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A multi objective optimization framework for robust and resilient supply chain network design using NSGAII and MOPSO algorithms

Ahmad Reza Rezaei[a] and Qiong Liu[a,b*]

[a] *State Key Laboratory of Digital Manufacturing Equipment & Technology, School of Mechanical Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China*
[b]*School of Mechanical and Electrical Engineering, Wuhan Qingchuan University, Wuhan 430204, China*

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A B S T R A C T

Robust supply chain network design that considers supply resiliency, plays vital role in supply chain risk management in dealing with various operational and disruption risks. This study developed a novel three-stage decision approach to consider two echelons robust and resilient supply chain networks. We present a mixed-integer non-linear programming model with two objective functions. The objectives are maximization of SCN profit and maximization of resiliency, where robustness, agility, leanness, flexibility, and integrity can be defined as the five resiliency criteria. Fuzzy Simultaneous Evaluation of Criteria and Alternatives (FSECA) and Simple Multi-Attribute Rating technique (SMART) have been used to obtain the supplier resiliency and weighted importance of resilience criteria. Then, a robust optimization model is built based on uncertainty parameters considering supplier resiliency. A Non-dominated Sorting Genetic Algorithm (NSGAII) and Multi Objective Particle Swarm optimization (MOPSO) were used to solve the robust model on a large scale. parameters calibrated by the Taguchi method and five metrics of performance evaluation were considered to compare the meta-heuristic algorithms. We demonstrate the proposed NSGAII algorithm over a competing method based on five performance metrics. The research findings reveal the optimal level of robust supply chain networks based on algorithm performance and Taguchi analyses. Moreover, the results indicate that when profit increases, resilience can increase simultaneously.

1. Introduction

Currently, supply chain networks (SCN) design is one of the most important problems for supply chain managers. Many companies strive to meet customer satisfaction and expand their business processes by using optimal supply network designs to maximize productivity and minimize risk. The SCN is a multi-echelon network that includes many entities that present services, such as wholesalers, distributors, retailers, or institutions that produce raw materials and finished products, such as suppliers and manufacturers, under various configurations. The major goal of the SCN is to produce a product and send it from one echelon to another to satisfy customer demand with minimum cost and maximum profit. robust and resilient supply chain (SC) can protect firms from environmental disturbances and disruptions (GOli et al., 2020). Raw material costs represent more than half of the total costs and have an impact on supply chain management. Therefore, Suppliers have an impact on supply chain costs and increase the resilience and profitability of an organization (Tirkolaee et al., 2020). However, risk can be minimized by selecting the best suppliers and creating a resilient supply chain (Çebi & Otay, 2016; Arabsheybani & Arshadi Khasmeh, 2021). Supplier resistance against disruptions, evaluated based on resiliency criteria. Today, managers and shareholders are increasingly interested in improving supply chain resilience to reduce disruption effects. Supply chain resiliency is the supply chain ability level to absorb disruptions and maintain basic function and structure when faced with risks (Pettit et al., 2010). The risks in supply chain networks are as follows:

* Corresponding author
E-mail qiongliu@hust.edu.cn (Q. Liu)
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1. Natural risk: These risks affect the supply chain process and transportation in any section of the supply chain. These risks, such as hurricanes, earthquakes, floods, and tsunamis, can affect the uncertainty parameters and availability of resources, ultimately leading to supply chain disruptions.

2. Man-made risk: These risks are disruptions caused by man-made disasters such as industrial accidents, strikes, and war, which disrupt the production and transportation of the supply chain network.

Supply chain specialists should know how to consider, mitigate, deal with, and model these risks. Scenario-based resilient and robust models for dealing with operational risks are presented. These scenarios can be demonstrated using the concepts of uncertainties and probabilistic models using known distribution functions and the fuzzy theory in stochastic models (Mulvey et al., 1995). In this study, a robust supply chain network (RSCN) that considers uncertainty parameters was developed to optimize the objective functions of the SCN model without considering the uncertainty scenario.

To reduce these risks, supply chain resiliency is introduced as a characteristic of SCN that mitigates the effects of disruptions and risks in SCN and attracts managers' attention (Ponomarov & Holcomb, 2009). Resilient SCM deals with functions that consider resilience values to maximize the resiliency in the SCN (Azadnia et al., 2015). Hosseini and Khaled (2019) proposed three resiliency metrics: geographical segregation, vulnerability, and reliability. They used these metrics to show a set of operational decisions for supplier selection and offered an MIP model to find the optimal value of supplier distance and minimum cost as objective functions. They used fuzzy C-mean clustering and ε constraint to optimize the objective functions. Sahebjamnia (2020) focuses on supplier selection and order location in his study, he explored four resilience factors and used DEMATEL and ANP method to investigate the overall performances of suppliers. Kaur & Prakash Singh, (2021) presented MIP model to optimize the order allocation model to suppliers, order allocation cost and disruption risk minimized simultaneously. Robles et al., (2020) presented a hydrogen supply chain (HSC) model. In their model, bi-objective functions minimized the cost and risk, and the demand parameter was under uncertain conditions. They used a metaheuristic algorithm, such as NSGAII, to produce solutions using fuzzy concepts. Nayeri et al. (2021) proposed a multi objective MIP model to minimize the total cost and maximize the social impacts and resilience levels in the supply chain network. Complexity and critically introduced as resiliency metrics. The fuzzy robust approach proposed for uncertainty. they developed the new version of meta goal programming to solve the multi objective programming model, finally authors investigated interactions between responsiveness and resilience metric.Arabsheybani and Arshadi Khasmeh (2021) introduced the food SCN as robust SCN with considering resilient suppliers. They find the weight of resilience criteria by using Fuzzy Analytic Hierarchy Process (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 programming model to maximize total profit and resilience values, finally they used ε constraint to solve the robust model and analysed the trade-off between optimization and robustness. Piya et al. (2022) identified fourteen drivers that have effect on resilient supplier selection in the oil and gas industry, drivers were analysed using Fuzzy-ISM-DEMATEL approach. Their study stated agility and robustness are essential drivers in supplier resiliency than other drivers. Implementation of resilience strategy in copper SCN investigated by Akbari et al. (2022) using backup supplier strategy. MILP model was presented to maximize profit and minimize social impact like water consumption and trade-off between these objectives by using ε constraint and Pareto solutions. Vali-Siar et al. (2022) offered the resiliency problem for open and closed loop supply chain network design under disruption risks. Five strategies introduced to deal with these risks. Stochastic programming model proposed with the objective of maximizing the profit. This model is solved by two metaheuristic algorithms including an Improved Genetic Algorithm (IGA) and an Improved Particle Swarm Optimization (IPSO). After the parameters are calibrated via the Taguchi method, numerical instances are applied to test the model validity. Their results showed that utilizing the resilient strategies has a significant effect on reducing the disruption risks.

Thevenin et al. (2022) applied robust optimization and integrated supplier selection problems under uncertainty. They proposed a heuristic method, including Genetic Algorithm (GA) and a hybrid robust counterpart, to solve large instances and indicated managerial insights for supplier selection. Mirzagoltabar et al. (2023) introduced sustainable CLSCN. maximize profit and reliability defined as function objectives. In their study, some parameters were uncertain, and robust fuzzy optimization was used to manage the uncertainty parameters. MOGWO and NSGAII were developed to solve large-scale size tests. Finally, the results show that uncertainty reduction can reduce the total profit and reliability in the SCN. The resilient vaccine, SCN, addressed by Tirkolaee et al. (2023). They developed a multi-echelon resilient network that considers supplier selection and demand uncertainty. They investigated five pillars to quantify resilience. In their study, resilient supplier selection was calculated using the best–worst method. Finally, a robust multi objective programming model is built and solved by NSGAII and MOPSO, the results are compared with the solution derived by ε constraint. Abbasian et al., (2023) developed a bi objective optimization model to improve the resiliency and sustainability of food SCN. They used pricing strategy to assess and quantify the resiliency. SC mathematical model presented as MINLP that have bi objective function including minimizing the total cost and CO2 emission. To solve this model, they used Heuristic Multi-Choice Goal Programming and Utility Function Genetics Algorithm (HMCGP-UFGA). Feng et al. (2023) studied the supplier selection and order allocation problem by considering occurrence probability of uncertainty. They presented a two-stage robust model and reformed model to MIP model with bi-objective functions including minimizing the cost and maximizing the resiliency. In their study three factors are incorporated to increase the resiliency and finally the fuzzy optimization applied to solve the model.

