteria of resilience capacity. Gan et al [23] proposed hybrid method which included the best-worst method (BWM) and modular TOPSIS in their research to rank alternatives for supplier selection in resilient supply chain. Aggarwal and Srivastava [24] considered eight criteria of collaborative resilience then they modelling and analyses of these criteria with using DEMATEL method to investigate the collaborative resilience in supplier and select the resilient suppliers. Sahebjamnia [25] focus on supplier selection and order location on his study, he explored four factor to determining the resilience weight of suppliers. He used DEMATEL and ANP method to investigate the overall performances of suppliers then he proposed the mathematical model to help to decision makers to select supplier and allocate the optimum order. Kaur and Singh [26] demonstrated multi stage hybrid model for integrated supplier selection and order allocation considering disruptions, suppliers evaluated based on set of criteria by using DEA. they presented MIIP model to optimize the order allocation model to suppliers, through this way, order allocation cost and risk of disruption simultaneously minimized. Piya, et all [27] identify fourteen drivers that have effect on resilient supply selection in oil and gas industry, drivers were analyzed with using Fuzzy-ISM-DEMATEL approach. Their study shows agility and robustness are essential drivers in supplier resilience than other drivers.

2.3 | Robust and resilient supply chain network

Bottani et al. [28] presented the resilient food supply chain problem. They proposed a bi-objective mixed-integer mathematical model. Their objective are maximize the profit and minimize the lead time. They used Ant Colony Optimization (ACO) algorithm to solve the model. Their resilient mode is suitable to deal with unpredictable demand and disruptions. Tirkolaee et al. [2] Used novel hybrid approach base on fuzzy logic to selecting suppliers. They used FANP method to ranking the sub criteria then consider DEMATEL technique to find relations between main criteria. After that, they used TOPSIS to prioritizing the suppliers. In their study, they proposed tri-objective model to optimize proposed supply chain. Objectives were minimizing the cost and maximizing the value of product by taking the account of suppliers' priorities. the food industry is modeled with using robust and resilient supply chain network model by Arabsheybani and Arshadi Khasmeh [3] .they find the weight of resilience criteria by using FAHP and fuzzy multi objective optimization on the basis of ratio analysis (FMOORA) employed to find the resilience performance of criteria, then they used robust bi-objective multi-product, multi-period mathematical model to maximize total profit and total scores of resiliency. Finally they used ε constraint to solve the robust model and analyzed the tradeoff between optimization and robustness.

This study has novelty because of the resilience knowledge has not been considered in our research area adequately, furthermore, there is not research that used interval base for designing supply chain network and also there is not multi product, multi supplier, multi time period and multi raw material model to consider resilient supplier selection and the robust supply chain network design, simultaneously.

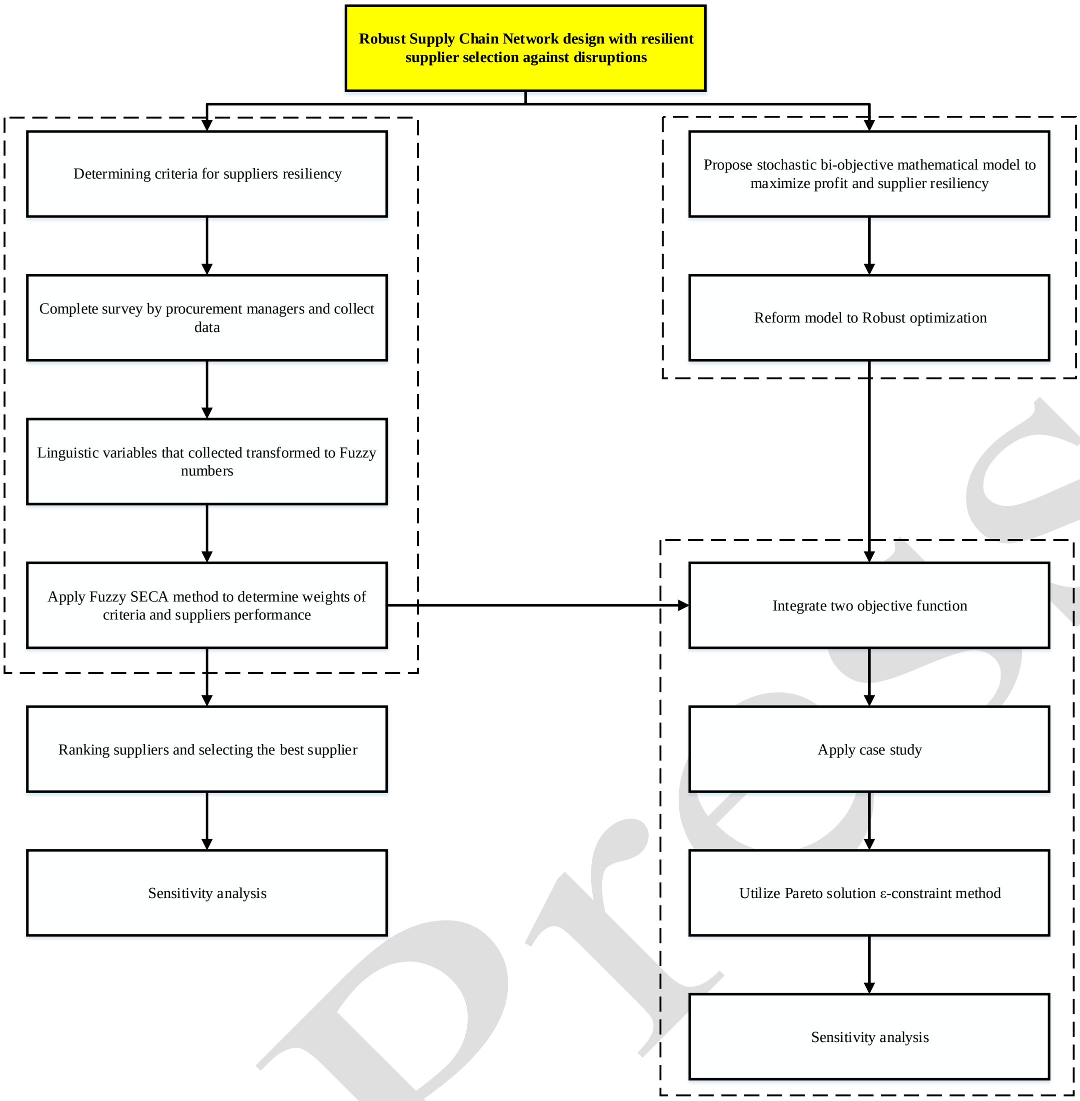


Fig1. the proposed framework

3 | Research methodology and problem description

To represent the current methodology , a diagram is presented as Fig 1. As shown in this Fig, our methodology divided to three phase. During the first phase, we proposed the stochastic bi-objective mathematical model then reform model to robust model against disruptions to maximize the profit. in second phase, . we identify the resilience factors with using literature review and collect data from experts, in this study, we present 5 resilience factors include: robustness, leanness, agility, integrity, flexibility. determine the suppliers performance as alternatives performance and importance weight of criteria with using Fuzzy SECA method. In the final phase, we implemented the results of the second phase in the first phase to optimize bi- objective model with using Pareto solution and ε constraint method.

The purpose of this study is helping to managers to determine optimal material flow with respect to suppliers resiliency performance. Therefore in this study, suppliers resiliency aspect and robust aspect of supply chain network are integrated. Fig.2 illustrates the supply chain under study which consists of two echelon. This research support decision makers in obtaining resilient and robust supply chain network with respect to uncertainty parameter and resilient performance of suppliers. Thus, multi criteria decision making techniques and developed multi objective optimization are integrated. Firstly, we suppose suppliers as resilience alternatives and 6 criteria to consider supplier resiliency. We suggest Fuzzy SECA method as on of the multi-criteria decision making (MCDM) techniques to assign importance weight to resilience factors and then determine supplier resiliency scores. In next phase, the resilience scores and importance weight of suppliers that has been derived from Fuzzy SECA method, are used in bi-objective model to maximize profit and resiliency. In order to uncertainty parameters, The bi-objective mathematical model developed in terms of robust programming . the ε -constraint method is used to obtain a set of Pareto optimal solutions and was presented trade-off between both of objective functions with Pareto solution set.

