Resilient supplier selection in complex product and its subsystems’ supply chain under uncertainty and risk disruption: A case study for satellite components

Omid Solgi\textsuperscript{a}, Jafar Gheidar-Kheljani\textsuperscript{b\*}, Ehsan Dehghani\textsuperscript{a}, Alireza Taromi\textsuperscript{c}

\textsuperscript{a} School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran
\textsuperscript{b} School of Industrial Engineering, Malek-\textit{e} Ashtar University Technology, Tehran, Iran
\textsuperscript{c} School of Industrial Engineering, Islamic Azad University, Science and Research, Tehran, Iran

Abstract

Recently, the manufactures of complex product and its subsystems have faced a series of disruptions and troublesome behaviors in supplying goods and items. Likewise, suppliers in this area are more likely to be affected by external risks, in turn eventuating in disturbances. Selecting resilient and expedient suppliers dramatically decreases the delay time and costs and contributes to the competitiveness and development of the companies and organizations in this field. In this regard, this paper aims at proposing a bi-objective robust mathematical model to provide resilience supplier selection and order allocation for complex products and its subsystems in response to uncertainty and disruption risks. In the proposed model, a robust optimization approach is deployed, providing stable decisions for the proposed problem. Also, different resilience strategies including restoring supply from occurred disruptions, fortification of the suppliers, using backup suppliers, and utilizing the extra production capacity for suppliers have been devised to tolerate disruptions. Meanwhile, the augmented $\varepsilon$-constraint method is used, ensuring the optimal strong Pareto solutions and preventing the weak ones for the proposed bi-objective model. The evaluation of the effectiveness and desirability of the developed model is explored by discussing a real case study, via which helpful managerial insights are gained.

Keywords: Resiliency, Supply chain design, Supplier selection, Uncertainty, Robust optimization, Disruption, Complex products and subsystems.
Indices

- $v$: Suppliers number
- $i$: First category of suppliers
- $j$: Second category of suppliers
- $E$: A set of possible incidents that may occur for suppliers.
- $E_i$: A set of possible incidents that may occur for suppliers in $E_i \subseteq E$.
- $K$: Outsourcing items set
- $S$: Set of disrupted scenarios ($|S|$ shows the total number of scenarios)
- $\tilde{V}_s$: A set of affected suppliers by disruption under the scenario $s$
- $V_s$: A set of suppliers who are not affected by the scenario $s$
- $U$: A set of resistant levels in the second category suppliers
- $L_{se}$: A set of possible recovery levels from the $i$ supplier after the event and disruption $e$
- $i$: Suppliers’ index ($i \in v$)
- $k$: Outsourcing items
- $s$: Disrupted scenarios list
- $u$: Possible strengthen level for the second category of suppliers
- $e$: Indicators of incidents that may occur in suppliers
- $e_{is}$: Indicators of events occurred in supplier $i$ under scenario $s$
- $l$: Recovery Level Index for second category suppliers
- $m$: Factories number

Parameters

- $\tilde{a}_k$: Request item $k$ on the decision horizon
- $\bar{A}_i$: Order fixed cost from supplier $i$ as a main supplier
- $\bar{f}_i$: Contract fixed price with supplier $i$ as a backup supplier
- $\bar{p}_k$: Purchase and shipping unit price of $k$ from supplier $i$
- $\bar{p}_a$: Purchase and shipping unit price $K$ from backup supplier “$i$”
- $FR_u$: The strengthen cost of $i$ at the $u$ level
- $\tilde{h}_{ik}$: The cost of the inventory required unit for the item $k$ from the supplier “$i$”
\( Ca_i \)  
Production capacity of supplier “i” in normal conditions

\( Sc_i \)  
Existing storage capacity for supplier “i”

\( a_{ik} \)  
Unit's consumption capacity of supplier “i” for item k

\( R_k \)  
Maximum deficiency amount in purchased item of k

\( \bar{\phi}_{ik} \)  
Expected defect level of supplier “i” for k case (predetermined target level)

\( LT_i \)  
“i” supplier delivery time

\( LT'_i \)  
Delivery time of the “i” backup provider

\( \pi_{ie} \)  
Disruption risk for supplier “i”

\( p_s \)  
Scenario occurrence probability

\( \theta_{ie} \)  
Residual capacity of supplier “i” after disruption “e”

\( B_{ieu} \)  
Increased residual capacity of supplier “i”

\( RT^l_{ie} \)  
Recovery time of the supplier “i” after the disruption “e” at the recovery level of “l”

\( CL^l_{ie} \)  
Supplier “i”’s capacity after disruption “e” and at recovery level “l”

\( b_{ik} \)  
Each required storage unit by item k in supplier “i”

\( n \)  
The maximum authorized number of suppliers to use in the normal situation in order to ignore the supply principles

\( M \)  
Arbitrary constant

\( e_m \)  
Unit cost for excess production capacity of factory “m”

\( w_m \)  
The initial production capacity of the “m” factory

\( k_m \)  
Maximum extendable capacity of the “m” factory

\( v_{ms} \)  
Percentage production capacity of factory m disrupted under scenario s

**Decision variables:**

\( X_{ik} \)  
Purchase of item “k” from the supplier “i” \((i \in \nu)\) under the disruption

\( z_i \)  
If the contract is provided with the supplier \( i \ (i \in \nu) \) as the main provider, this value is equal to 1, otherwise it is 0

\( z'_i \)  
If the contract is provided with the supplier \( i \ (i \in \nu) \) as the backup provider, this value is equal to 1, otherwise it is 0

\( y_{iu} \)  
If the supplier “i” is strengthened at “u” level, this value equals to 1 and otherwise equals to 0

\( w_{ia} \)  
Preset amount of the item “k” to strengthen supplier “i”

\( x'_{iks} \)  
The amount of the "k" item that the manufacturer receives from the supplier “i” after the disruption the scenario \( S \)
1. Introduction