Although there are different studies in supply chain resiliency and RSCN, individually, there are only a few studies that design resilient and RSCN systems by considering supplier selection and present an optimization framework using meta-heuristic algorithms. For this purpose, this study develops two echelon SCN under uncertainty by considering resilient suppliers and a robust reform model. The goal of the present study is to develop a resilient and robust SCN model and propose MCDM model to measure supplier resiliency, ranking suppliers based on resiliency values, and reformulating the SCN model to a robust model. presented a mixed-integer non-linear programming (MINLP) model solved using metaheuristic algorithms in a large-scale problem. This study defines how the fuzzy MCDM method, in terms of resilience criteria, can assist managers in forming a robust supply chain considering uncertainty conditions while meeting the resilience requirements of suppliers. The contribution of this study was defined to consider resiliency in the RSCN, deviating from previous studies that used MCDM to identify resilient suppliers and implement scenarios in a robust mathematical model. Unlike previous studies on supplier resiliency, we used the Fuzzy Simultaneous Evaluation of Criteria and Alternatives (FSECA) model introduced in 2018. This method uses criteria weights to present the supplier resiliency. Another contribution of this study was presented as implementation of fuzzy theory in RSCNs under uncertainty parameters and the optimization of robust and resilient SCN. This contributes to the aim to obtain more accurate results than the use of a single technique.

2. Methodology

The proposed three-stage decision framework included a resilient supplier in the first stage, a multi objective robust model in the second stage, and an integrated robust SCN model and resilient supplier selection in the third stage, as depicted in Fig. 1.

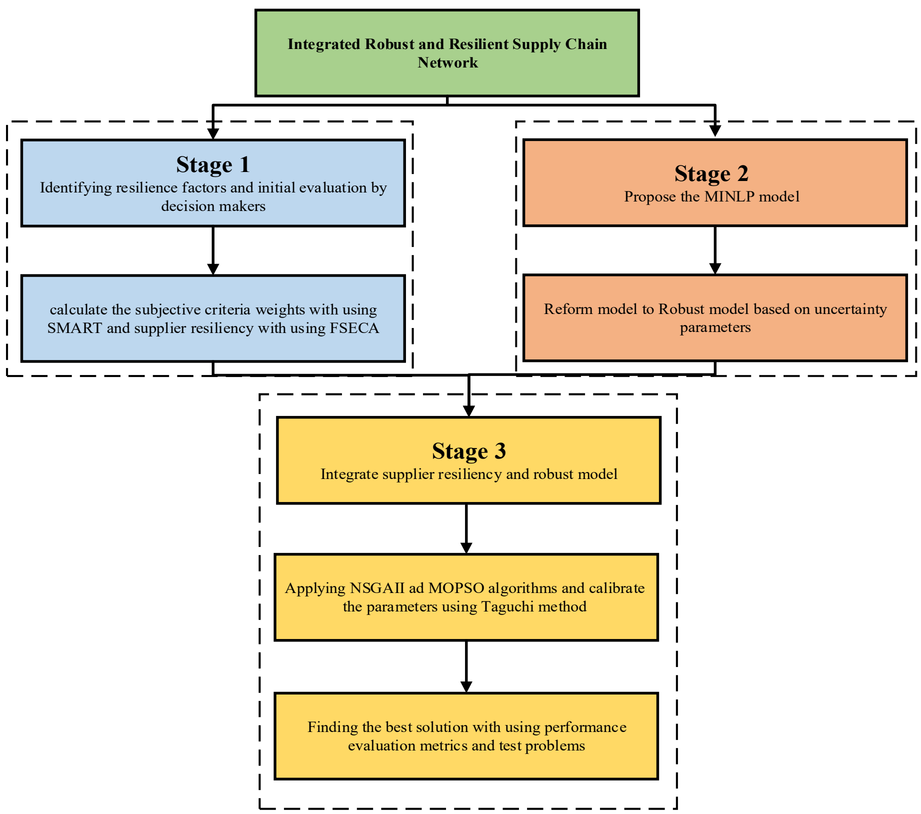

Fig. 1. Proposed three-stage framework

Integrated resilient and RSCN design enables us to tackle most of the challenges and risks that can occur in SCN (Agarwal et al., 2020). In a global SCN, one of the manager's duties is to consider the supply process using quantitative tools (Margolis et al., 2018). In the first stage of this research framework, addressing quantitative decisions such as supplier selection based on resilience values owing to their vital role in minimizing costs. In this regard, the FSECA method, which is a new MCDM model, helps managers evaluate and rank suppliers while considering resilience. Therefore, an integrated MCDM model is built using the SMART to calculate the criteria weight after collecting data from decision makers (DC) and the FSECA method to specify the resiliency value under a fuzzy environment. supplier evaluation is upstream of the SCN and managers should consider this upstream flow with multiple decisions. Considering the entire supply chain based on probable risk and uncertainty parameters handles the design of a robust SCN. Suppliers are evaluated and ranked based on their resiliency values. Unlike other studies, the FSECA method is a relatively new MCDM method that evaluates the criteria weight and alternative performance simultaneously. This method considers variations in the decision maker using the standard deviation of criteria and thus can provide more reliable results. Second, we developed an SCN model in which robust modelling handles the uncertainty parameters. The robust model integrates the resilience values of suppliers and develops an integrated model. The MINLP model is formulated to design the SCN by considering the resiliency performance of suppliers and then reform the mathematical model to a robust model based on uncertainty parameters. Third, owing to the large-scale problem, the metaheuristic solution approach used, NSGAII and MOPSO were applied and compared using different problem dimensions. This approach empowers managers to make highly reliable and accurate decisions.

3. Resiliency and Supplier Selection

This section presents the value of supplier resiliency, the weighted importance of resilience criteria, and prioritizes suppliers according to resilience values. For this purpose, resiliency criteria were defined. Then, FSECA method and SMART were utilized to specify the supplier resiliency and weight importance of resilience criteria.

3.1 Resiliency criteria and initial evaluation

One of the purposes of this study was to obtain resilient suppliers. Supplier selection ensures managers cope with disruption risks and handle high amounts of raw materials from suppliers. Researchers have used various metrics to consider supplier resilience. In this study, we used five criteria (robustness, flexibility, agility, leanness, and integrity) to conduct comprehensive research on supplier resiliency. These criteria have been defined as follows.

Robustness (W1) measures the ability to prevent disruptions within SCN, either by replacing the new supplier or by immediately planning to be available as an alternative supplier(Yazdani et al., 2022). **Agility** (**W2**) evaluates the ability to produce products quickly by having the partner handle unexpected demands(Tirkolaee et al., 2023). **Leanness** (**W3**) assesses waste cutting while ensuring quality. However, this criterion is the most efficient way to deliver products to end users (Mohammed et al., 2019). **Flexibility (W4)** represents the corresponding level of disruptions and risks with a logical amount of costs and lead time. **Integrity** (**W5**) states standards that are set for the supply chain to address collaboration, between all supply chain amounts, and implementation and evaluation processes for controlling the quality of the supply chain (Davoudabadi et al., 2020).

First, we should collect DC opinions about resiliency criteria. We can use any scoring method for collecting the DC opinions.in this study, we used a scale between 0 and 100 for criteria evaluation. We used a SMART proposed by Edwards et al. (2007) to calculate the subjective criteria weights, therefore, the following Equation presents the criteria weight (ω_j^s). Table 1 presents the decision-maker scores with the criteria weights calculated using Eq. (1).

$$\omega_j^s = \frac{\sum_k I_{jk}}{\sum_k \sum_j I_{jk}} \tag{1}$$

In this Equation, I_{jk} shows the importance of jth resiliency criteria assigned by kth decision maker.