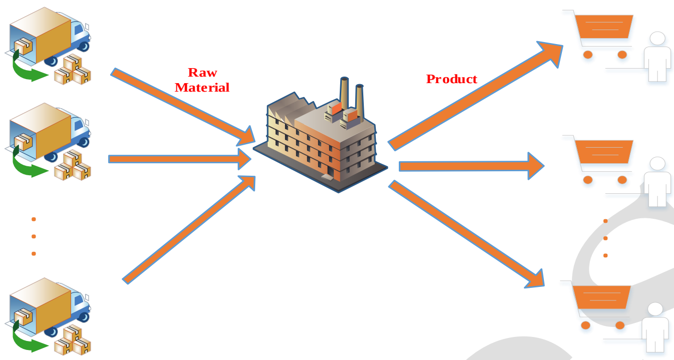


Fig 2. Schematic view of the proposed two-echelon SCN

4 | SCN formulation

In this section, the deterministic mathematical model is described. Indices, parameters and decision variables are used in this model are as follows:

indices	
S	Set of suppliers. $S=1\ldots s$
I	Set of raw materials .$I=1\ldots i$
P	Set of markets. $P=1\ldots p$
T	Set of time periods. $T=1\ldots t$
parameters	
SP_{pt}	selling price of product p in time period t
D_{pmt}	demand of market m for product p in time period t
MC_{si}	maximum capacity of supplier S to supply the raw material i
Q_{ip}	required amount of raw material i for produce product p
PT_t	total available time for production in time period t
PS_P	production time of product p
CO_{pt}	operational cost of producing product p in time period t
SC_{pm}	shortage cost for unsatisfied demand of product p in market m
FO_{st}	fix ordering cost from supplier s in time period t
TCR_{si}	transportation cost of raw material i from supplier s
TCP_{pm}	transportation cost of product p from manufacturer to market m
HC_i	holding cost of per unit raw material i
HP_p	holding cost of per unit product p
PC_{si}	purchasing cost of per unit raw material i from supplier s
IWR	Importance weight of robustness
IWF	Importance weight of flexibility

IWA	Importance weight of agility
IWL	Importance weight of leanness
IWI	Importance weight of integrity
RCR_s	resilience score supplier s for robustness
RCF_s	resilience score supplier s for flexibility
RCA_s	resilience score supplier s for agility
RCL_s	resilience score supplier s for leanness
RCI_s	resilience score supplier s for integrity
decision variables	
x_{sit}	order quantity of raw material i from supplier *s* in time period *t*
ypt	quantity of product *p* in time period *t*
u_{pmt}	quantity of unsatisfied demand for product p in market m in time period t
qs_{pmt}	quantity of shipped product *p* to market *m* in time period *t*
ir_{it}	inventory level of raw material *i* in time period *t*
ip_{pt}	inventory level of product *p* in time period *t*
vf_{st}	binary variable; equal 1.if an order placed with supplier *s* in time period t; 0, otherwise

$$MaxZ_1 = \sum_p \sum_m \sum_t SP_{pt} qs_{pmt} - \sum_p \sum_t CO_{pt} y_{pt} - \sum_s \sum_t FO_{st} vf_{st} - \sum_s \sum_i \sum_t TCR_{si} x_{sit} - \sum_p \sum_m \sum_t TCP_{pm} qs_{pmt} - \sum_i \sum_t HC_i\, ir_{it} - \sum_p \sum_t HP_p ip_{pt} - \sum_s \sum_i \sum_t PC_{si} x_{sit} - \sum_p \sum_m \sum_t SC_{pm} u_{pmt} \quad (1)$$

$$MaxZ_2 = IWR(\sum_s RCR_s(\sum_i \sum_t x_{sit})) + IWA(\sum_s RCA_s(\sum_i \sum_t x_{sit})) + IWL(\sum_s RCL_s(\sum_i \sum_t x_{sit})) + IWF(\sum_s RCF_s(\sum_i \sum_t x_{sit})) + IWI(\sum_s RCI_s(\sum_i \sum_t x_{sit})) \quad (2)$$

$$D_{pmt} = qs_{pmt} + u_{pmt} \qquad \forall p.m.t \qquad (3)$$

$$\sum_m qs_{pmt} + ip_{pt} = y_{pt} + ip_{p(t-1)} \qquad \forall p.t \qquad (4)$$

$$\sum_s x_{sit} + ir_{i(t-1)} = ir_{it} + \sum_p \sum_i Q_{ip} y_{pt} \qquad \forall i.t \qquad (5)$$

$$\sum_p PS_p y_{pt} \le PT_t \qquad \forall t \qquad (6)$$

$$\sum_t x_{sit} \le MC_{si} \qquad \forall s.i \qquad (7)$$

$$x_{sit} \le M * vf_{st} \qquad \forall s.i.t \qquad (8)$$

$$x_{sit}.\, y_{pt}.\, u_{pmt}.\, qs_{pmt}.\, ir_{it}.\, ip_{pt} \in R^+ \qquad (9)$$
$$vf_{st} \in \{0.1\}$$

In this model, first objective function present maximum profit from selling final product minus supply chain network costs(include: operational cost, fix order cost, transportation cost, holding cost, purchasing cost of raw material and shortage cost).the second objective function maximize the total value of supplier resiliency . in this objective function, we calculate each supplier resiliency based on proposed resiliency factors and their importance weight.

Equation 3 propose demand in each time period, this equation states demand is equal to satisfy demand and unsatisfied demand. Constraint 4 and 5 show inventory level of product and raw material. Equation 4 states quantity of product in each period time equal to quantity of product produced in the same period time plus product inventory from last time period. Same as equation 4, in equation 5 we calculate quantity of raw material in each period that is related to inventory of last time period. Constraint 6, described that total production time in each period time should be less than or equal to the total available time in that time period. Equation 7 states that order quantity from each supplier should be less than or equal to maximum capacity of supplier. Equation (8) are defined to control quantity order from supplier be activated when a supplier is open. if a supplier is open, the right side of the constraint can take amount

4.1 | The robust model formulation

In this study, we considered introduced approach by Bertsimas and Sim to obtain the robust optimization. this approach present the robust formulation that can deal with to parameter uncertainty and extend to discrete optimization problem [6].

We consider set of uncertainty coefficient a ̃_ij.j∈J that take values according to a symmetric distribution in interval [a_ij-a ̂_ij.a_ij+a ̂_ij] where a_ij,a ̂_ij show nominal and maximum deviation from nominal, respectively. for every i, the budget of uncertainty is defined as Γ_i, it's not necessarily integer and can take values in the interval [0.|J_i |], that |J_i | shows number of uncertainty parameters of constraint ith. Decision makers can choose Γ_i values base on risk level. If they choose Γ_i=0 , all parameters will take nominal value and Γ_i=|J_i | denotes worst case introduced by Soyster [29].

This approach goal is to be protected against all cases above ⌊Γ_i⌋, and one coefficient a ̂_it change to worst case with value (Γ_i-⌊Γ_i⌋) a ̂_it . based on above explanations, Bertsimas and Sim introduced following nonlinear formulation:

$$\max C'x \tag{10}$$

$$\sum_{j\in J}\bar{a}_{ij}x_j + \underset{\{s_i\cup t_i|\ s_i\subseteq J_i.|s_i|=\lfloor\Gamma_i\rfloor.t_i\in J_i\setminus s_i\}}{\mathrm{Max}}\left\{\sum_{j\in s_i}\hat{a}_{ij}y_i + (\Gamma_i-\lfloor\Gamma_i\rfloor)\hat{a}_{it}y_t\right\}\le b_i \qquad -y_j \le x_i \le y_j \qquad \forall i$$

$$-l_j \le x_j \le l_j \qquad \forall j$$

$$y_j \ge 0 \qquad \forall$$

If Γ_i chosen as integer, Bertsimas and Sim introduced protective function of i th constraint as follow:

$$\beta(x.\Gamma_i) = \underset{\{s_i\cup t_i|\ s_i\subseteq J_i.|s_i|=\lfloor\Gamma_i\rfloor.t_i\in J_i\setminus s_i\}}{\mathrm{Max}}\left\{\sum_{j\in s_i}\hat{a}_{ij}|x_j| + (\Gamma_i-\lfloor\Gamma_i\rfloor)\hat{a}_{it}|x_t|\right\} \tag{11}$$

If $\Gamma_i = 0, \beta(x.\Gamma_i) = 0$ constraints will be equivalent to nominal and model change to deterministic. If $\Gamma_i = |J|$

, $\beta(x.\Gamma_i) = 0$ so we have Robust Formulation of Soyster. By varying $\Gamma_i \in [0.|J_i|]$, we adjust robustness of the model with conservation level of the solution.