Due to the advancement in technology, the competitiveness in complex product and its subsystems’ (CoPS’) market and the high added value of the field, manufacturers in this area outsource some of their products and components to stay in the market. Outsourcing can assist manufacturers in reducing costs, increasing competition and speed of future progresses. CoPS plays a vital role in the distribution of modern technology through economics and the shaping of the economic, industrial and technological process in the developed and developing countries [1]. Furthermore, CoPS can be any product, having high costs, advanced technology, modern engineering, subsystems, or infrastructures, which is supplied by a production unit and purchased by one or more consumers [2]. Generally speaking, there are strategic products in this area, making this issue more important, such as in the airspace (e.g., Acha et al. [3], Davies and Brady [4] and Davies and Hobday [2]), transportation (e.g., Acha et al. [3], Özdemir et al. [5] and Davies and Hobday [2]), military (e.g., Davies and Hobday [2], Davies and Brady [4] and Hansen and Rush [6]). In this regard, Du et al. [7] provided a multi-objective model to select the supplier, which takes into account the risks and costs. Solgi et al. [8] developed a new data envelopment analysis model to evaluate different suppliers in CoPS based on a set of economic, technical and geographic criteria. Hongzhuan et al. [9] deployed a model for collaboration between the manufacturer and the supplier of CoPS equipment. Regarding the literature, an article addressing resilience of suppliers in this area was not observed. Therefore, an interesting issue can be considering for the resilience supplier selection of CoPS.

Today in business markets, a set of parameters and variables in the CoPS supplier selection area, are faced with by high levels of uncertainty and disruption of risk. CoPS suppliers often

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_{is}$</td>
<td>The amount of the “$k$” item used from the proposed inventory in the supplier $i$, at the failure and the disruption under the scenario “$s$” stages</td>
</tr>
<tr>
<td>$q'_{is}$</td>
<td>The amount of “$k$” purchasing from the “$i$” ($i \in v$) backup supplier in the disruption under scenario $S$</td>
</tr>
<tr>
<td>$RL_{is}^j$</td>
<td>1, if disrupted supplier $i$ ($i \in J$) is recovered at level $l$ after event $e_{is}$ ($e_{is} \in E_i$) at post-disruption stage under scenario $s$; 0, otherwise</td>
</tr>
<tr>
<td>$E_{ms}$</td>
<td>Extra production capacity for the “$m$” factory</td>
</tr>
<tr>
<td>$p_{ms}$</td>
<td>“$m$” factory production capacity under “$s$” scenario</td>
</tr>
</tbody>
</table>
entangled with external risks, which have contributed to the emergence of a wide range of disruptions and events in the supply chain. Accordingly, the selection of appropriate and resilient suppliers can dramatically decline the purchase cost and delay time, and also will increase the ability to compete in the market at disruptions. These disruptions are the result of factors such as globalization, increased outsourcing activities, increased demand fluctuations, declined product life cycles and declined inventories [10]. Moreover, the supply chain confronts major disruptions such as natural disasters (floods, earthquakes, storms, fire), cyberattacks, sanctions, disruptions in the supply system, production and distribution and so on. On the other side, a series of global events such as the Japan tsunami in 2004 and 2011, the hurricane Katrina in 2005, the Taiwan earthquakes in 1999, 2009 and 2010, the Turkey earthquake in 2012; the flood in Thailand in 2011; the terrorist attacks, diseases, recessions, etc, make that the world constantly be unpredictable and changing. Thus, these disruptions should be explored to propose methods with aim of preventing them [11].

The term resilience was first introduced by Sheffi and Rice Jr [12]. The resilience of the supply chain is the ability of the supply chain to return to its original state (before the disruption) and even move to a new state that is more favorable than the previous one. The supply chain of the CoPS supplier selection, including the supply chain, has a high sensitivity to disruptions [12]. Therefore, the subject of resiliency is of paramount importance in this area. To increase the resilience level of a supply chain, a numbers of resilience strategy are virtually implemented, pointed out some of them below:

- Exploiting multiple sources of supply rather than using one source (e.g., Zhang et al. [13] and Sadghiani et al. [14]).
- Using back-up supplier when disruptions may occur (e.g., Torabi et al. [15] and Jabbarzadeh et al. [16]).
- Fortifying supplier to cope with disruption (e.g., Torabi et al. [15] and Hasani and Khosrojerdi [17]).
- Maintaining additional inventory for times that suppliers are not available (e.g., Torabi et al. [15] and Garcia-Herreros et al. [18]).
- Adding extra supply / production lines to the capacities to of factories (e.g., Jabbarzadeh et al. [16], Ivanov and Morozova [19]).
• Restoring the suppliers from disruptions (e.g., Torabi et al. [15], Jabbarzadeh et al. [16] and Torabi et al. [20]).

• Reducing complexity of flow and nodes (e.g., Zahiri et al. [21]).

Hosseini et al. [22] considered a multi bi-objective stochastic planning model for resilience supplier selection. Najafabadi et al. [23] devised a non-linear integer programming model for supplier selection and order allocation taking into account the risk of disruption and the Emergency stock allocation policy. They showed that with the increasing the probability of failure, decision factors related to supplier selection and order allocation are changed. Hosseini et al. [24] proposed a review article to examine the quantitative approaches for supply chain resilience. They pointed out that the body of literature in using the two-stage stochastic programming is very scarce. Parkouhi et al. [25] introduced two measures to increase and decrease the resilience level of the supplier selection segments. Jabbarzadeh et al. [16] used a hybrid methodology to design a sustainability and resilience supply chain network and developed a multi-objective mathematical model using fuzzing programming. In their model, a case study of plastic industry was deployed to evaluate the proposed model. Dehghani et al. [26] deployed a resilient supply chain design using different resilience strategies, including fortify suppliers and multiple sources. Meena and Sarmah [27] proposed a mixed integer non-linear programming (MINLP) for the supplier selection problem in the presence of disruption. Kamalahmadi and Mellat-Parast [28] presented a two-stage mixed-integer programming model to study a supply chain under disruption and applied a numbers of resilience strategies for it. Torabi et al. [15] used a bi-objective mixed possibilistic scenario-based model for investigating the supplier selection and order allocation under operational and disruption risks. To ameliorate the resilience level of the selected supply base, they also proposed different strategie, including multiple sourcing, fortification and maintaining extra inventories. Hasani and Khosrojerdi [17] introduced a supply chain design problem and proposed resilience and flexible strategies to cope with the risk of correlated disruptive events. Namdar et al. [29] applied a resilient supply chain for single- and multi- source(s) under disruption risk. This research examined the use of resource strategies to achieve a resilient supply chain.