Table 1
The summary of the weights of the criteria

	W1	W2	W3	W4	W5
DC1	30	40	35	25	60
DC2	40	50	45	35	50
DC3	50	40	30	30	70
DC4	45	40	30	30	40
DC5	30	50	50	30	60
ω_j^s	0.1884	0.2125	0.1835	0.1449	0.2705

3.2 Determination of supplier resiliency using FSECA

In this section, based on the weight of the resilience criteria, we used the FSECA method to determine supplier resiliency. First, we collect decision-makers' opinions on alternative performance on any criterion. in this study, alternatives are defined as suppliers. we define MCDM problem with n alternative and m criteria and x_ij that shows decision maker scores related to *i th* ith alternative on *j th* criteria (x_ij >0) by considering the FSECA model; scores in this step are stated using linguistic variables. Then linguistic variables are transformed into fuzzy data and aggregate alternative performance to constitute a fuzzy decision matrix. The mathematical details of the FSECA method are as follows (Keshavarz-Ghorabaee et al., 2022).

Step1. The elements of the fuzzy decision matrix ($\tilde{x}_{ij}$) were defined as $x_{ij} = \left(x_{ij}^a . x_{ij}^b . x_{ij}^c . x_{ij}^d\right)$ then aggregates the fuzzy decision matrix introduced to propose an interval decision matrix ($x_{ij}^\alpha = \left[x_{ij}^{L\alpha} . x_{ij}^{U\alpha}\right]$) using Eq. (2) and Eq. (3). then, we should have an interval decision matrix in standard range, so normalized the interval decision matrix with using Eq. (4).

$$x_{ij}^{L\alpha} = \alpha\left(x_{ij}^{b} - x_{ij}^{a}\right) + x_{ij}^{a}, \tag{2}$$

$$x_{ij}^{U\alpha} = x_{ij}^{d} - \alpha\left(x_{ij}^{d} - x_{ij}^{c}\right), \tag{3}$$

$$x_{ij}^{N\alpha} = \left[x_{ij}^{NL}.x_{ij}^{NU}\right]$$

$$x_{ij}^{N\alpha} = \begin{cases} \left[\dfrac{x_{ij}^{L\alpha}}{Ux_j}.\dfrac{x_{ij}^{U\alpha}}{Ux_j}\right] \\ \left[\dfrac{Lx_j}{x_{ij}^{U\alpha}}.\dfrac{Lx_j}{x_{ij}^{L\alpha}}\right] \end{cases}, \tag{4}$$

where α shows uncertainty level that set to 0.5, $Ux_j = \underset{i}{max x_{ij}^{U\alpha}}$, $Lx_j = \underset{i}{min x_{ij}^{L\alpha}}$ represent sets of beneficial and non-beneficial criteria, respectively. In this study, all criteria are beneficial, and there are non-beneficial criteria between suppliers. Based on interval decision matrix, we should present the crisp matrix elements, standard deviation, degree of conflict, and correlation between matrix columns, these parameters defined with using Eqs. (5-8). respectively. $x_{ij}^{C\alpha}$ denotes matrix elements.

$$x_{ij}^{C\alpha} = \frac{x_{ij}^{NL} + x_{ij}^{UL}}{2} \tag{5}$$

$$\sigma_j^{C} = \frac{\sigma_j}{\sum_l \sigma_l} \tag{6}$$

$$\pi_j^{C} = \frac{\pi_j}{\sum_l \pi_l} \tag{7}$$

$$\pi_j = \sum_{l=1}^{m} (1 - r_{jl)} \tag{8}$$

$x_{ij}^{C\alpha}$ denotes the elements of crisp matrix. σ_j is the standard deviation columns of interval decision matrix and π_j^{C} is the conflict degree criteria. The values of π_j is described by the correlation between the jth and lth column (r_{jl}). Finally, we solved mathematical models based on the SECA method. The first model defines beneficial criteria and the second model related to non-beneficial criteria. we defined another variable as the subjective weight (λ), and both models used the same reference parameters to determine the criteria weights. The models are defined as follows:

Model 1:

$$\begin{array}{ll} \max Z^{l} = \lambda_a^{L} - \beta(\lambda_b^{L}.\lambda_c^{L}.\lambda_d^{L}) & \\ \lambda_a^{L} \le S_i^{L} & \forall i \in \{1.2 \ldots..n\} \\ S_i^{L} = \sum_{j=1}^{m} \omega_{j1} x_{ij}^{NL} & \forall i \in \{1.2 \ldots..n\} \\ \lambda_b^{L} = \sum_{j=1}^{m} \left(\omega_{j1} - \sigma_j^{C}\right)^2 & \\ \lambda_c^{L} = \sum_{j=1}^{m} \left(\omega_{j1} - \pi_j^{C}\right)^2 & \\ \lambda_d^{L} = \sum_{j=1}^{m} \left(\omega_{j1} - \omega_j^{s}\right)^2 & \\ \sum_{j=1}^{m} \omega_{j1} = 1 & \\ \omega_{j1} \le 1 & \forall j \in \{1.2 \ldots..m\} \\ \omega_{j1} \ge \varepsilon & \forall j \in \{1.2 \ldots..m\} \end{array} \tag{9}$$

Model 2:

$$\begin{array}{ll} \max Z^{U} = \lambda_a^{U} - \beta(\lambda_b^{U}.\lambda_c^{U}.\lambda_d^{U}) & \\ \lambda_a^{U} \le S_i^{U} & \forall i \in \{1.2 \ldots..n\} \\ S_i^{U} = \sum_{j=1}^{m} \omega_{j2} x_{ij}^{NU} & \forall i \in \{1.2 \ldots..n\} \\ \lambda_b^{U} = \sum_{j=1}^{m} \left(\omega_{j2} - \sigma_j^{C}\right)^2 & \\ \lambda_c^{U} = \sum_{j=1}^{m} \left(\omega_{j2} - \pi_j^{C}\right)^2 & \\ \lambda_d^{U} = \sum_{j=1}^{m} \left(\omega_{j2} - \omega_j^{s}\right)^2 & \\ \sum_{j=1}^{m} \omega_{j2} = 1 & \\ \omega_{j2} \le 1 & \forall j \in \{1.2 \ldots..m\} \\ \omega_{j2} \ge \varepsilon & \forall j \in \{1.2 \ldots..m\} \end{array} \tag{10}$$

Based on model solution results, we can determine resiliency values and criteria weight as shown as follows:

$$S_i = [S_i^L . S_i^U] \quad (11)$$

$$\omega_j = [\omega_j^L . \omega_j^U] = [\min(\omega_{j1} . \omega_{j2}) . \max(\omega_{j1} . \omega_{j2})] \quad (12)$$

According to the obtained interval decision matrix, we compare the intervals or averages of the upper and lower bounds to ranked alternatives (suppliers) performance and final criteria weights, as shown in Table 2. The final ranking of suppliers was S1 > S4 > S3 > S2.

Table 2
Supplier resiliency and criteria weight 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

4. SCN design

The second stage of this research framework is related to the MINLP model to design two echelon SCN, as shown in Fig. 2. The main objective of this research stage is designing a resilient and robust SCN to maximize the total profit and supplier resiliency. The proposed network includes a set of suppliers, raw materials, one manufacturer, and a set of markets in different time periods. The main assumptions of this model are as follows:

a) Capacity of suppliers is limited
b) The production time for each product was considered and should be lower than the total time required to produce the product.
c) Shortages are allowed at markets
d) Operational cost included production cost and purchasing cost
e) Failure at satisfy demand imposes shortage cost
f) Considering to multiple products
g) supply chain resiliency included suppliers' resiliency values, weighted importance of resilience criteria, and order quantity of raw material from the supplier.
h) production processing time and demand are uncertainty parameters

Now, the proposed multi objective MINLP model described as following:

Indices	
S	Set of suppliers. $S=1...s$
I	Set of raw materials. $I=1...i$
P	Set of markets. $P=1...p$
T	Set of time periods. $T=1...t$
Parameters	
SP_{pt}	selling price of product p in period t
D_{pmt}	demand of market m for product p in 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 period t
PS_p	production time of product p
CO_{pt}	operational cost of product p in period t
SC_{pm}	shortage cost for unsatisfied demand of product p in market m
FO_{st}	fix ordering cost from supplier s in 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	Weighted importance of robustness
IWF	Weighted importance of flexibility
IWA	Weighted importance of agility
IWL	Weighted importance of leanness
IWI	Weighted importance of integrity
RCR_s	Resiliency value of supplier s for robustness
RCF_s	Resiliency value supplier s for flexibility
RCA_s	Resiliency value supplier s for agility
RCL_s	Resiliency value supplier s for leanness
RCI_s	Resiliency value supplier s for integrity
Decision variables	
x_{sit}	order quantity of raw material i from supplier s in time period t
y_{pt}	quantity of product p in time 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 t
ir_{it}	inventory level of raw material i in time t
ip_{pt}	inventory level of product p in time t
vf_{st}	binary variable; equal 1. if an order placed with supplier s in time period t; 0, otherwise

$$\max Z_1 = \sum_p \sum_m \sum_t SP_{pt} qs_{pmt} - \sum_p \sum_t CO_{pt} y_{pt} - \sum_s \sum_t FO_{st} vf_{st} - \sum_s \sum_i \sum_t TCR_{si} x_{sit} - \sum_p \sum_m \sum_t TCP_{pm} qs_{pmt} - \sum_i \sum_t HC_i\, ir_{it} - \sum_p \sum_t HP_p ip_{pt} - \sum_s \sum_i \sum_t PC_{si} x_{sit} - \sum_p \sum_m \sum_t SC_{pm} u_{pmt} \tag{13}$$

$$\max Z_2 = IWR\left(\sum_s RCR_s\left(\sum_i \sum_t x_{sit}\right)\right) + IWA\left(\sum_s RCA_s\left(\sum_i \sum_t x_{sit}\right)\right) + IWL\left(\sum_s RCL_s\left(\sum_i \sum_t x_{sit}\right)\right) + IWF\left(\sum_s RCF_s\left(\sum_i \sum_t x_{sit}\right)\right) + IWI\left(\sum_s RCI_s\left(\sum_i \sum_t x_{sit}\right)\right) \tag{14}$$

$$\sum_t x_{sit} \leq MC_{si} \qquad \forall s.i \tag{15}$$

$$D_{pmt} = qs_{pmt} + u_{pmt} \qquad \forall p.m.t \tag{16}$$

$$\sum_m qs_{pmt} + ip_{pt} = y_{pt} + ip_{p(t-1)} \qquad \forall p.t \tag{17}$$

$$\sum_s x_{sit} + ir_{i(t-1)} = ir_{it} + \sum_p \sum_i Q_{ip} y_{pt} \qquad \forall i.t \tag{18}$$

$$\sum_p PS_p y_{pt} \leq PT_t \qquad \forall t \tag{19}$$

$$x_{sit} \leq M * vf_{st} \qquad \forall s.i.t \tag{20}$$

$$x_{sit}. y_{pt}. u_{pmt}. qs_{pmt}. ir_{it}. ip_{pt} \in R^+ \quad vf_{st} \in \{0.1\} \tag{21}$$

In this model, the first objective function (13) presents the maximum profit obtained from selling the final product minus the six terms of supply chain network costs. operational cost of product, fixed order cost from supplier, transportation cost of raw material and products in each echelon of SCN, holding cost of raw material and product, purchasing cost of raw material, and shortage cost derived from unsatisfied market demand. Eq. (14), as the second objective function, tries to maximize the total supply chain resiliency value considering the supplier resiliency values and weighted importance of resilience criteria. In other words, this objective function maximizes the total quantity order from more resilient suppliers. Eq. (15) states supplier capacity to satisfy the raw material orders. This equation displays that the order quantity of raw materials should be less than or equal to the supplier's capacity. Equation (16) proposes each market demand in each time, which states that demand is equal to the satisfied and unsatisfied demand. Eq. (17) and Eq. (18) show the inventory levels of the product and raw materials. Eq. (17) states that the quantity of product in each period is equal to the quantity of product produced in the same period plus product inventory from the previous time. Like Eq. (17), we calculated the quantity of raw material in each period related to the previous time inventory in Eq. (18). Eq. (19) indicates that the total production time in each period should be less than or equal to the total available time in that time. Eq. (20) is defined to control the order quantity from the activated supplier when the supplier is open ($vf_{st} = 1$). Eq. (21) displays the types of positive integers and binary variables.

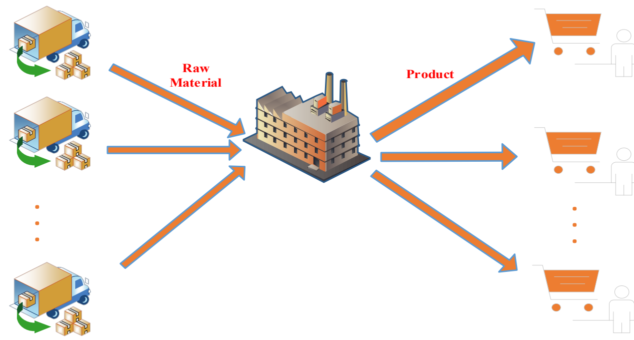

Fig. 2. Two-echelon SCN

4.1 Robust counterpart model

Here, robust optimization is presented to address the uncertainty parameters including production processing time and demand. We introduced a robust optimization approach (Bertsimas & Sim, 2004) that reaches feasible near-optimal solutions. This approach presents a robust formulation that can be extended to a discrete optimization problem. Here, we consider a set of uncertainty coefficients $\tilde{a}_{ij}.j \in J$ that takes the value according to a symmetric distribution in the interval $[a_{ij} - \hat{a}_{ij}.a_{ij} + \hat{a}_{ij}]$. For every i, the uncertainty budget is defined as Γ_i, it can take a value in the interval $[0.|J_i|]$, which $|J_i|$shows the number of uncertainty parameters of the i^{th} constraint. Decision makers can choose Γ_i values based on the risk level. $\hat{a}_{it}$ changes to the worst case ($\Gamma_i = |J_i|$) with value $(\Gamma_i - \lfloor\Gamma_i\rfloor)\hat{a}_{it}$. Based on the above explanations, Bertsimas and Sim (2004) introduced the following non-linear formulation.

$$\max C'x \tag{22}$$
$$\sum_{j\in J}\bar{a}_{ij}x_j + \underset{\{s_i\cup t_i|\, s_i\subseteq J_i.|s_i|=\lfloor\Gamma_i\rfloor.t_i\in J_i\setminus s_i\}}{\text{Max}}\left\{\sum_{j\in s_i}\hat{a}_{ij}y_i + (\Gamma_i - \lfloor\Gamma_i\rfloor)\hat{a}_{it}y_t\right\} \le b_i \tag{23}$$
$$-y_j \le x_i \le y_j \quad \forall i$$
$$-l_j \le x_j \le l_j \qquad \forall j \tag{24}$$
$$y_j \ge 0 \qquad \forall j \tag{25}$$

If Γ_i is chosen as an integer, the protection function of i^{th} constraint is introduced as follows:

$$\beta(x.\Gamma_i) = \max_{\{s_i\cup t_i|\, s_i\subseteq J_i.|s_i|=\lfloor\Gamma_i\rfloor.t_i\in J_i\setminus s_i\}}\left\{\sum_{j\in s_i}\hat{a}_{ij}|x_j| + (\Gamma_i - \lfloor\Gamma_i\rfloor)\hat{a}_{it}|x_t|\right\} \tag{26}$$