In order to linearization of model 10 and using protective function with x^* vector, the robust counterpart of the model presented as follow:

$$\beta(x^*.\Gamma_i) = Maximize\ \sum_{j\in J_i}\hat{a}_{ij}|x^*{}_j|\eta_{ij} \tag{12}$$

$$\sum_{j\in J_i}\eta_{ij} \le \Gamma_i \qquad \forall i \tag{13}$$

$0 \leq \eta_{ij} \leq 1 \qquad \forall i.j \qquad (14)$

Model 10 has linear formulation as follow:

$$Maximize = c'x \qquad (15)$$

$$\sum_{j\in J} \bar{a}_{ij}\, x_j + \lambda_i \Gamma_i + \sum_{j\in J_i} \rho_{ij} \leq b_i \qquad \forall i \qquad (16)$$

$$\lambda_i + \rho_{ij} \geq \hat{a}_{ij} y_j \qquad \forall i.j \qquad (17)$$

$$-y_j \leq x_j \leq y_j \qquad \forall i.j \qquad (18)$$

$$l_j \leq x_j \leq u_j \qquad \forall j \qquad (19)$$

$$\rho_{ij} \geq 0 \qquad \forall i.j \qquad (20)$$

$$y_j \geq 0 \qquad \forall j \qquad (21)$$

$$\lambda_i \geq 0 \qquad \forall i \qquad (22)$$

By strong duality, in order to model 10 is feasible and bounded so dual of model 10 is feasible and bounded with the objective function values are coincide. In constraint 16, λ _i and ρ _ij are dual variables and used for linearization.

In this paper, processing time is very uncertain. And has influence on productivity. Also demand is related to predicting so this parameter has large uncertainty in model. therefore, we consider constraints 4 and 7 that have uncertain parameters. we states the robust counterpart of these constraints [30].

For constraint 7, according to Bertsimas and Sim, the protection function $\beta(x^*.\Gamma_t)$ is defined as equation 23 where $\Gamma_t \in [0.|J|]$.

$$\beta(x^*.\Gamma_t) = Maximize \sum_{j\in|J|} \widehat{PS}_p |x^*| \mu_{pt} \qquad (23)$$

$$\sum_{j\in J} \mu_{pt} \leq \Gamma_t \qquad \forall t \qquad (24)$$

$$0 \leq \mu_{pt} \leq 1 \qquad \forall p.t \qquad (25)$$

Finally this constraint can be written as equation 26-29 , with using dual variables, we can make robust counterpart as following:

$$\sum_{j\in J} \overline{PS}_p y_{pt} + \sum_{j\in J} \rho_{pt} + \Gamma_t \lambda_t \leq PT_t \qquad \forall t \qquad (26)$$

$$\lambda_t + \rho_{pt} \geq \widehat{PS}_p y_{pt} \qquad \forall p.t \qquad (27)$$

$$\rho_{pt} \geq 0 \qquad \forall p.t \qquad (28)$$

$$\lambda_t \geq 0 \qquad \forall t \qquad (29)$$

to deal with uncertainty of demand in constraint 4, we suppose $\hat{d}$ take values between $\bar{d} + \hat{d}$ and $d - \hat{d}$ which $\hat{d}$ denotes to deviation from nominal value. Equation 4 can be written as follows (Liu Lei, Zhang & Wu, 2018):

$$tr_{pmt} \geq \bar{d}_{pmt} + \frac{\Gamma_{pmt}}{|J|}\hat{d}_{pmt} - b_{pmt} \qquad \forall p.m.t \qquad (30)$$

To optimize multi objective robust model , ε constraint method is used. This method is an algorithm transformation method that transforms objective functions to single objective function by using main objective and consider other objective functions as constraints. In this research, we have two objective function, total profit and supplier resiliency. We consider total profit as main objective function and another objective function divided to 10 points between minimum and maximum values, for more detail about this method please refer to [31].

5 | Computational results

In this section, proposed model implemented in real-world case in food industry [3]. Model solved by Lingo18 with process Intel core i7 2.8 GHz and 8 GB RAM.

Supplier resilience aspect of this study, investigated with using MCDM process and Fuzzy SECA method has been used to calculate resilient supplier selection, importance weight of criteria and resilience scores of suppliers for second objective function. robust mathematical model that presented in section 4, is considered for four products (P2,P2,P3,P4), five supplier (S1,S2,S3,S4,S5), four raw materials (i1,i2,i3,i4), two markets (m1,m2) and four time periods (t1,t2,t3,t4). This model introduce as mixed-integer linear programming (MILP) model.

5.1 | Resilient supplier selection

The SECA method is relatively new MCDM method that evaluate criteria weight and alternatives performance simultaneously. The original of fuzzy SECA proposed in 2018 and evaluation process was made by solving a deterministic multi-objective mathematical model[32]. The original SECA method made based on crisp inputs and mathematical model also output of this method present crisp output. but in this study, with using of α-cut approach we extend the SECA method based on fuzzy inputs and mathematical model to handle uncertainty of information. In this method consider the variations in decision matrix and with using interval matrix related to standard deviations of criteria can determine criteria weights [33].

Firstly we should determine the resilience factors, in this study resilience factors include: robustness, flexibility, leanness, integrity and agility. Then, get the initial evaluations of the factors from each decision maker (DM). We can use any scoring method for collecting the decision makers opinions.in this study, used scale between o and 100 for criteria evaluations. we use Simple Multi-Attribute Rating (SMART) Technique that proposed by Von Winterfeldt and Edwards [34] to calculate the subjective criteria weights, so the following equation used to determine the weight of each criterion (ω_j^s).table (1) present decision makers scores with criteria weights that calculated with equation 31

$$\omega_j^s = \frac{\sum_k I_{jk}}{\sum_k \sum_j I_{jk}} \qquad (31)$$

In this equation I_{jk} shows that importance of jth criteria that assigned by kth decision maker

Table1.weights of the criteria.

	C1	C2	C3	C4	C5
D1	30	40	35	25	60
D2	40	50	45	35	50
D3	50	40	30	30	70
D4	45	40	30	30	40
D5	30	50	50	30	60
ω_j^s	0.1884	0.2126	0.1835	0.1449	0.2705

In next step, collect decision makers opinions for alternative performance on each criteria. We should know, in this study, alternatives defined as suppliers. suppose that we have MCDM problem with n alternatives and m criteria and x_{ij} shows decision makers scores related to ith alternative on jth criteria (x_{ij} >0). Scores in this step show with using linguistic variables as shown in table 2. the main advantage of linguistic variables is that can easily transformed to fuzzy numbers. The list of these variables with equivalent of their fuzzy numbers can be seen in table 3.

Table2.The performance of the alternatives on each criterion given by each DM.

		C1	C2	C3	C4	C5
D1	S1	VH	H	ML	H	ML
	S2	VH	H	MH	MH	VL
	S3	MH	MH	H	L	M
	S4	H	MH	ML	MH	ML
D2	S1	H	H	MH	MH	ML
	S2	VH	MH	ML	H	ML
	S3	H	M	M	L	M
	S4	MH	H	M	H	M
D3	S1	H	M	M	MH	ML
	S2	H	MH	M	MH	ML
	S3	H	MH	MH	M	M
	S4	M	M	MH	H	L
D4	S1	H	MH	MH	M	ML
	S2	VH	H	M	H	L
	S3	H	ML	M	L	L
	S4	H	M	ML	H	ML
D5	S1	H	MH	MH	MH	M
	S2	H	M	ML	MH	VL
	S3	MH	MH	M	L	M
	S4	H	M	ML	MH	L

Table3. The linguistic variables and fuzzy numbers

Linguistic Variables	Fuzzy Numbers
Very Low (VL)	(0, 0, 0.1, 0.2)
Low (L)	(0.1, 0.2, 0.2, 0.3)
Medium Low (ML)	(0.2, 0.3, 0.4, 0.5)
Medium (M)	(0.4, 0.5, 0.5, 0.6)
Medium High (MH)	(0.5, 0.6, 0.7, 0.8)
High (H)	(0.7, 0.8, 0.8, 0.9)
Very High (VH)	(0.8, 0.9, 1, 1)

In next step, linguistic variables transformed to fuzzy data then aggregate alternatives performance related to different decision makers to constitute fuzzy decision matrix that presented in table 4 The elements of the fuzzy decision-matrix ($\tilde{x}_{ij}$) are defined as $x_{ij} = \left(x_{ij}^{a}.x_{ij}^{b}.x_{ij}^{c}.x_{ij}^{d}\right)$. then presented in table 5, we should make interval decision matrix ($x_{ij}^{\alpha} = \left[x_{ij}^{L\alpha}.x_{ij}^{U\alpha}\right]$) with using equation 32 and 33.

$$x_{ij}^{L\alpha} = \alpha\left(x_{ij}^{b} - x_{ij}^{a}\right) + x_{ij}^{a} \qquad (32)$$

$$x_{ij}^{U\alpha} = x_{ij}^{d} - \alpha\left(x_{ij}^{d} - x_{ij}^{c}\right) \qquad (33)$$

In this study the value of α which shows the level of uncertainty, is set to 0.5 for calculation of the elements of this matrix the interval of decision matrix is also shown in table 6.