1.1. Analysis of literature and motivations

Regarding the literature, to the best of our knowledge, no work can be found in the relevant literature to address disruption for CoPS. In this manner, there is also no work, which considers
resiliency for the supplier selection of CoPS. Likewise, the body of relevant literature in using the two-stage stochastic programming is very thin. Another notable shortcoming in this regard is that quantitative modeling efforts to systemically determine the decisions of CoPS supply chain are very scarce. Also, a handful of studies in the literature have conducted real case study to evaluate their models.

According to the above-mentioned discussions, important contributions of this article, which distinguishes it from existing articles, can be stated as follows:

- Determining systemically the decisions of CoPS supply chain by applying a quantitative optimization model.
- Incorporating different resilience strategies into the proposed optimization model to mitigate the disruptions and enhance the resilience level of the decisions taken.
- Applying a robust model to increase the robustness of the solutions and deliver stable decisions for the concerned supply chain.
- Deploying the augmented $\varepsilon$-constraint method, ensuring optimal strong Pareto solution and preventing the weak Pareto solutions.
- Eventually, exploring the effectiveness and desirability of the proposed model through discussing a real case study via which useful managerial results are earned.

The remainder of the paper is organized as follows. In the next section, the steps of the proposed approach to design a resilient supply chain for CoPS supply chain are elaborated. In Section 3, the robust optimization model is proposed. In Section 4, the mathematical optimization model is developed. Section 5 explains the augmented $\varepsilon$-constraint method to solve the multi-objective optimization model. Section 6 provides the case study, computational results, and discussions. Finally, Section 7 concludes this paper and proposes some promising avenues for further research.

2. Proposed method

The structure of the methodology proposed for this paper is illustrated in Figure 1. As can be seen, at first, a multi-objective mathematical model is devised for a resilience supplier selection problem. After that, a robust model is applied to cope with data uncertainty. Deploying the augmented $\varepsilon$-constraint method, the next phase aims at solving the bi-objective function. Finally,
a simulation will be performed to examine the efficiency and desirability of the proposed robust model.

3. Robust optimization model

One of the most popular areas for control and optimization problems under the uncertainty is the robust optimization model. In this regard, we propose a robust optimization method for scenarios-based stochastic planning models. This robust optimization method provides a series of solutions to reduce the sensitivity and correlation of data under the scenario [30]. The method can be applied for many applications, for example: logistics planning (e.g., Yu and Li [31]), production planning (e.g., Leung et al. [30]), reverse logistics (e.g., De Rosa et al. [32]), design of blood supply chain (e.g., Jabbarzadeh et al. [33]). In the robust optimization problem, two types of measurements are virtually taken into account. The first one is the solution robustness, and the second is the robustness [34]. For all scenarios, solution robustness aims at finding an optimal solution, and the model robustness is intended to obtain feasible for the model.

Now, let us to consider the following linear optimization model:

\[
\text{Min} \quad c^T x + d^T y
\]

\[\text{s.t.}\]

\[Ax = b\]  \hspace{1cm} \text{(2)}

\[Bx + cy = e\]  \hspace{1cm} \text{(3)}

\[X, y \geq 0.\]  \hspace{1cm} \text{(4)}

Where, \(x\) is the vector of decision variables, \(y\) is the control variable, and \(B, C\) and \(e\) are the technical coefficients, and the right side of the constraints, respectively. Equation (2) declares the structural constraint, having constant and free coefficients for the disruption. In addition, Equation (3) illustrates the control constraint of the model. The definition of the robust optimization problem is based on introducing a set of scenarios, denoted by \(S = \{1, 2, 3, \ldots, s\}\), which pictures the data uncertainty. The set of parameters that hemmed in by uncertainty is considered to be \(\{d_s, B_s, C_s, E_s\}\). Each scenario happens with fixed probability \(P_s\) in such a way
we have $\sum_{s=1}^{S} P_s = 1$. With regards to optimality, a robust solution is ‘near’ to optimal for different realizations of the scenario (i.e. solution robust). Also, with regards to feasibility, a robust solution is ‘almost’ feasible for different realizations of the scenario (i.e. model robust). This is very unlikely that a solution be optimal as well as feasible for all scenarios. Generally, in the robust optimization model, the tradeoff between solution and model robustness is measured and determined based on decision maker’s opinion.

For each scenario, we define control variable $y_s$. That is, the objective function proposed in Equation (1) is a random variable, which with probability $P_s$, takes the value $\zeta_s = c^T x + d^T y_s$.

Additionally, for each scenario, the error vector $z_s$ is introduced to measure the infeasibility in the control constraints proposed in Equation (7). In accordance with the mathematical model (1)-(4), the robust optimization model will be:

$$\text{Min} \sigma(x, y_1, \ldots, y_s) + \lambda \rho(z_1, z_2, \ldots, z_s)$$

(5)

S.t.

$$Ax = b$$

(6)

$$B_s x + C_s y_s + z_s = e_s \quad \text{for all } s \in S$$

(7)

$$x \geq 0, y_s \geq 0, \quad \text{for all } s \in S$$

(8)

The first term of the objective function (5) shows the solution robustness, which aims at approaching the solution to optimal for different realizations of the scenario. The second term of the objective function (5) illustrates the model robustness, aiming to propose a feasible solution under each scenario. It is worth to note that the parameter $\lambda$ is utilized to adjust the tradeoff between solution and model robustness. For example, if $\lambda = 0$, the objective function only minimizes $\sigma(x, y_1, \ldots, y_s)$ and the chance that we face an infeasible solution is high. On other side, if the value of $\lambda$ in is very large, the model robustness dominates the solution robustness in the objective function. It is not quite straightforward to choose the appropriate functions for $\sigma(x, y_1, \ldots, y_s)$ and $\rho(z_1, z_2, \ldots, z_s)$. Conventionally, the mean value $\sum_{s \in S} p_s \zeta_s$ and $\sum_{s \in S} p_s \delta_s$ are
selected for $\sigma(x, y_1, ..., y_s)$ and $\rho(z_1, z_2, ..., z_s)$, respectively. A more appropriate choice for $\sigma(x, y_1, ..., y_s)$ is given as follows [34]:

$$
\sigma(x, y_1, ..., y_s) = \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s \left( \xi_s - \sum_{s' \in S} p_{s'} \xi_{s'} \right)^2
$$

(9)