If $\Gamma_i = 0$, $\beta(x.\Gamma_i) = 0$ constraints are equivalent to nominal and model changes to deterministic constraints. If $\Gamma_i = |J|$, $\beta(x.\Gamma_i) = 0$ so we have a robust formulation of the Soyster (1973) by varying $\Gamma_i \in [0.|J_i|]$, we adjusted the robust model based on the conservation level of the solution. To linearize Eq. (26) and using the protective function with x^* vector, the robust counterpart of the Equation is presented as follows:

$$\beta(x^*.\Gamma_i) = max\ \sum_{j\in J_i}\hat{a}_{ij}|x^*{}_j|\eta_{ij} \tag{27}$$

$$\sum_{j\in J_i}\eta_{ij} \le \Gamma_i \qquad \forall i \tag{28}$$

$$0 \le \eta_{ij} \le 1 \qquad \forall i.j \tag{29}$$

Model (26) has linear formulation as follow:

$$max = c'x \tag{30}$$
$$\sum_{j\in J}\bar{a}_{ij}x_j + \lambda_i\Gamma_i + \sum_{j\in J_i}\rho_{ij} \le b_i \qquad \forall i \tag{31}$$
$$\lambda_i + \rho_{ij} \ge \hat{a}_{ij}y_j \qquad \forall i.j \tag{32}$$
$$-y_j \le x_j \le y_j \qquad \forall i.j \tag{33}$$
$$l_j \le x_j \le u_j \qquad \forall j \tag{34}$$

$$\rho_{ij}.y_j.\lambda_i \geq 0 \qquad \forall i.j \tag{35}$$

In Eq. (31), λ_i and ρ_{ij} are dual variables that are used for linearization. In this study, processing production time is an uncertainty parameter that has an influence on productivity, and demand is related to prediction; this parameter has a large uncertainty in model. Therefore, we consider Eq. (16) and Eq. (19), which have uncertainty parameters. We state the robust counterparts of these equations. for Eq. (19), and protection function $\beta(x^*.\Gamma_t)$ is defined by Equation. (36), where $\Gamma_t \in [0.|J|]$.

$$\beta(x^*.\Gamma_t) = max\ \sum_{j\in|J|}\widehat{PS}_p|x^*|\mu_{pt} \tag{36}$$
$$\sum_{j\in J}\mu_{pt} \leq \Gamma_t \qquad \forall t \tag{37}$$
$$0 \leq \mu_{pt} \leq 1 \qquad \forall p.t \tag{38}$$

Finally, this constraint can be defined as Eqs. (39-42), and using dual variables, we can make a robust counterpart as follows:

$$\sum_{j\in J}\overline{PS}_p y_{pt} + \sum_{j\in J}\rho_{pt} + \Gamma_t\lambda_t \leq PT_t \quad \forall t \tag{39}$$
$$\lambda_t + \rho_{pt} \geq \widehat{PS}_p y_{pt} \qquad \forall p.t \tag{40}$$
$$\rho_{pt} \geq 0 \qquad \forall p.t \tag{41}$$
$$\lambda_t \geq 0 \qquad \forall t \tag{42}$$

For robust counterpart of Eq. (16), we suppose $\hat{d}$ takes values between $\bar{d}+\hat{d}$ and $d-\hat{d}$ where $\hat{d}$ denotes the deviation from the nominal value. Eq. (16) can be rewritten as follows (Liu et al., 2018).

$$tr_{pmt} \geq \bar{d}_{pmt} + \frac{\Gamma_{pmt}}{|J|}\hat{d}_{pmt} - b_{pmt} \quad \forall p.m.t \tag{43}$$

5. Solution approach

NP hard problems cannot be solved with the exact method in a reasonable time. in this paper, since SCN and its extensions to robust models are NP- hard, two meta heuristic algorithms namely NSGAII and MOPSO are proposed to solve the multi-objective RSCN model aiming to maximize the profit of SCN and maximize the resilience of suppliers simultaneously, these algorithms described as following subsections.

5.1 NSGAII Algorithm

NSGA-II algorithm defined based on non-dominance concepts. In the first cycle of this algorithm, population ($p0$) is generated and then populations ranked using non-dominated sorting function, and ranked solutions which were created Pareto fronts. After initializing, in the next step, the initial population ($p0$) tournament selection was used for *N* parent solutions(chromosomes) from the population by considering the fitness value, rank front, and crowding distance. In the parent-selection process, two elements are chosen for the population, and one element was selected as the parent. In this process, if population elements were in the same Pareto front, an population element with a higher crowding distance will be selected, but if two elements were in different Pareto fronts, an element with a lower rank will be selected as the parent (Babaveisi et al., 2018). Then, offspring populations (Q) were created using crossover and mutation operators. At this stage, a new population was created by the initial population and populations formed from crossover and mutation, and the new population calculated its objective function and determined dominance until the termination criterion was reached (Mousavi et al., 2016). Crowding distance directs the population toward the less crowded region and indicates the diversity index in the population. The crowding distance is determined by the adjacent neighbor value and the first and last members of the population. Solutions with a high crowding distance have better quality. Eq. (44) expresses the crowding distance formula:

$$CD_i = \sum_{k=1}^{M}\frac{f^p_{k.i+1} - f^p_{k.i-1}}{f^p_{k.max} - f^p_{k.min}} \tag{44}$$

In this equation, M is the number of objective functions,$f^p_{k.i+1}$ and $f^p_{k.i-1}$ are k-th objective function values $i+1$ th and $i-1$ th solutions from p-th Pareto front. $f^p_{k.max}$ and $f^p_{k.min}$ are the maximum and minimum values of k-th objective function from the last member of p-th Pareto front and first member of the Pareto front, respectively. The important parameters and operators, including crossover, and mutation, are described in more detail as follows.

5.1.1 Crossover and mutation operators

Crossover is the main operator in the NSGAII algorithm. Using the crossover operator, we can search the solution area and exploit new solutions. This operator transfers the same characteristics from parents to the next generation to produce offspring with inherent features from the parents (Alizadeh Afrouzy et al., 2018). simplest type of crossover, including a single cut point, two cut points, and a uniform crossover. In this study, a two-cut-point crossover is applied. First, two parents are selected randomly, the cutoff point is used, and the first child inherits from the second parent, and the second child inherits from the first parent. crossover structure is illustrated.

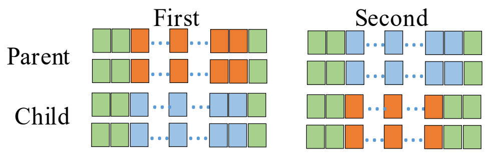

Fig. 3. Proposed crossover representation

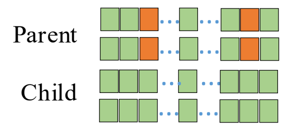

Fig. 4. Mutation representation

In the case of mutations, the structure of some chromosomes in each generation changed. In this study, two chromosomes of the parent were selected randomly, and their positions were changed. This mutation is shown in Fig. 4.

5.2 MOPSO Algorithm

Particle swarm optimization (PSO) works based on a determined population from candidate solutions that are named particles. PSO is defined for one objective function but multi objective function is solved by MOPSO, which was originally employed by Coello Coello and Lechuga, (2002) solution space in MOPSO using the particles. Each particle is updated in each iteration and is specified using two factors: the position and velocity. In each iteration, particles are modified in accordance with a set of rules and take the new position and velocity according to two experiences: personal and global best. Local best (Lbest) is the best experience for each particle, and global best (Gbest) is to find the best position. Considering these two experiences, they are updated their velocity and position (Chaudhry et al., 2019). The velocity update was related to the local and global coefficients of the particles. A specific mechanism is used for updating, which keeps priority values exclusive. In this algorithm, solutions are presented as vectors. The updated velocity is defined as the way the current vector changes between the current position and Lbest position and the Gbest position. Positions are updated using velocities that are integer.

5.3 Performance Evaluation

There are some metrics for the evaluation of meta-heuristic algorithms, of which four metrics are considered for assessing the algorithm performance.

1) **The number of Pareto solutions (NPS):** This metric expresses the number of optimal Pareto solutions. Algorithms with greater Pareto solutions performed better than the other algorithms.
2) **Divergence Metric (DM):** This index measures the distance between the best solutions in pareto front and can be expressed by Eq. (45).

$$SM = \frac{\sqrt{\sum_{i=1}^{N}(\bar{d}-d_i)^2}}{N} \quad (45)$$

d_i is the Euclidian distance between the solutions, expressed by Eq. (46). $\bar{d}$ is mean value of d_i.

$$d_i = \min_{j=1.2\ldots.N} \sum_{k=1}^{M}\left(obj_{ki} - obj_{kj}\right) \quad \forall i = 1.2 \ldots.N \quad (46)$$

where M indicates the number of objective functions and obj_{ki} is i-th solution for k-th objective function and obj_{kj} is j-th solutions for k-th objective function. higher value of DM indicates better algorithm performance.