Table4. Fuzzy decision matrix

		C1	C2	C3	C4	C5
D1	S1	(0.8,0.9,1,1)	(0.7,0.8,0.8,0.9)	(0.2,0.3,0.4,0.5)	(0.7,0.8,0.8,0.9)	(0.2,0.3,0.4,0.5)
	S2	(0.8,0.9,1,1)	(0.7,0.8,0.8,0.9)	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.0,0.0,0.1,0.2)
	S3	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.7,0.8,0.8,0.9)	(0.1,0.2,0.2,0.3)	(0.4,0.5,0.5,0.6)
	S4	(0.7,0.8,0.8,0.9)	(0.5,0.6,0.7,0.8)	(0.2,0.3,0.4,0.5)	(0.5,0.6,0.7,0.8)	(0.2,0.3,0.4,0.5)
D2	S1	(0.7,0.8,0.8,0.9)	(0.7,0.8,0.8,0.9)	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.2,0.3,0.4,0.5)
	S2	(0.8,0.9,1,1)	(0.5,0.6,0.7,0.8)	(0.2,0.3,0.4,0.5)	(0.7,0.8,0.8,0.9)	(0.2,0.3,0.4,0.5)
	S3	(0.7,0.8,0.8,0.9)	(0.4,0.5,0.5,0.6)	(0.4,0.5,0.5,0.6)	(0.1,0.2,0.2,0.3)	(0.4,0.5,0.5,0.6)
	S4	(0.5,0.6,0.7,0.8)	(0.7,0.8,0.8,0.9)	(0.4,0.5,0.5,0.6)	(0.7,0.8,0.8,0.9)	(0.4,0.5,0.5,0.6)
D3	S1	(0.7,0.8,0.8,0.9)	(0.4,0.5,0.5,0.6)	(0.4,0.5,0.5,0.6)	(0.5,0.6,0.7,0.8)	(0.2,0.3,0.4,0.5)
	S2	(0.7,0.8,0.8,0.9)	(0.5,0.6,0.7,0.8)	(0.4,0.5,0.5,0.6)	(0.5,0.6,0.7,0.8)	(0.2,0.3,0.4,0.5)
	S3	(0.7,0.8,0.8,0.9)	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.4,0.5,0.5,0.6)	(0.4,0.5,0.5,0.6)
	S4	(0.4,0.5,0.5,0.6)	(0.4,0.5,0.5,0.6)	(0.5,0.6,0.7,0.8)	(0.7,0.8,0.8,0.9)	(0.1,0.2,0.2,0.3)
D4	S1	(0.7,0.8,0.8,0.9)	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.4,0.5,0.5,0.6)	(0.2,0.3,0.4,0.5)
	S2	(0.8,0.9,1,1)	(0.7,0.8,0.8,0.9)	(0.4,0.5,0.5,0.6)	(0.7,0.8,0.8,0.9)	(0.1,0.2,0.2,0.3)
	S3	(0.7,0.8,0.8,0.9)	(0.2,0.3,0.4,0.5)	(0.4,0.5,0.5,0.6)	(0.1,0.2,0.2,0.3)	(0.1,0.2,0.2,0.3)
	S4	(0.7,0.8,0.8,0.9)	(0.4,0.5,0.5,0.6)	(0.2,0.3,0.4,0.5)	(0.7,0.8,0.8,0.9)	(0.2,0.3,0.4,0.5)
D5	S1	(0.7,0.8,0.8,0.9)	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.4,0.5,0.5,0.6)
	S2	(0.7,0.8,0.8,0.9)	(0.4,0.5,0.5,0.6)	(0.2,0.3,0.4,0.5)	(0.5,0.6,0.7,0.8)	(0.0,0.0,0.1,0.2)
	S3	(0.5,0.6,0.7,0.8)	(0.5,0.6,0.7,0.8)	(0.4,0.5,0.5,0.6)	(0.1,0.2,0.2,0.3)	(0.4,0.5,0.5,0.6)
	S4	(0.7,0.8,0.8,0.9)	(0.4,0.5,0.5,0.6)	(0.2,0.3,0.4,0.5)	(0.5,0.6,0.7,0.8)	(0.1,0.2,0.2,0.3)

Table5. aggregated fuzzy decision matrix

	C1	C2	C3	C4	C5
S1	(3.6,4.1,4.2,4.6)	(2.8,3.3,3.5,4)	(2.1,2.6,3.0,3.5)	(2.6,3.1,3.4,3.9)	(1.2,1.7,2.1,2.6)
S2	(3.8,4.3,4.6,4.8)	(2.8,3.3,3.5,4)	(1.7,2.2,2.5,3.0)	(2.9,3.4,3.7,4.2)	(0.5,0.8,1.2,1.7)
S3	(3.1,3.6,3.8,4.3)	(2.1,2.6,3.0,3.5)	(2.4,2.9,3.0,3.5)	(0.8,1.3,1.3,1.8)	(1.7,2.2,2.2,2.7)
S4	(3,3.5,3.6,4.1)	(2.4,2.9,3.0,3.5)	(1.5,2.0,2.4,2.9)	(3.1,3.6,3.8,4.3)	(1.0,1.5,1.7,2.2)

Table6. interval decision matrix

	C1	C2	C3	C4	C5
S1	(3.85,4.4)	(3.05,3.75)	(2.35,3.25)	(2.85,3.65)	(1.45,2.35)
S2	(4.05,4.7)	3.05,3.75)	(1.95,2.75)	(3.15,3.95)	(0.65,1.45)
S3	(3.35,4.05)	(2.35,3.25)	(2.65,3.25)	(1.05,1.55)	(1.95,2.45)
S4	(3.25,3.85)	(2.65,3.25)	(1.75,2.65)	(3.35,4.05)	(1.25,1.95)

In all matrixes we should have elements with standard range, so we can use equation 34 to normalized the interval decision matrix $x_{ij}^{N\alpha} = \left[x_{ij}^{NL}.x_{ij}^{NU}\right]$

$$x_{ij}^{N\alpha} = \begin{cases} \left[\frac{x_{ij}^{L\alpha}}{Ux_j}.\frac{x_{ij}^{U\alpha}}{Ux_j}\right] \\ \left[\frac{Lx_j}{x_{ij}^{U\alpha}}.\frac{Lx_j}{x_{ij}^{L\alpha}}\right] \end{cases} \quad (34)$$

Where $Ux_j = \frac{max x_{ij}^{U\alpha}}{i}$, $Lx_j = \frac{min x_{ij}^{L\alpha}}{i}$ shows the sets of beneficial and non beneficial criteria, respectively. respectively.in this study all criteria are beneficial and we don't have non beneficial criteria between suppliers. the normalized interval decision matrix is presented at table (7)

Table7. normalized interval decision matrix

	C1	C2	C3	C4	C5
S1	(0.875,1)	(0.693,0.852)	(0.534,0.739)	(0.648,0.829)	(0.329,0.534)
S2	(0.862,1)	(0.649,0.798)	(0.415,0.585)	(0.670,0.840)	(0.138,0.308)
S3	(0.827,1)	(0.580,0.802)	(0.654,0.802)	(0.259,0.382)	(0.481,0.605)
S4	(0.802,0.951)	(0.654,0.802)	(0.432,0.654)	(0.827,1)	(0.309,0.481)

Now, we should calculate the average of the lower and upper bounds to determine a crisp decision matrix based on normalized interval decision matrix. $x_{ij}^{C\alpha}$ denotes the elements of this matrix

$$x_{ij}^{C\alpha} = \frac{x_{ij}^{NL}+x_{ij}^{UL}}{2} \quad (35)$$

In next step we should calculate two important parameters of the SECA method like σ_j and π_j. The calculation of these parameters are based on the crisp decision matrix. The following equations are used in this step:

$$\sigma_j^C = \frac{\sigma_j}{\sum_l \sigma_l} \quad (36)$$

$$\pi_j^C = \frac{\pi_j}{\sum_l \pi_l} \quad (37)$$

$$\pi_j = \sum_{l=1}^{m}(1 - r_{jl}) \quad (38)$$

σ_j is standard deviation of each column of the matrix and π_j is the degree of conflict between any criteria and other criteria. The values of π_j is described as the correlation between jth and lth columns(r_{jl}).the crisp matrix with these two parameters are also presented in table 8.