As can be seen in above-mentioned Equation, there is a quadratic equation in Equation (9), which requires a large computation time for solving. Yu and Li [31] proposed the following formulation for solution robustness:

$$
\sigma(.) = \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s \left( \xi_s - \sum_{s' \in S} p_{s'} \xi_{s'} \right)
$$

(10)

By defining two sets of non-negative deviational variables per scenario, the aforementioned Equation can be converted to a linear form. A more efficient formulation for above Equation was also proposed by Yu and Li [31], which is given as follows:

$$
\text{Min } \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s \left[ \left( \xi_s - \sum_{s' \in S} p_{s'} \xi_{s'} \right) + 2\theta_s \right]
$$

subject to:

$$
\xi_s - \sum_{s' \in S} p_{s'} \xi_{s'} + \theta_s \geq 0
$$

(13)

$$
\theta_s \geq 0
$$

(14)

It should be pointed out that this formulation only needs one non-negative deviational variable per scenario. As can be perceived, if $\xi_s$ is larger than $\sum_{s' \in S} p_{s'} \xi_{s'}$, we have $\theta_s = 0$ and the robustness of the solution will be measured by $\sum_{s \in S} p_o \xi_s + \lambda \sum_{s \in S} p_o \left( \xi_s - \sum_{s' \in S} p_{s'} \xi_{s'} \right)$. On the other side, as $\sum_{s' \in S} p_{s'} \xi_{s'}$ is larger than $\xi_s$, Equation (13) guarantees that $\theta_s = \sum_{s \in S} p_{s'} \xi_{s'} - \xi_s$, which
solution robustness will be here $\sum_{x \in S} po_x \xi_x + \lambda \sum_{x \in S} po_x \left( \sum_{x' \in S} po_{x'} \xi_{x'} - \xi_x \right)$. Indeed, solution robustness measurement equals $\sum_{x \in S} po_x \xi_x + \lambda \sum_{x \in S} po_x \left| \xi_x - \sum_{x' \in S} po_{x'} \xi_{x'} \right|$ in both cases.

4. Problem definition

In the concerned model, the suppliers of CoPS are divided into two groups. In accordance with the traditional criteria, the first group of suppliers has plausible performance, but they have no specific plans for their continuity and improvement in the presence of disruption. The second group encompasses those suppliers, following a specific business continuity management system. To tackle the main disruptions, the second group uses a predetermined plans. Specifically, it is presumed that the second group encompasses suppliers that are better in terms of quality and delivery against the first group. However, with regard to cost criteria, the first group outperforms the second one. In addition, for each supplier in the second group, disruption characteristics comprise of the main features of the business continuity management system. Meanwhile, the failure characteristics of each supplier include:

- Various types of disruptions that can misadjust each of the suppliers
- The probability of occurrence of these disruptions and their impact on the critical processes/operations and then on the production capacity. This subject can be specified by the results of the "business impact analysis" and "risk assessment" process. The aforementioned processes are an important step in developing the business continuity management system.
- Approximating time recovery estimates for various levels of reinforcement in accordance with the continued business development or retrieval program for failure to tackle disruptions.

It should be pointed out that for the risks of suppliers’ disruptions, all conceivable disruption scenarios are addressed. Each supplier may encounter a malicious event, and any malicious event may affect several suppliers in each possible scenario. Each supplier of the first group is negatively affected, as an event happens. In this case, it can solely meet part of its obligation. Nevertheless, the second group of suppliers are capable of carrying their business continuity, or incident recovery programs, and are capable of fulfilling their obligations. To create a more realistic model, we presume that suppliers may not use some of their production capacity after the
disruptions. In real life, companies occasionally use excessive processing capacity in other places to provide important business functions, contributing to recovery quickly. Thus, even after disruptions, these suppliers can have some production capacities. In addition, some disruptions may completely destroy the supplier's supply capacity. For example, incidents such as a hunger strike or power outage for weeks that are taken into account horizons can only reduce the supplier's production capacity by 50%. Also, we assume that the quantity of items shipped from the supplier of the second group that is in interrupted condition is less than a supplier being in normal condition. Nevertheless, the major advantage of the suppliers of second group is that even as they are experiencing a disruption, they are capable of fulfilling their obligations. Therefore, if a supplier belonging to the second group suppliers does not encounter with disruption, it can purchase more items from other suppliers, that is, it is considered as the back-up provider. In addition, in practice, due to the likelihood of simultaneous occurrence of several malicious events on a supplier is very low, we assumed that in each scenario, one event happens in a supplier. In practice, those suppliers located in the same geographic regions can be affected jointly after a disruption such as earthquake. However, this paper assumes that suppliers are scattered. so that a malicious event does not affect all supplier, simultaneously. In the model, the following strategies are employed to increase the supply resilience level of the manufacturer:

- Enabling multiple sources for any kind of outsourcing
- Fortifying of second group suppliers in the presence of disruption. These suppliers can be fortified in various strategies, which have different costs and various levels of mitigation.
- Preservation of inventory already stored in warehouses; this inventory can be used after disruption in each supplier. It is worth noting that the capacity of each supplier is restricted.
- Contracting with some of the suppliers as backup suppliers to utilize them when a disruption occurs. These suppliers may render additional items with high service times and costs.
- Taking into account different recovery levels and business continuity programs for the second group of suppliers. This strategy can assist the supplier in meeting higher levels of requirements.
- Appending extra supply for CoPS suppliers’ capacity to remove supply-side deprivation, caused by disruptions during the manufacturing process of these products.
Moreover, it is assumed that the planning horizon is as a single mid-term period and under any circumstances, the demand is met. However, the costs are paid by manufacturers for product that are delivered. Meanwhile, we presume that the total defective volume of each item bought by the manufacturer should not exceed a predetermined value. Additionally, in the normal condition, the number of suppliers must be less than a predetermined bound. Noteworthily, one of the main challenges in the supply chain planning is that the supply data and demand are hemmed in by uncertainty. Accordingly, to cope with the uncertainty, we deploy a scenario-based model proposed by Mulvey, Vanderbei [34] in this paper.

4.1. Formulation

4.1.1 Objective functions

The first objective function aims at minimizing the total costs of the related decisions, which includes the order cost ($F_{0_i}$), purchase cost ($P_{0s}$), shipping cost ($T_{0s}$), backup supplier cost ($B_{0s}$), strengthening cost ($F_{0s}$), inventory cost ($I_{0s}$), the cost of purchasing from backup supplier ($p_{0s}$), shipping cost of backup supplier ($T_{0s}$), inventory cost to strengthen the supplier ($I_{0s}$), expected cost of ordering the undelivered items ($U_{0s}$), the cost of factories’ extra production capacity ($A_{0s}$). Below, the description and formulation of these components are given.