3) **Mean Ideal Distance (MID):** This index represents the Pareto optimal solution distance from the ideal solution in each algorithm. minimum value of the MID has the best performance. Eq. (47) represents the performance index:

$$MID = \frac{\sum_{i=1}^{n}\sqrt{f_{1i}^2+f_{2i}^2}}{n} \quad (47)$$

4) **Spread of non-dominated Solution (SNS):** This measure shows the spread of non-dominance solutions in algorithms. algorithm with a higher SNS value is the best algorithm.

$$SNS = \sqrt{\frac{\sum_{i=1}^{n}(MID-DM)^2}{n-1}} \quad (48)$$

5.4 Parameter settings

Parameter setting is a necessary process in multi objective optimization to run the algorithms with the best performances. Optimization algorithms use different parameter setting approaches, such as trial and error, the Taguchi method, response level, and neural networks (Talaei et al., 2016). In this study, Taguchi (Genichi Taguchi, 1986) method has been utilized. In this method, the factors are divided into two groups: controllable and noise factors. The objective of this method is maximizing the effect of controllable factors and minimizing the effect of noise factors. This method was designed for various experiments. Several experiments were conducted based on the factors and defined levels (Babaveisi et al., 2018). Two methods are recommended for the Taguchi method analysis: analysis by variance (ANOVA) and signal-to-noise ratio (S/N). For the same experiment, when this ratio is higher, the variance around a specific amount will be lower (Roy, 2010).

6. Computational results

This section presents numerical analysis to display meta heuristic algorithms performance. Based on calibrated parameters, we have defined three levels for algorithm parameters and then parameter characteristics at each algorithm are listed in Table 3. The computational results are presented based on 15 test problems, where test problems 1-5 are considered as small size problems, 6- 10 are problems with medium size and 10-15 considered as large size problems. Problem dimensions are presented in Table 4 and parameters value are generated, randomly based on Table 5.

Table 3
Meta-heuristic algorithm parameters and their levels

	parameters	level1	level2	level3
MOPSO	Inertia weight	0.25	0.5	0.75
	Grid number	8	16	24
	Iteration	150	200	250
	Population	80	100	120
	Repository	40	50	60
	Personal learning coefficient	0.75	1	1.25
	Global learning coefficient	1.25	1.75	2
	Selection pressure	1.5	2	2.5
NSGAII	Population	50	75	100
	Iteration	100	150	200
	Crossover rate	0.7	0.8	0.9
	Mutation rate	0.3	0.4	0.5

Table 4
Dimension of each instance

	No.of problems	No.of suppliers	No.of Raw material	No.of Products	No.of Periods	No.of Markets
Small Size	1	3	4	4	4	2
	2	3	4	4	5	2
	3	3	4	4	6	2
	4	4	4	4	6	2
	5	4	4	4	6	3
Medium Size	6	6	4	4	6	3
	7	6	6	4	6	4
	8	6	8	4	8	4
	9	6	8	5	8	4
	10	8	8	5	8	6
Large Size	11	8	10	6	8	8
	12	8	10	8	8	8
	13	10	12	8	8	10
	14	10	12	8	8	12
	15	10	12	10	8	12

Table 5
Range of parameters

Parameters	Range	Parameters	Range
SE	[50×104 ,100×103]	FO	[1000,5,000]
D	[10,60]	TCR	[1000,7,000]
MC	[100×103,170×103]	TCP	[1000,10,000]
Q	[1 10]	HC	[1,2]
PT	[6 16]	HP	[2,3]
SP	[5 10]	PC	[1,6]
CO	[10,000 20,000]	R	[200,600]
SC	[1000,5000]	C	[300,500]

In this study, the number of test problem runs was specified by the Taguchi method. Based on Taguchi, The L^9 and L^{27} designs were implemented for the NSGAII and MOPSO algorithms, we should solve each instance in each presented design of orthogonal arrays, 15 instances generated. Therefore, 405 test problems solved for the MOPSO algorithm according to the L^{27} design, and 135 test problems solved for the NSGAII algorithm according to the L^9 design. Therefore.540 runs were performed for the Taguchi analysis. All the test problems were solved on a PC with a Core i7 CPU and 8 GB RAM in a MATLAB R2022a environment. The outputs were normalized using Equation (49) while considering the $best\ sol$ for each objective function in each test problem, and performance values were calculated for each test problem. Then, using Eq. (50), they are summed together, where w_i is the weight of each performance metric determined by the decision makers. Here, weights are considered as 1 for NPS and 2 for MID, DM, and SNS metrics. $P_i$is the normalized value of the performance metric and is calculated by considering $Best\ sol$. $Best\ sol$ presents the desirable value that defines different values in each performance metric based on the inherent metric. The proper value for the $Best\ sol$ of NPS, SNS, and DM is the higher value of each metric; conversely, for MID, the lower value is considered as the $Best\ sol$. Table 6 shows the results of these performance evaluation metrics obtained by the MOPSO and NSGAII algorithms using 15 test problems.

$$R = \frac{|Present\ Sol - Best\ Sol|}{|Best\ Sol|} \tag{49}$$

$$W = \sum_{i=1}^{I} w_i P_i \tag{50}$$

w_i: weight of metric performance.
P_i: normalized value of the performance metrics

Table 6 compares NSGA-II and MOPSO algorithms in terms of the average values of MID, DM, NPS, SNS metrics and W. as presented in this table on average, NSGAII outperforms MOPSO in terms of the MID, DM, NPS and SNS metrics and total value of algorithms' performance, W, for NSGAII is less than that of MOPSO, so NSGAII algorithm ranked first for decision makers. Furthermore, the performance of all metrics has been compared based on t-test, statically. The null hypothesis assumes that the difference in values between NSGAII and MOPSO for each metric is insignificant while the alternative hypothesis assumes that NSGAII outperforms MOPSO in all terms of performance metrics. Before performing the paired t-test, the normality of all metrics was checked by Anderson–Darling test. In all cases, at 0.05 significance level, the normality of metrics was not rejected.

Table 1
Performance evaluation results

	MOPSO					NSGAII				
Test problems	MID	DM	SNS	NPS	W	MID	DM	SNS	NPS	W
1	0.538	0.005	0.261	0	0.726	0.386	0.007	0.187	0.359	0.296
2	0.349	0.006	0.254	0	0.762	0.301	0.007	0.265	0.5	0.020
3	0.632	0.005	0.278	0	0.646	0.385	0.007	0.312	0.4	0.216
4	0.722	0.004	0.335	0	0.366	0.261	0.009	0.297	0.4	0.000
5	0.576	0.004	0.285	0	0.613	0.471	0.009	0.322	0.148	0.621
6	0.634	0.011	0.356	0	0.267	0.552	0.010	0.325	0.269	0.473
7	0.685	0.013	0.337	0	0.357	0.711	0.010	0.341	0.25	0.510
8	0.675	0.012	0.356	0	0.265	0.658	0.014	0.338	0.429	0.159
9	0.540	0.011	0.335	0	0.365	0.741	0.019	0.343	0.0583	0.533
10	0.603	0.010	0.410	0	1.410	0.658	0.022	0.376	0.291	0.429
11	0.699	0.013	0.345	0	0.320	0.623	0.025	0.371	0.223	0.413
12	0.778	0.016	0.339	0	0.350	0.714	0.026	0.404	0.325	0.273
13	0.688	0.013	0.369	0	0.202	0.843	0.032	0.425	0.51	0.727
14	0.738	0.018	0.369	0	0.135	0.883	0.065	0.454	0.418	0.057
15	0.614	0.019	0.409	0	0.000	0.944	0.069	0.468	0.378	0.000
Average	0.631	0.011	0.336		0.452	0.609	0.022	0.349	0.510	0.315