Author's LastName | J. Appl. Res. Ind. Eng. X(x) (xx) x-x

Table8.crisp matrix

	C1	C2	C3	C4	C5
S1	0.9375	0.7727	0.6363	0.7386	0.4318
S2	0.9308	0.7234	0.5000	0.7553	0.2234
S3	0.9135	0.6913	0.7283	0.3209	0.5432
S4	0.8765	0.7283	0.5432	0.9135	0.3950
σ_j^C	0.0498	0.0610	0.1854	0.4619	0.2417
π_j^C	0.1912	0.1693	0.1933	0.2476	0.1984

In the final step, we solve two mathematical model based on SECA method. the first model is for beneficial criteria and the second model is for non beneficial criteria. These models are based on lower and upper bounds of interval decision matrix. we defined another variable as subjective weight (λ) and both models used the same reference parameters for determine of the criteria weights. defined models are as following.

$$MaxZ^l = \lambda_a^L - \beta(\lambda_b^L.\lambda_c^L.\lambda_d^L)$$

$$\lambda_a^L \leq S_i^L \qquad \forall i \in \{1.2 \ldots\ldots n\} \tag{39}$$

$$S_i^L = \sum_{j=1}^{m} \omega_{j1} x_{ij}^{NL} \qquad \forall i \in \{1.2 \ldots\ldots n\} \tag{40}$$

$$\lambda_b^L = \sum_{j=1}^{m} \left(\omega_{j1} - \sigma_j^C\right)^2 \tag{41}$$

$$\lambda_c^L = \sum_{j=1}^{m} \left(\omega_{j1} - \pi_j^C\right)^2 \tag{42}$$

$$\lambda_d^L = \sum_{j=1}^{m} \left(\omega_{j1} - \omega_j^s\right)^2 \tag{43}$$

$$\sum_{j=1}^{m} \omega_{j1} = 1 \tag{44}$$

$$\omega_{j1} \leq 1 \qquad \forall j \in \{1.2 \ldots\ldots m\} \tag{45}$$

$$\omega_{j1} \geq \varepsilon \qquad \forall j \in \{1.2 \ldots\ldots m\} \tag{46}$$

Model 2:

$$MaxZ^U = \lambda_a^U - \beta(\lambda_b^U.\lambda_c^U.\lambda_d^U) \tag{47}$$

$$\lambda_a^U \leq S_i^U \qquad \forall i \in \{1.2 \ldots\ldots n\} \tag{48}$$

$$S_i^U = \sum_{j=1}^{m} \omega_{j2} x_{ij}^{NU} \qquad \forall i \in \{1.2 \ldots\ldots n\} \tag{49}$$

$$\lambda_b^U = \sum_{j=1}^{m} \left(\omega_{j2} - \sigma_j^C\right)^2 \tag{50}$$

$$\lambda_c^U = \sum_{j=1}^{m} \left(\omega_{j2} - \pi_j^C\right)^2 \tag{51}$$

$$\lambda_d^U = \sum_{j=1}^{m} \left(\omega_{j2} - \omega_j^s\right)^2 \tag{52}$$

$$\sum_{j=1}^{m} \omega_{j2} = 1 \tag{53}$$

$$\omega_{j2} \le 1 \qquad \forall j \in \{1.2 \ldots .m\} \qquad (54)$$

$$\omega_{j2} \ge \varepsilon \qquad \forall j \in \{1.2 \ldots .m\} \qquad (55)$$

Based on model solution results, we can determine intervals as shown as follows:

$$S_i = [S_i^L . S_i^U] \qquad (56)$$

$$\omega_j = [\omega_j^L . \omega_j^U] = [\min(\omega_{j1} . \omega_{j2}) . \max(\omega_{j1} . \omega_{j2})] \qquad (57)$$

According of interval obtained. We compare intervals or average of the upper and lower bounds to ranked alternatives (suppliers) performance and determined final criteria weights as shown in table 9.

Table9. Supplier and criteria ranking

alternatives	S_i	criteria	ω_j
S1	0.6816	W5	0.2705
S4	0.6590	W2	0.2126
S3	0.6463	W1	0.1884
S2	0.5908	W3	0.1836
		W4	0.1449

Using the current results, we can determine resiliency score for each supplier and also we presented weight importance of any criteria as shown in table 10 and 11.

Table10. resilience scores of suppliers

	S1	S2	S3	S4
Resilience	0.6815	0.5908	0.6462	0.659

Table11. importance weight of criteria

	robustness	agility	leanness	flexibility	integrity
Importance weight	0.1884	0.2125	0.1835	0.1449	0.2705

5.2 | Robust computational results

After determining the importance weight of resilience criteria and resilience scores of suppliers, the results imported to Second objective function. Now, we should optimize the robust model with considering the first objective function. We use ε - constraint method to solve the robust model of supply chain network. therefore main objective function, will be maximize the supply chain profit and the second objective function change to constraint.

Using the current approach helps managers to deal with against disruptions and maximize the profit in different situations. They can find out product inventory and raw material inventory in different levels and make decisions based on situations. Furthermore, this results, help to procurement managers to allocate the optimum order to best resilient supplier according the resiliency and costs. Therefore, optimum amount of decision variables for different uncertain variables are shown in table 12 and 13 as mentioned in previous section, when Γ =0 model change to deterministic model for any conservation level. furthermore, it is clear by increasing the conservation level, total inventory level increased.

Table 12) Results under different setting of processing time parameter

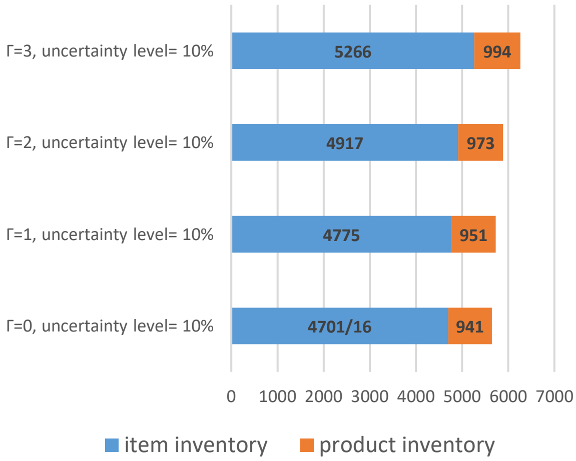
			item inventory				Total production				purchase				product inventory			
Γ	Uncertainty level	Objective	t1	t2	t3	t4	t1	t2	t3	t4	t1	t2	t3	t4	t1	t2	t3	t4
0	-	1673957	2088.9	1256	1356.26	0	28329	19199	9920	11856	9130	9130	9279	9920	524	259	157	0
1	0.05	1652757	20104	1285	1346		28279	19199	9920	11263	9130	9130	9279	9920	524	259	157	0
1	0.1	1638861	2155	1289	1230	0	28281	19174	9916	11189	8980	8898	9125	9752	524	259	157	0
1	0.2	1618439	2265	1300	1452	0	28282	19156	9889	11176	8920	8798	9112	9685	524	259	157	0
2	0.05	1652757	2265	1350	1510	0	28356	19452	9942	11220	9562	7256	9200	8654	525	263	158	0
2	0.1	1625787	2389	1410	1523	0	28298	19191	9920	11020	9200	7130	8580	8450	524	259	157	0
2	0.2	1608607	2120	1436	1890	0	28312	19195	9920	10988	9056	6998	8410	8098	524	259	157	0
3	0.05	1626752	1900	1446	1560	0	28333	19273	9983	10563	10256	7562	7120	9263	525	260	189	0
3	0.1	1623159	2223	1560	1600	0	28302	19196	9978	10489	9995	7120	6860	9123	524	259	158	0
3	0.2	1607709	2285	1600	1800	0	28315	19188	9902	10320	9456	6890	6520	8825	524	259	157	0