Order cost: $F_{0_i} = \sum_{i \in e} f_i z_i$ (15)

Purchase cost: $P_{0s} = \sum_{i \in e} \sum_{k \in k} \tilde{p}_{ik} x_{ik}$ (16)

Shipping cost: $T_{0s} = \sum_{i \in e} \sum_{k \in k} g_{ik} x_{ik}$ (17)

Backup supplier cost: $B_{0s} = \sum_{i \in e} \tilde{f}_i z'_i$ (18)

Strengthening cost: $F_{0s} = \sum_{i \in e} \sum_{w \in a} F \tilde{R}_{iw} y_{iw} (19)$

Inventory cost: $I_{0s} = \sum_{i \in J} \sum_{k \in K} \tilde{h}_{ik} w_{ik}$ (20)

The cost of purchasing from backup supplier: $p_{0s} = \sum_{i \in e} \sum_{k \in k} \tilde{p}_{ik} q'_{ik}$ (21)

Shipping cost of backup supplier: $T_{0s} = \sum_{i \in e} \sum_{k \in k} g'_{ik} q'_{ik}$ (22)

Inventory cost to strengthen the supplier: $I_{0s} = \sum_{i \in J} \sum_{k \in K} \tilde{p}_{ik} q_{ik}$ (23)
Expected cost of ordering the undelivered items: \( UCO_s = -\sum_{i\in\mathbb{I}_s} \sum_{k\in\mathbb{K}_s} \tilde{p}_{ik} (x_{ik} - x_{ik}') \) \hspace{2cm} (24)

The cost of factories’ extra production capacity: \( AO_s = \sum_{m\in\mathbb{M}_s} e_{ms} E_{ms} \) \hspace{2cm} (25)

Given the method presented in Equation (11), the first objective function of the model can be formulated utilizing the above-mentioned cost components.

\[
\begin{align*}
\min \text{obj} &= \sum_{s\in\mathbb{S}} (F_0 + PO_s + TO_s + BO_s + FFO_s + IO_s + ppo_s + TTO_s + IIO_s + UCO_s + AO_s) \\
&+ \lambda \sum_{s\in\mathbb{S}} po_s \left[ (F_0 + PO_s + TO_s + BO_s + FFO_s + IO_s + ppo_s + TTO_s + IIO_s + UCO_s + AO_s) \\
&- \sum_{i\in\mathbb{I}_s} po_i (F_0 + PO_i + TO_i + BO_i + FFO_i + IO_i + ppo_i + TTO_i + IIO_i + UCO_i + AO_i) + 2\theta_s \right] \\
&+ \psi \sum_{i\in\mathbb{I}_s} \sum_{s\in\mathbb{S}} po_i \tau_i'
\end{align*}
\]

\hspace{2cm} (26)

The first two parts of the above objective function is to obtain the mean and variance of the model under all scenarios, which aim to measure the robustness of the solutions, and the third part is the model's feasibility, aiming at measuring the robustness of the model.

**4.1.2 Second objective function**

Figure 2 indicates the recovery process in the proposed model. From Figure 2, the amount of items, that are reached via three various strategies are illustrated by \( A, B \) and \( C \). In addition, the times, which the pertaining resilience strategies are received, are denoted by \( LTA, LTB \) and \( LTC \), respectively.

\{Please insert Figure 2 about here.\}

In this Figure, the first part is dictated to the impacts of disruptions on the manufacturer. Also, the second part is related to the ability of manufacturer to tolerate disruptions. It is apparent that the loss of resilience for this process is calculated by the following relation:

\[ A \ast LTA + B \ast LTB + C \ast LTC \]

Noteworthy, in this relation, the resilience strategies such as inventory prediction and contracting with a backup provider, in which items are receive by customers, are taken into account. To calculate the loss of resilience, a quantitative measure is given as follows:
\[ RE' = \sum_{s \in S} P_s \left[ \sum_{i \in I} \sum_{k \in K} LT_i q_{iks}^l + \sum_{i \in I} \sum_{k \in K} LT_i q_{iks} + \sum_{i \in I} \sum_{k \in K} \left( x_{iks} - \theta_{i_s} - x_{ik} \right) \left( LT_i + \sum_{k \in K} RT_i \right) \right] \] (27)

The first and second parts of Equation (27) calculates the amount of bought items from the suppliers and predetermined inventory multiplied by their arrival times. The third term also considers the amount of items provided by second type suppliers after disruption.

As mentioned before, Equation (27) computes the loss of resilience. However, to directly obtain the normalized resilience level, the following formula can be used:

\[ RE = 1 - \frac{RE'}{Q.T} \] (28)

Where, \( Q \) represents quantity of required items for the manufacturer.

### 4.1.3 Model constraints

\[ \sum_{i \in I} \sum_{k \in K} (x_{ik} + q_{iks}^l) + \sum_{i \in I} \sum_{k \in K} \sum_{s \in S} q_{iks} + \sum_{i \in I} \sum_{k \in K} \sum_{s \in S} \left( x_{iks} - \theta_{i_s} - x_{ik} \right) \left( LT_i + \sum_{k \in K} RT_i \right) \geq \delta_k \quad \forall s \in S, k \in K \] (29)

\[ \sum_{k \in K} a_{ik} (x_{ik} + q_{iks}^l) \leq Ca_i \quad \forall s \in S, k \in K \] (30)

\[ \sum_{k \in K} a_{ik} x_{iks}^l \leq \theta_{i_s} \quad \forall s \in S, i \in I \setminus \bar{V}_s \] (31)

\[ \sum_{k \in K} a_{ik} x_{iks}^l \leq \left( \theta_{i_s} + \beta_{i_s} \nu_{i_s} \right) \left( 1 - \sum_{l \in L_{i_s}} RL_{i_s}^l \right) + \sum_{l \in L_{i_s}} CL_{i_s}^l + RL_{i_s} \] (32)

\[ \theta_{i_s} x_{ik} \leq x_{iks}^l \quad \forall s \in S, i \in \bar{V}_s, k \in K \] (33)