Table 7
Comparison of algorithms' performance results

		N	Mean	St Dev	SE Mean	MAD	T-value	sig	test result
MID	Differences	15	0.144	0.120	0.032		-0.370	0.008	null hypothesis rejected
	NSGAII	15	0.609	0.210	0.050	0.145			
	MOPSO	15	0.631	0.030	0.100	0.058			
DM	Differences	15	0.012	0.016	0.004		2.150	0.007	null hypothesis rejected
	NSGAII	15	0.022	0.020	0.005	0.007			
	MOPSO	15	0.011	0.005	0.001	0.005			
SNS	Differences	15	0.039	0.024	0.006		0.563	0.0205	null hypothesis rejected
	NSGAII	15	0.349	0.073	0.019	0.035			
	MOPSO	15	0.336	0.048	0.012	0.03			
NPS	Differences	15	0.331	0.126	0.033		10.170	0.000	null hypothesis rejected
	NSGAII	15	0.331	0.126	0.033	0.08			
	MOPSO	15	0.000	0.000	0.000	0			

Table 7 shows the results of paired t-tests. In all cases, the null hypothesis is rejected at 0.05 significance level, indicating the superiority of NSGAII compared to MOPSO in terms of all performance metrics at 0.05 significance level. Also based on St Dev, SE Mean and MAD scales, NSGAII outperforms MOPSO. Figs. 5-8 show comparison between test problem sizes and performance metric values. The results illustrate that when test problems sizes increase the trend of performance metrics DM. MID SNS and CPU for MOPSO and NSGAII algorithms are increasing.

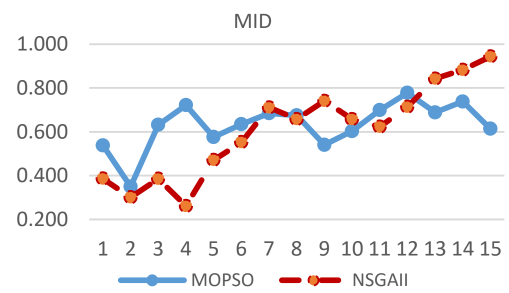

Fig. 5. Comparison of algorithms based on MID

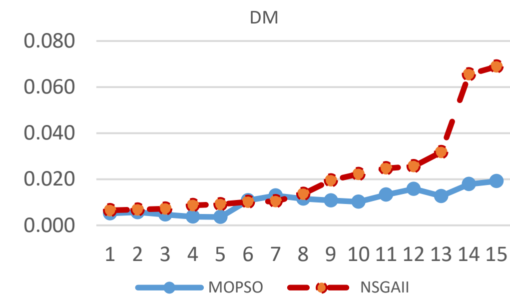

Fig. 6. Comparison of algorithms based on DM

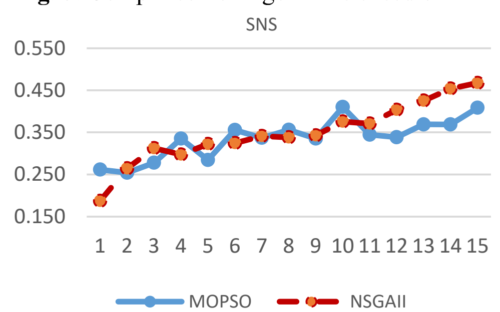

Fig. 7. Comparison of algorithms based on SNS

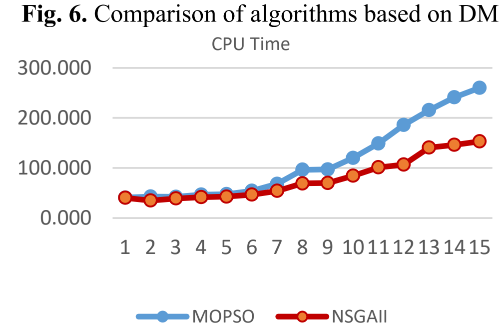

Fig. 7. Comparison of algorithms based on CPU

Table 8
Value of response variable (S/N) for MOPSO algorithm

Run order	W	N- grid	Max-iter	Npop	Nrep	C1	C2	β	(S/N)
1	0.25	8	150	80	40	0.75	1.25	1.5	0.420149
2	0.25	8	150	80	50	1	1.75	2	0.283054
3	0.25	8	150	80	60	1.25	2	2.5	0.292795
4	0.25	16	200	100	40	0.75	1.25	2	0.418494
5	0.25	16	200	100	50	1	1.75	2.5	0.283361
6	0.25	16	200	100	60	1.25	2	1.5	0.358046
7	0.25	24	250	120	40	0.75	1.25	2.5	0.498979
8	0.25	24	250	120	50	1	1.75	1.5	0.288752
9	0.25	24	250	120	60	1.25	2	2	0.309898
10	0.5	8	200	120	40	1	2	1.5	0.296934
11	0.5	8	200	120	50	1.25	1.25	2	0.372639
12	0.5	8	200	120	60	0.75	1.75	2.5	0.296498
13	0.5	16	250	80	40	1	2	2	0.318142
14	0.5	16	250	80	50	1.25	1.25	2.5	0.320846
15	0.5	16	250	80	60	0.75	1.75	1.5	0.266891
16	0.5	24	150	100	40	1	2	2.5	0.298574
17	0.5	24	150	100	50	1.25	1.25	1.5	0.352967
18	0.5	24	150	100	60	0.75	1.75	2	0.287631
19	0.75	8	250	100	40	1.25	1.75	1.5	0.292512
20	0.75	8	250	100	50	0.75	2	2	0.321191
21	0.75	8	250	100	60	1	1.25	2.5	0.328695
22	0.75	16	150	120	40	1.25	1.75	2	0.309577
23	0.75	16	150	120	50	0.75	2	2.5	0.358464
24	0.75	16	150	120	60	1	1.25	1.5	0.336387
25	0.75	24	200	80	40	1.25	1.75	2.5	0.299412
26	0.75	24	200	80	50	0.75	2	1.5	0.339787
27	0.75	24	200	80	60	1	1.25	2	0.40068

Taguchi approaches were used to calibrate parameters that can enhance the algorithm performance (Abbasian et al., 2023). In this regard, Taguchi analysis was performed using Minitab software to calculate the response variable (S/N ratio) for the MOPSO and NSGAII algorithms. Table 9, Table 10 list the obtained S/N ratios by implementing the L27 and L9 designs for the MOPSO and NSGAII algorithms, respectively. The response variable (S/N ratio) was the weighted average of the performance metrics for each experiment. Fig. 9 and Fig. 10 show the S/N ratio plots for the MOPSO and NSGAII algorithms, respectively. The optimal level for each factor was the highest value of the corresponding S/N ratio. The optimal levels for each algorithm are presented in Table 11. For further clarifications of the Pareto-based algorithms, three instances were selected from each size of the test problems, that is, 5 - 10, and 15 test problems. The Pareto fronts of the optimal solutions for these problems are presented in Fig. 11 for the MOPSO and NSGAII algorithms.