Table 13) Results under different setting of demand parameter

			item inventory				Total production				purchase				Product inventory			
Γ	Uncertainty level	Objective	t1	t2	t3	t4	t1	t2	t3	t4	t1	t2	t3	t4	t1	t2	t3	t4
0	-	1673957	2088.9	1256	1356.26	0	28329	19199	9920	11856	9130	9130	9279	9920	524	259	157	0
0.2	0.05	1674000	2102	1210	1346	0	28423	19295	9968	11201	9178	9178	9327	9968	526	261	158	0
0.2	0.1	1673800	2155	1265	1355	0	28591	19407	10024	10658	9234	9252	9383	10024	529	262	159	0
0.2	0.2	1672150	2265	1298	1381	0	28927	19631	10136	10895	9346	9346	9495	10136	536	265	161	0
0.6	0.05	1673600	2129	1310	1410	0	28759	19519	10080	9887	9290	9322	9439	10250	533	264	160	0
0.6	0.1	1672850	2274	1345	1298	0	29263	19855	10248	10121	9458	9380	9607	10450	542	268	163	0
0.6	0.2	1671800	2164	1420	1288	0	30301	20585	10639	10201	9795	9786	9935	10576	561	278	169	0
1	0.05	1672500	2315	1256	1468	0	29095	19743	10192	10187	9402	9526	9551	10263	539	267	162	0
1	0.1	1671600	2312	1502	1452	0	29911	20287	10464	10215	9674	9725	9823	10478	554	274	166	0
1	0.2	1670952	2223	1498	1490	0	31567	21391	11016	10832	10226	10302	10375	11123	585	289	175	0

Corresponding Author:

As shown in table 13, based on different setting in demand parameter, it is clear that, by increasing Γ and uncertainty level , the total purchase is increased. Inventory level is most important for managers to predict satisfied demand. According to the current model, raw material inventory and product inventory have been pointed as sources for satisfy demand . with attention of this issue, the robust model with uncertainty level 10% and different conservatism are shown in Fig 2 and 3, in deterministic model, the total inventory level is 5642 which is increased to 6260 by rising conservatism in demand parameter under uncertainty level. So it is clear that changing conservatism level on demand parameter has huge influence on satisfy demand than processing time.



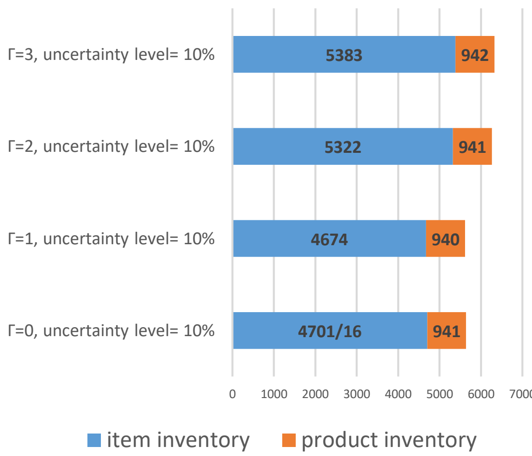


Fig. 2. total inventory by changing the processing time

Fig. 3. total inventory by changing the demand

By looking Fig 4 and 5 we can conclude that in linear condition, conservatism model is not protected against uncertainty conditions because of model with conservatism approach give worst- case than deterministic model but conservatism model with setting conservation level (Γ) is closer to real world case. With increasing uncertainty level in any conservation level, objective function value is reduced, In fact, with increasing conservation level, model chooses variables within determined range strictly and finally, objective function value has gotten worse that is due to robust modelling features.

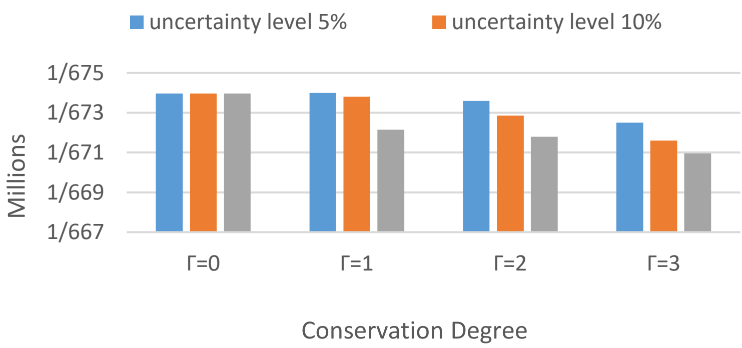


Fig. 4. objective function value under demand uncertainty

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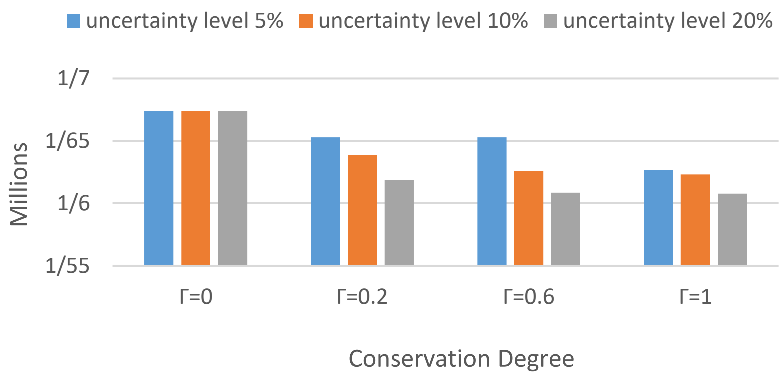

Fig. 5. objective function value under processing time uncertainty

6| Multi objective analysis

Multi objective problems is more difficult than single objective problems because of some objective functions are maximization and some of them are minimization so there is not unique solution for objectives. There is set of optimal solutions that present trade-off solutions for objectives. This set called Pareto front. In fact, multi objective optimization considered as MCDM process that consist of determining all optimal solutions in Pareto sense and preferred solution is selected from Pareto set.(P. Ngatchou, A. Zarei and A. El-Sharkawi,2005)

The two objective functions are optimized simultaneously using the ε -constraint method as follows:

1. The minimum and maximum values for each objectives are obtained, table 14 shows the obtained objective values.These values are used for assigning ε values and the correspondence membership functions for each objective.

2. Objective one (maximization of profit) is left as aim objective function and the second objective(maximization of resilience) are shifted to constraint.

3. The range between the maximum and minimum values for second objective function are divided into ten points. These points are assigned as ε values

Table 14 Shows a set of obtained pareto optimal solutions that represent trade offs amongst two objective. objectives which include maximizing the profit and supplier resiliency . Also, these solutions show the correspondence number of Trade-off solutions among the two objectives are illustrated in Fig. 6

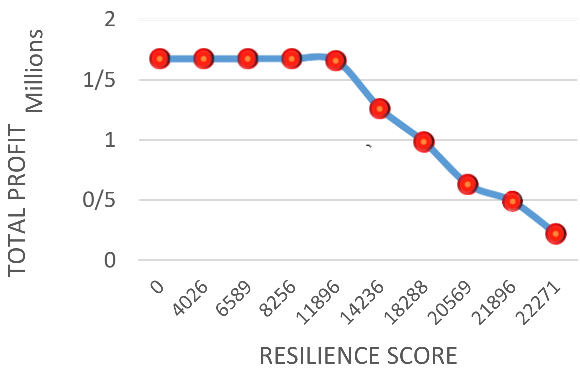

Fig 6) Trade-off solution of both objective functions

Table14) Pareto solutions

#	first objective	second objective
0	0	1.673.957
1	4025.987	1.673.957
2	6589.36	1.673.957
3	8256.29	1.673.957
4	11895.86	1.656.123
5	14235.98	1.258.321
6	18287.59	981.256
7	20569.33	628.749
8	21896.25	489..845
9	22270.98	217.236

According to decision makers preference in resiliency score and robust conservation, Most of the time, resilience supply chain imposes cost to supply chain in industries and decision makers prefer to have robust supply chain than resilience supply chain to minimize costs, but as shown in Fig 6 we can obtain 11000 resilience scores without losing profits or spending cost.