\[ \sum_{k \in K} b_{ik} w_{ik} \leq S c \sum_{i \in L_1} y_{iu} \quad \forall i \in J, s \in S \] (34)

\[ \sum_{i \in V_1} \sum_{k \in K} (x_{ik} + q_{iks}^l) + \sum_{i \in V_1} \sum_{k \in K} \sum_{s \in S} q_{iks} + \sum_{i \in I} \sum_{k \in K} \sum_{s \in S} \left( x_{iks} - \theta_{i_s} - x_{ik} \right) \left( LT_i + \sum_{k \in K} RT_i \right) \leq R_k \] (35)

\[ \sum_{i \in I} y_{iu} \quad \forall i \in J \] (36)

\[ q_{iks} \leq w_{ik} \quad \forall s \in S, k \in K, i \in J \] (37)

\[ \sum_{k \in K} x_{ik} \leq M \cdot z_i \quad \forall i \in V \] (38)
\[
x'_{iks} \leq x_k \quad \forall i \in \overline{V}_s, k \in K, s \in S \\
q'_{iks} \leq M \cdot z_i' \quad \forall i \in V, k \in K, s \in S \\
q'_{iks} = 0 \quad \forall s \in S, k \in K, i \in \overline{V}_s \\
\sum_{i \in V} z_i \leq n \\
\sum_{l \in L_{iru}} RL'_{iru} \leq 1 \quad \forall s \in S, i \in J, \cap \overline{V}_s \\
E_m \leq k_m \quad m \in M
\]

(39)  
(40)  
(41)  
(42)  
(43)  
(44)  

\[
P_{ms} \leq (1 - v_{ms})(w_{m} + E_m) \quad \forall m \in M, \forall s \in S
\]

(45)  

\[
F_{s} + PO_{s} + TO_{s} + BO_{s} + FFO_{s} + IO_{s} + ppo_{s} + TTO_{s} + IIO_{s} + UCO_{s} + AO_{s}
\]

(46)  

\[
- \sum_{i \in S} p_{oi}(F_{oi} + PO_{oi} + TO_{oi} + BO_{oi} + FFO_{oi} + IO_{oi} + ppo_{oi} + TTO_{oi} + IIO_{oi} + UCO_{oi} + AO_{oi}) + \theta_s \geq 0
\]

\forall s \in S

(47)  

\[
x'_{ik}, x'_{iks}, w_{ik}, q_{iks}, q'_{iks} \geq 0 \quad \forall i \in V, k \in K, s \in S
\]

(48)  

\[
y_{iu} \in \{0,1\} \quad \forall i \in J, u \in U
\]

(49)  

\[
z_i, z_i' \in \{0,1\} \quad \forall i \in V
\]

(50)  

Constraint (29) ensures the demand for builders under any scenario. Constraint (30) ensures that the total ordered amount to a main or backup undisrupted supplier is smaller than the supplier's production capacity. Constraint (31) restricts the purchasing amount of the first group to limit supply suppliers to the available capacity after the disruption. Constraint (32) limits the amount purchased from second group’s disrupted suppliers after disruption, considering their recovery and strengthen levels, to their available production capacity. It’s also necessary to mention that this constraint is nonlinear. Constraint (33) ensures that the quality of the items shipped from the disrupted supplier under each scenario should be greater than or equal to the amount of items purchased from the supplier in the normal state multiplied by supplier’s residual capacity percentage after disruption occurrence. Constraint (34) presents inventories that are stored to strengthen suppliers and the amount of available inventory. Constraint (35) guarantees the expected defective rate of each item purchased proportional to a maximum acceptable defective rate. Constraint (36) states that the second category supplier can be strengthened at a certain
level. The constraint (37) limits the delivery amount of items from a preset amount to the amount provided in the previous step. Constraint (38) describes that the purchased amount of each item from the main supplier will be equal to zero, if the contract is not made with the supplier as the main supplier. Constraint (39) indicates that the sent amount of each item from a disrupted supplier (especially after the recovery of the second group's suppliers) should be less than or equal to the amount purchased from the seller in normal circumstances. Constraint (40) ensures that if the contract is not set with the supplier as the backup supplier, the amount of each item purchased from the him/her is zero. Constraint (41) ensures that disruptive suppliers under any scenario can’t be used as back-up suppliers under this scenario. The constraint (42) states that the total number of main suppliers in the normal situation (i.e. the pre-event stage) should be less than the maximum number in the normal situation in accordance with the supply chain principles. Constraint (43) indicates that each supplier of the second group under the disruption can recover at the highest rate of recovery in each scenario. The constraint (44) represents the maximum capacity of the factory production. The constraint (45) indicates the capacity limitation of the primary supplier of the plant. Constraint (46) shows the auxiliary Equation defined in equation (13). The constraints (47-50) show the type of decision variables. Also, the probability of occurrence of each scenario can be calculated as follows:

$$p_s = \left[ \prod_{i \in K_s} \left( 1 - \sum_{e \in E_i} \pi_{we} \right) \right]$$

(51)

Also, constraints (28) and (32) are nonlinear, which, according to Torabi, Baghersad15 [ become linear.

5. Augmented ε-constraint method

In solving a multi-objective problem, we seek the methods, that produce Pareto’s solutions. In this context, Hwang and Masud [35] classified the multi-objective mathematical models into three sections (1) priori, (2) interactive, and (3) posterior. In the posterior approach, weights of functions should be determined before the resolution process, which is a very difficult task Mavrotas [36]. In interactive approaches, the decision maker aims at achieving to the desire solutions interactively [37]. The main weakness of this approach is that it can’t provide an image of the Pareto's solution set and only focuses on the decision maker’s desired solutions, and the
remaining efficient ones will be eliminated. In priori methods, a set of Pareto’s solutions will first be determined, and if these solutions are not appropriate for it, then some other solutions will be generated. According to the above-mentioned discussion, we will use the third method in this article. The \( \varepsilon \)-constraint method is one of the famous posterior methods used to find optimal Pareto solutions for multi-objective problems. In this method, an objective function will be optimized and the rest once will be added as constraints as shown below:

\[
\begin{align*}
M & \text{ in } f_1(x) \\
 f_q(x) & \leq r_q \quad \forall \ q = 2,...,q \\
x & \in X
\end{align*}
\]