Table 9
Value of response variable (S/N) for NSGAII algorithm

Run order	N-pop	Max-iter	Crossover rate	Mutation rate	Response (*S/N*)
1	50	100	0.7	0.3	0.4710
2	50	150	0.8	0.4	0.4381
3	50	200	0.9	0.5	0.4566
4	75	100	0.8	0.5	0.4517
5	75	150	0.9	0.3	0.4586
6	75	200	0.7	0.4	0.5647
7	100	100	0.9	0.4	0.4590
8	100	150	0.7	0.5	0.4582
9	100	200	0.8	0.3	0.5128

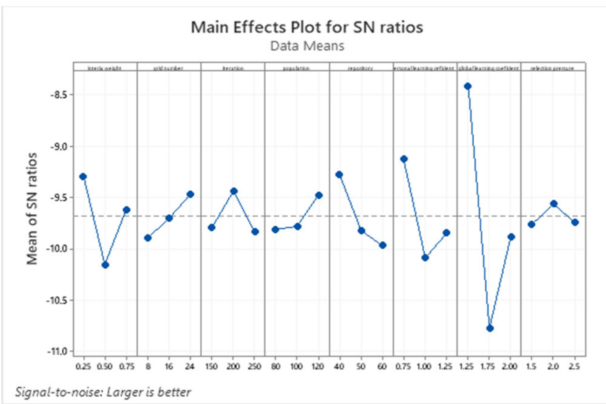

Fig. 9. S/N ratio for MOPSO algorithm

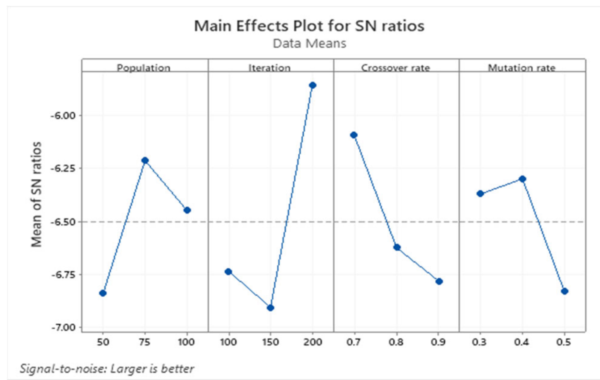

Fig. 10. S/N ratio for NSGAII algorithm

Table 10
Optimal level of all parameters for NSGAII and MOPSO algorithms

	Factors	level1	level2	level3	Optimal level
MOPSO	W	0.25	0.5	0.75	0.25
	N-grid	8	16	24	24
	Max-iter	150	200	250	200
	N-pop	80	100	120	120
	N-rep	40	50	60	40
	C_1	0.75	1	1.25	0.75
	C_2	1.25	1.75	2	1.25
	β	1.5	2	2.5	2
NSGAII	N-pop	50	75	100	75
	Max-iter	100	150	200	200
	Crossover rate	0.7	0.8	0.9	0.7
	Mutation rate	0.3	0.4	0.5	0.4

The determined optimal level of the NSGA-II algorithm presents an optimal solution for this research model. Finally, 15 Pareto optimal solutions were obtained at this optimal level, as shown in Fig. 12. The Pareto points in Fig. 12 show the trade-off between the two objectives. When the first objective function obtained a higher value, the second one obtained a higher value. the first and second objective functions increase together. Some sections of Pareto fronts have more density than other sections, and a feasible optimal solution can be found in these sections with more density solutions; therefore, we found the feasible optimal solution for both objective functions that presented the optimum value of the first objective function as 707027.9173 and the optimum value of the second objective function as 3173.7595. These results show that multi objective functions in SCN give more reliable results than single objective functions.

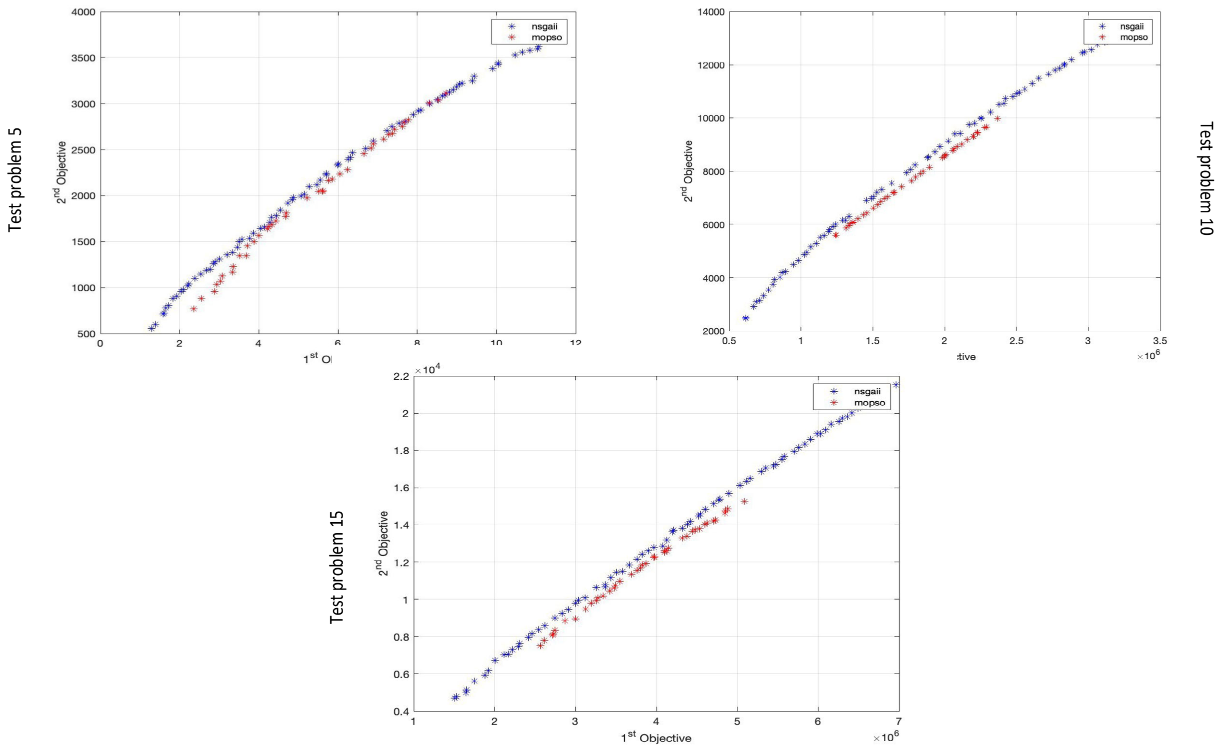

Fig. 11. Representation of optimal Pareto fronts for test problem No. 5, 10, 15

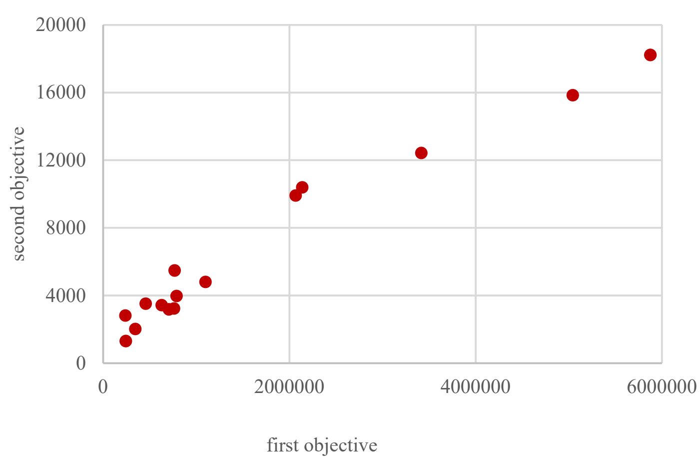

Fig. 12. Pareto front obtained for optimal level of proposed model

7. Conclusion

This research developed a framework to represent resilient suppliers, designed a robust optimization model, and used the MOPSO and NSGAII algorithms to address resilient and robust SCN design. The main contributions of this study are to propose a novel integrated decision model to measure and rank suppliers based on resiliency and criteria weighted importance using the FSECA and SMART methods, formulating an MINLP model for designing the SCN, reformulating the model to robust model based on uncertainty parameters, and implementing meta-heuristic algorithms to solve the problem in different dimensions. In this study, two meta-heuristic algorithms, NSGAII and MOPS, were used to optimize the proposed mathematical model. Priority based encoding was used in both algorithms. Algorithm parameters defined in three levels and 15 instances were suggested to evaluate the algorithm performance using performance evaluation factors, including MID, DM, SNS, NPS, and CPU time. The Taguchi approach was used in this study to analyze the results and enhance algorithm performance. According to the results, the NSGAII algorithm has the best performance in obtaining the optimal solution and optimal level determined based on performance weights and the Taguchi method in the NSGAII algorithm. The Pareto points of the optimal level are shown by increasing the first objective function; the second objective function will be increased, and these two objectives directly affect each other.

In the future, we will apply other metaheuristic algorithms. Moreover, there are other methods for calibrating uncertainty parameters, such as fuzzy programming and stochastic optimal control. In addition, can use this research in real world SCN with another type of objective functions, other MCDM techniques can be used to consider supplier resiliency such as DEMATEL, MAIRCA and MARKOS.

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