7 | Sensitivity analysis

7.1 | Robust model Sensitivity analysis

In this section, we investigate solutions sensitivity of model in terms of important and changeable. Selecting the conservatism level and uncertainty level for robust model is important for managers and can change the objective value. Therefore, a sensitivity analysis is presented to compare objective function values with different conservatism level on uncertainty levels. Fig 4 and 5 Illustrate increasing uncertainty level in determined conservation degree, reduce the objective function value. This is a reliable result because of, as the level of uncertainty increases, generally, the value of the objective function decrease

In this section, we investigate solutions sensitivity of model in terms of important and changeable. Selecting the conservatism level and uncertainty level for robust model is important for managers and can change the objective value. Therefore, a sensitivity analysis is presented to compare objective function values with different conservatism level on uncertainty levels. Two sensitivity analyse are presented to show the efficiency and applicability of the results. First analyses, Fig 4 and 5 Illustrate increasing uncertainty level in determined conservation degree, reduce the objective function value. This is a reliable result because of, as the level of uncertainty increases, generally, the value of the objective function decrease. In second analyses, for all points of pareto solution total selling price, production cost, transportation cost of products and lost sale are the same, however by decreasing the second objective function, the inventory level cost of raw material, purchasing cost of raw material ordering and transportation of raw material decreased dramatically. moreover, one of the resiliency policies is supply raw materials fro multiple suppliers instead of one supplier. Hence, by decreasing the second objective, fixed ordering cost will be decreased.

Table15) sensitivity analysis of robust model

first objective	second objective	ordering cost of raw material	transportation cost of raw material	holding cost of raw material	purchasing cost of raw material
0	1.673.957	6.800.000	7.379.530	4.576.232	11.103.000
4025.987	1.673.957	6.800.000	7.289.742	4.576.230	11.059.005
6589.36	1.673.957	6.800.000	6.905.621	4.576.233	10.084.561
8256.29	1.673.957	6.754.000	6.598.622	4.102.562	9.600.616
11895.86	1.656.123	5.984.000	6.412.302	3.802.561	9.140.890
14235.98	1.258.321	5.452.000	6.302.510	3.501.242	8.715.362
18287.59	981.256	5.325.000	6.102.353	3.002.655	7.148.925
20569.33	628.749	5.120.000	5.901.232	2.950.008	6.565.412
21896.25	489..845	4.900.000	5.821.451	2.300.032	6.458.936
22270.98	217.236	4.200.365	4.975.633	2.054.781	5.900.302

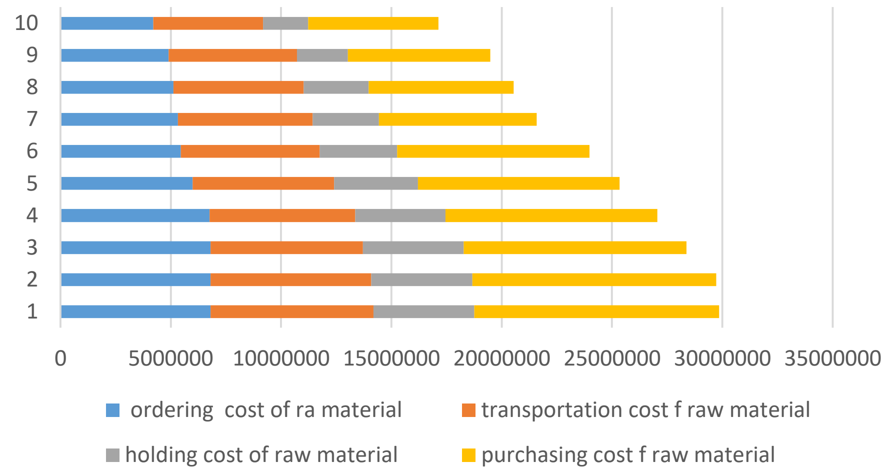

Fig 8. influence of problem parameters on supply chain resiliency

7.2 | Resilient supplier selection Sensitivity analysis

We should investigate the correctness of the supplier selection results with using sensitivity analysis. Because of criteria weights and alternatives performance are resilience variables of this research, so this is not reasonable to use these variables for sensitive analysis by varying their values. in this section, sensitivity analysis of reliability made with changing the uncertainty level (α) .

Another parameter that can use for sensitivity analysis is β . but in this study, we used β according to original model of SECA (β =3). Based on table 15-17 model solved by using 11 values of α between [1,0]. The upper and lower bounds and crisp values of alternative performance and criteria weights calculated according to different values of α .

Table 15) The sensitivity analysis results of lower bounds for criteria and alternatives

	$\alpha=0$	$\alpha=0.1$	$\alpha=0.2$	$\alpha=0.3$	$\alpha=0.4$	$\alpha=0.5$	$\alpha=0.6$	$\alpha=0.7$	$\alpha=0.8$	$\alpha=0.9$	$\alpha=1$
S_1^L	0.5360	0.5529	0.5661	0.5817	0.5976	0.6139	0.6306	0.6486	0.6693	0.6906	0.5509
S_2^L	0.5102	0.5207	0.5318	0.5817	0.5542	0.5657	0.6306	0.5912	0.6092	0.6278	0.5210
S_3^L	0.4641	0.4809	0.4985	0.5163	0.5345	0.5532	0.5722	0.5912	0.6092	0.6278	0.4811
S_4^L	0.4938	0.5106	0.5280	0.5458	0.5641	0.6375	0.6024	0.6237	0.6489	0.6749	0.5107
S_5^L	0.5729	0.5764	0.5913	0.6065	0.6218	0.1548	0.6024	0.6702	0.6889	0.7079	0.5764
C_1^L	0.1598	0.1585	0.1578	0.1569	0.1559	0.1548	0.1538	0.1528	0.1519	0.1512	0.1589
C_2^L	0.1121	0.1113	0.1578	0.1107	0.1104	0.1548	0.1101	0.1103	0.1113	0.1123	0.1116
C_3^L	0.1934	0.1113	0.1956	0.1966	0.1104	0.1983	0.1988	0.1978	0.1931	0.1883	0.1945
C_4^L	0.1934	0.1927	0.1923	0.1922	0.1104	0.1924	0.1927	0.1952	0.2029	0.2105	0.1923
C_5^L	0.1803	0.1816	0.1825	0.1833	0.1104	0.1846	0.1849	0.1952	0.1757	0.1681	0.1814
C_6^L	0.1619	0.1613	0.1607	0.1603	0.1599	0.1597	0.1597	0.1610	0.1651	0.1697	0.1613

Table16) The sensitivity analysis results of upper bounds for criteria and alternatives

	$\alpha = 0$	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.4$	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	$\alpha = 1$
S_1^L	0.8166	0.8134	0.8108	0.8014	0.8045	0.8020	0.7991	0.7961	0.7930	0.7899	0.8134
S_2^L	0.7730	0.7675	0.7627	0.7418	0.7523	0.7478	0.7428	0.7377	0.7327	0.7275	0.7675
S_3^L	0.7063	0.7027	0.7009	0.7176	0.6938	0.6929	0.6901	0.6874	0.6846	0.6818	0.7027
S_4^L	0.7918	0.7898	0.7876	0.7677	0.7837	0.7813	0.7790	0.7767	0.6846	0.7719	0.7898
S_5^L	0.8490	0.8449	0.8405	0.7677	0.8322	0.8274	0.8230	0.8185	0.8140	0.8094	0.8449
C_1^L	0.1558	0.1564	0.1592	0.7677	0.1608	0.1644	0.1661	0.1678	0.1695	0.1711	0.1564
C_2^L	0.1558	0.1014	0.1592	0.1268	0.1006	0.1023	0.1030	0.1039	0.1049	0.1061	0.1014
C_3^L	0.1732	0.1014	0.1740	0.1946	0.1743	0.1746	0.1030	0.1748	0.1749	0.1751	0.1735
C_4^L	0.2401	0.2411	0.2387	0.1842	0.2402	0.2360	0.2348	0.2336	0.1749	0.2309	0.2411
C_5^L	0.1618	0.1612	0.1594	0.1842	0.1570	0.1550	0.1534	0.1519	0.1749	0.1488	0.1612
C_6^L	0.1663	0.1664	0.1668	0.1583	0.1672	0.1677	0.1679	0.1680	0.1681	0.1680	0.1664

Table17) The sensitivity analysis results of crisp data for criteria and alternatives