Where, \( x \) is the decision variable’s vector, \( X \) is feasible available, \( f_1(x), f_2(x), ..., f_q(x) \) are the objective functions that must be minimized. By parametric changes in the right of the objective functions, being in the constraints, pareto's solution will be obtained [38]. To this end, the of range of each \( \varepsilon \) must first be earned. For this, the pay table is created by optimizing the \( (q-1) \) objective function, that is, those that are in the constraints. Then, the values of \( \varepsilon \) are obtained by spilling , the obtained ranges to \( n_q \) interval as follows [39]:

\[
\text{rang}_{\text{p}} = f_{q}^{\text{max}} - f_{q}^{\text{min}} \quad ; \quad \varepsilon^j_p = f_{q}^{\text{max}} - (\text{rang}_{\text{p}}) / n_q \quad ; \quad \forall \ p \neq 1, k = 0,1, n_q = 1
\]

Where, \( f_{q}^{\text{max}} \) and \( f_{q}^{\text{min}} \) are the maximum and minimum values of the objective function of \( q \). However, as pointed out by Mavrotas [36], the general form of the \( \varepsilon \)-constraint method does not guarantee an efficient solution to the vector \( \varepsilon \). To prevent this problem, a developed version of this method will be used, which is called the augmented \( \varepsilon \)-constraint method. By deploying the \( \varepsilon \)-constraint method, the following model can be obtained:

\[
\begin{align*}
\min \ & \theta_1 \cdot f_1(x) - \text{rang}_{q} \cdot \delta \cdot (\beta_2 \cdot j_{l_2} / (\text{rang}_{r_2}) + \beta_3 \cdot j_{l_3} / (\text{rang}_{r_3}) + ... + \beta_q \cdot j_{l_q} / (\text{rang}_{r_q})) \\
\text{s.t.} \quad & f_q(x) + \beta \cdot j_{l_q} = r_{(q)} \quad \forall \ q = 2,...,q \\
x & \in X; \ j_{l_q} \in R^*
\end{align*}
\]
Where, $\delta$ is a very small number (between $10^{-6}$ and $10^{-3}$), $\beta_q$ is the priority value of the objective function of $q^{th}$, and $j'_p$ is the shortage variable of the relevant constraint. Note that the complementary term of $\beta_q \frac{j'_q}{\tau an \sigma q}$ will ensure that only the efficient solution is obtained for the vector $\varepsilon$.

6. Case study
Choosing a resilient and appropriate supplier in the CoPS supply chain is one of the most important needs in this area, and the its literature needs to be enriched due to presence of important and strategic products (aircraft and satellites). To this end, in an attempt to bridge the gaps in the literature, a case study is conducted in the field of air and supply of complex products, in which important and reliable managerial results are obtained. Also, real data was provided for estimating and collecting historical data and practical report from electronic sites of different organizations, such as (https://www.sst-us.com/shop), (https://www.saftbatteries.com), (http://www.azurspace.com), (www.nasa.gov/inde), (www.surrey.ac.uk).

6.1. Implementation and evaluation
To employ the proposed mathematical model for the studied case, it coded in GAMS software, and CPLEX solver used to solve it. Meanwhile, all computational experiments are performed using a laptop with Intel R Pentium R T 4500, 2.5 GHz and 4GB of RAM. To this end, for the concerned case study, we consider 10 suppliers who provide items. In addition, three scenarios encompassing low, medium and high demand for delivery components are considered. The objective is to take tactical, strategic along with operational decisions to ensure the optimal decision for them.

The solutions are obtained by solving the objective functions using the augmented $\varepsilon$-constraint method. This approach is one of the famous methods belonged to posterior method. It is used to find optimal Pareto solutions for multiple objective functions, and provides strong optimal Pareto solutions and prevents weak ones. In this method, an objective function is optimized and the rest are added as constraints to the problem.

Figure 3 indicates the number of delivery components for different suppliers under the concerned scenarios. From Figure 3, it can be concluded that in pessimistic scenario (i.e., scenario 1), more number of delivery components is needed to be used, whist in optimistic scenarios (i.e., scenario 3), fewer number of them is applied. Another appealing result is that the suppliers 1, 3, 5 and 6
are more suitable for supplying items under any scenario. Contrariwise, supplier 10 is selected only for the low scenario and is not chose in other scenarios.

{Please insert Figure 3 about here.}

In the next step, we intend to obtain the tradeoff between the solution robustness and model robustness by changing the risk aversion $\Psi$. A risk averse decision maker tends to choose high values of $\Psi$, which prevent inventory shortages and items. On the other hand, a risk-taker decides to minimize the costs. Therefore, he/she tends to choose large values of $\Psi$. Thus, the value of $\Psi$ can be changed to obtain tradeoffs between demand fulfillment and costs. The following Figure 4 shows the trade-off between the solution robustness and the model robustness according to the variations in risk aversion. What is clear from this figure is that the large amounts of this weight increase the costs that reflect the solution robustness, while reduce the under-fulfillment of demand representing model robustness decreases that represents the model robustness. Given these observations, it can be deduced that the model provides almost feasible solutions for high risk-aversion weight. Also, the average amount of under-fulfillment demand eventually reaches zero in the high values of this weight. This test can help managers to decide on more favorable responses by adjusting risk aversion weight. Here the decision maker will probably choose 250 for the value of $\Psi$. This is due to the fact that the under-fulfillment demand reaches zero and the value of the objective function does not change from 250 onwards. Put differently, the solution robustness and the model robustness come to an equilibrium with a constant value. Certainly, according to the decision maker's goals and particular model conditions, other values may be selected for $\Psi$.

{Please insert Figure 4 about here.}

In the next step, we aim at analyzing the effects of the resilient strategies on the total costs. As previously noted, this model takes into account the following strategies to tackle disruption:

- Maintaining extra capacity
- Fortifying the suppliers
- Using backup suppliers
- Recovering the supplier after disruption (i.e., suppliers’ business continuity plans)
To this end, we calculate the total expected costs by applying different resilient strategies. The relevant results are illustrated in Figure 5:

{Please insert Figure 5 about here.}

As shown in the figure 5, all resilient strategies are effective in reducing the overall cost of supply chain in presence of disruptions. In addition, it can be inferred that the recovery strategy has the greatest effect on improving the resilience level. This test can help respective managers to make better decision and reduce supply chain costs by applying the resilience strategy.