	$\alpha = 0$	$\alpha = 0.1$	$\alpha = 0.2$	$\alpha = 0.3$	$\alpha = 0.4$	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	$\alpha = 1$
S_1^L	0.6744	0.6808	0.6868	0.6932	0.6998	0.7066	0.7137	0.7209	0.7269	0.7361	0.6805
S_2^L	0.6381	0.6400	0.6439	0.6471	0.6504	0.6539	0.6576	0.6615	0.6640	0.6698	0.6409
S_3^L	0.5857	0.5905	0.6001	0.6075	0.6150	0.6230	0.6309	0.6391	0.6640	0.6560	0.5928
S_4^L	0.6405	0.5905	0.6556	0.6636	0.6719	0.6804	0.6892	0.6983	0.7081	0.7175	0.6479
S_5^L	0.7098	0.7099	0.7149	0.7203	0.7259	0.7315	0.7373	0.1580	0.7505	0.7555	0.7096
C_1^L	0.1551	0.1529	0.1559	0.1563	0.1566	0.1572	0.1576	0.1065	0.1526	0.1586	0.1555
C_2^L	0.1075	0.1045	0.1067	0.1064	0.1061	0.1062	0.1063	0.1890	0.1064	0.1073	0.1071
C_3^L	0.1870	0.1876	0.1882	0.1886	0.1890	0.1891	0.1063	0.2126	0.1884	0.1882	0.1876
C_4^L	0.2134	0.2175	0.2129	0.2127	0.2129	0.1620	0.2126	0.2126	0.2196	0.2130	0.2131
C_5^L	0.1747	0.2175	0.1745	0.1741	0.1737	0.1729	0.1721	0.1710	0.1704	0.1682	0.1747
C_6^L	0.1622	0.1618	0.1618	0.1618	0.1618	0.1620	0.1624	0.1629	0.1626	0.1646	0.1620

The graphical presentation of table 15, 16 and 17 illustrated in Fig 7,8 and 9 respectively. It can be seen, with changing alpha between [0,1], the values of the lower, upper and crisp data in any alternative and criteria changed very little, as it is clear that they are almost in a straight line. we can verify the stability of the final evaluation of the criteria and alternatives in different levels of uncertainty. according to Fig 1 variation between alternatives in lower bounds are greater than upper bounds and crisp data, however the rank of them are stable.

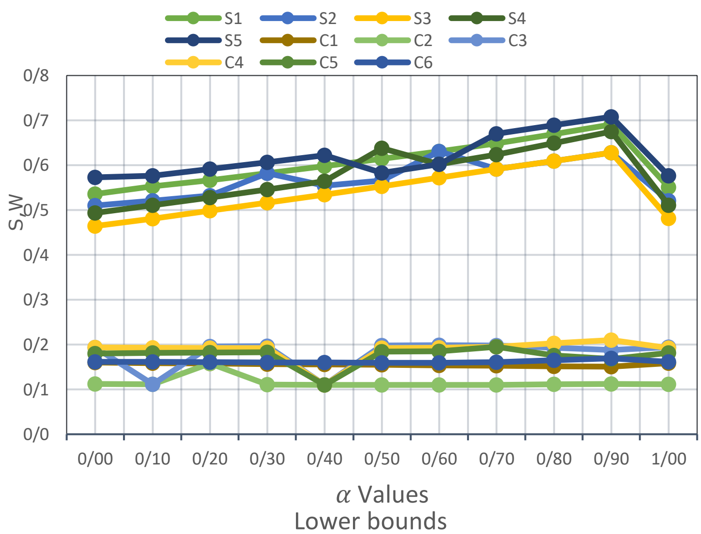

Fig 7) Graphical view of lower bounds by changing uncertainty level

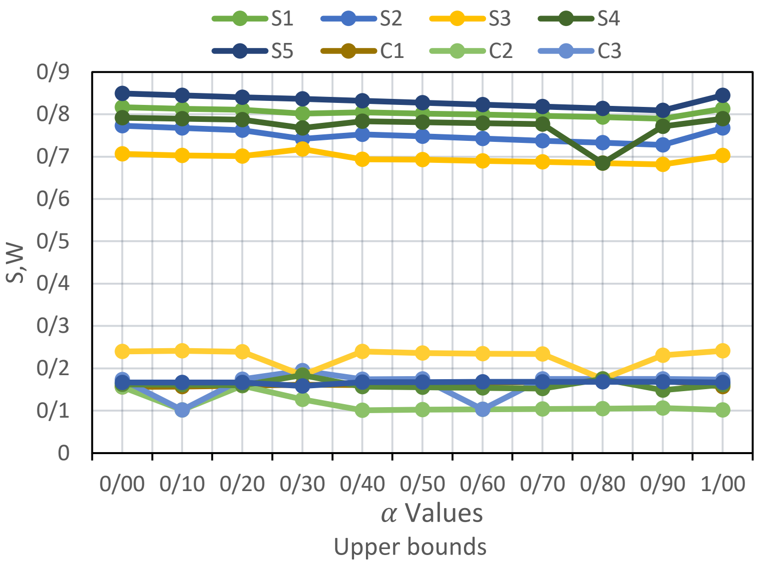

Fig 8) Graphical view of upper bounds by changing uncertainty level

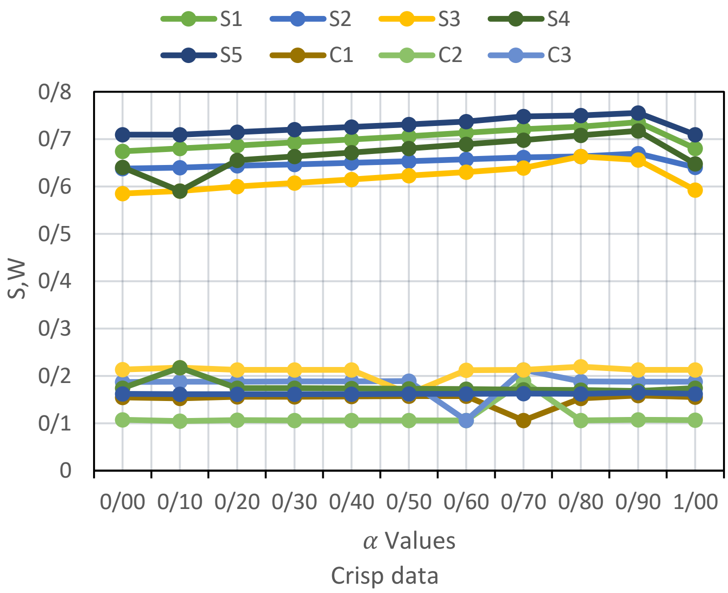

Fig 9) Graphical view of crisp data by changing uncertainty level

8 | Conclusion

In this paper we develop a robust stochastic model to designing a supply chain network structure with resilient suppliers which includes several product, period time and markets to deal with disruptions under demand and processing time uncertainty based on Bertsimas and Sim method. this model guarantee to provide robust supply chain network with resilient supplier selection.

As mentioned in section5, the first step of this study is obtaining the importance weight of four criteria which effect on suppliers resiliency. Therefore, Fuzzy SECA method is used to calculate suppliers resilience score and ranked the suppliers selection. In the next step, we designed the supply chain network model with two objective. First objective is maximize the profit and second objective is maximize the supplier resilience. Therefore model is MILP problem and is difficult to tackle. For optimize the model, results of Fuzzy SECA are imported in second objective function and present robust model with considering demand and processing time uncertainty. Multi objective mathematical Model solved with using ε constraint method and Pareto solution used to calculate feasible area..

By implementing a current approach, the procurement managers can select the best supplier by considering resiliency and they can rank the suppliers to order optimum quantity of raw materials. Furthermore, using Bertsimas and Sim robust model help to managers to select the best decision with considering demand and processing time uncertainty . They can compare deterministic and robust supply chain model and select the best objective value according to conservatism level.

We examined inventory level and robust objective value with different conservatism degree on demand and processing time parameter, our results revealed that demand parameter under uncertainty condition and conservatism degree has more influence on total profit than processing time under uncertainty condition. Finally, we have analyzed the multi objective model in 10 points between min and max second objective function to present trade-off between resilience and profit in our model. Results are shown that with supplier resilience score 4000, the first objective function of model present highest value, therefore in this point we can have resilient supplier with maximum profitability.

As for future research, other type of robust optimization methods such as data driven method can be useful. The resilient supplier selection can be calculate with other type of MCDM process Like OPA, MARKOS. the efficiency of supply chain could be improved by considering reliable aspects as third objective function or sustainable aspects as another objective function. Moreover, to solve the multi objective model in larger scale, could be used metaheuristic algorithms.

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Data Availability

The data that support the findings of this study are available on request from the corresponding author

Conflicts of Interest

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article.

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