To evaluate the effectiveness and desirability of the proposed model, its performance is compared with the deterministic model. Note that the values of uncertain parameters in the deterministic model are replaced by their mean values and only one scenario model for the model (15) to (50) is considered. The methodology deployed to compare these two models is described in Figure 6. As can be seen, at first, the strategic decisions related to the supplier selection (binary variables) are determined for both robust and deterministic models. In addition, 100 random realization parameters are generated. After that, binary variables are embedded in the realization model that its compact form are proposed as follows.

\[
\begin{align*}
\text{Min } \text{Obj} & \quad j_1 = f_{\text{real}}^* x^* + c_{\text{real}}^* y + v S \\
A y + S & \geq D_{\text{real}} \\
B y & \leq 0 \\
D y & = 0 \\
N y & \leq E x^* \\
S & \geq 0
\end{align*}
\]

(69)

Where, \(f_{\text{real}}\) and \(c_{\text{real}}\) vectors represent simulated values for the objective function coefficients. The vectors \(x^*\) and \(y^*\) respectively are the binary and continuous variables derived from robust and deterministic models. Likewise, the \(A, B, D\) and \(N\) are the technical coefficients of the constraints. \(D_{\text{real}}\) is simulated values for demand. The limitation violation degree can also be measured by the decision variable \(S\). Finally, the penalty of unsatisfied demand is indicated by \(V\).

It should be noted that the simulated model is solved 100 times for both robust and deterministic models. Eventually, the mean deviation of the objective function under this simulation is
calculated for both models to compare them.

Figures 7 and 8, respectively, compare these two models in terms of mean and standard deviation. As illustrated, when the amount of risk aversion is less than the suggested value, that is $\Psi = 250$, the robust model and the deterministic model have almost the same performance in both of these criteria. When $\Psi$ equals to 250 or more, a robust model is better than the deterministic model in terms of mean and standard deviation. Note that the advantage of the robust model in terms of standard deviation shows the non-sensitive nature of solutions against that of deterministic model. More precisely, the robust model is able to provide a stable structure for a CoPS’ supplier supply chain.

7. Conclusions

The eventual goals of each problem in the evaluation and selection of the CoPS suppliers are choosing the appropriate and high-quality suppliers, being substantially resilient in the presence of disruption. In this paper, a mathematical model for the resilience supplier selection of CoPS is considered to deal with uncertainty and risk of disruption. To provide stable decisions for the proposed problem under uncertainty, a robust optimization approach is employed. Likewise, different resilience strategies including restoring supply from occurred disruptions, fortification of the suppliers, using backup suppliers, and utilizing the extra production capacity for suppliers have been applied to tolerate disruptions. To solve the proposed bi-objective model, the augmented $\varepsilon$-constraint method is proposed, which ensures the strong Pareto solutions and prevents the weak solutions. Also, to examine the effectiveness and desirability of the optimization model, a case study is discussed, trough which important managerial results are
extracted. The results reveal the utility and applicability of the proposed model and propose significant managerial insights. A prominent finding is that the selected suppliers can reduce the delivery time, in addition to reducing the cost of the supply chain. Meanwhile, suppliers 1, 3, 5 and 6 are more suitable for supplying items under any scenario. Contrariwise, supplier 3 is selected only for the low scenario and is not chose in other scenarios. We also endorse that by changing the value of $\psi$, the trade-off between robustness of the solution and model can be achieved. As such, the results corroborate that the robust model in terms of average performance is more suitable than the deterministic model. This test can assist managers in deciding the most desirable answers. For future research, several research avenues can be recommended to enrich its literature. For example, considering a multi-source strategy for risk reduction can be an interesting avenue for the proposed model. Also, given the complex complexity of the proposed model, future research may be aimed at proposing the exact solution procedure such as benders algorithm to solve it.

References

Biographies

Omid Solgi received his MSc and BSc degrees in Industrial Engineering from Iran University of Science and Technology, and Bu-Ali Sina University. His research interest are supply chain network design and data envelopment analysis.

Jafar Gheidar-Kheljani is an Assistant Professor in the Department of Industrial Engineering at Malek-Ashtar University of Technology. He received his PhD in Industrial Engineering from Amirkabir University of Technology. He has been involved in a variety of research projects about supply chain and logistics optimization, project management and system analysis.

Ehsan Dehghani is a PhD student at Iran University of Science and Technology. He received his MSc and BSc degrees from Iran University of Science and Technology, and Golpayegan University of Technology, respectively. His research interests are facility location, inventory control and queuing theory.

Alireza Taromi is a MSC student at Science and Research Branch, Islamic Azad University. He received his BSc degrees in Industrial Engineering from Tehran Province Payame Noor University, respectively. His research interests are supply chain and portfolio analysis.

Figure Captions

Figure 1. Structure of the methodology proposed for the paper.

Figure 2. Supply disruption recovery process [15].

Figure 3. Scenarios used based on the number of delivery components by suppliers for CoPS.

Figure 4. A tradeoff between the solution and model robustness

Figure 5. Costs performance considering different resilient strategies.

Figure 6. The evaluation approach to compare the robust optimization model with the deployed average model.

Figure 7. Average performance of robust optimization and expected value of the model with \( \psi \) changes.

Figure 8. Standard deviation performance of robust optimization and expected value of the model with \( \psi \) changes.
Generate a multi-objective mathematical optimization model for suppliers’ resiliency

Generate a scenario-based robust optimization model

First term

Generate an augmented $\varepsilon$-constraint model to transform a model into a single-objective model

Solve a single-objective model to get the desired values of the decision variables

Use the simulation used to compare two deterministic and robust models

Second term

Calculate the mean and standard deviation of two definite models for simulation

Comparison the performance of two deterministic and robust models

**Figure 1.** Structure of the methodology proposed for the paper.
Figure 2. Supply disruption recovery process [15].

First scenario
Figure 3. Scenarios used based on the number of delivery components by suppliers for CoPS.
Figure 4. A tradeoff between the solution and model robustness.

Figure 5. Costs performance considering different resilient strategies.
Figure 6. The evaluation approach to compare the robust optimization model with the deployed average model.
Figure 7. Average performance of robust optimization and expected value of the model with $\psi$ changes.

Figure 8. Standard deviation performance of robust optimization and expected value of the model with $\psi$ changes.