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Resilient supplier selection in complex products and their subsystem supply chains under uncertainty and risk disruption: A case study for satellite components

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Abstract. Recently, the manufacture of complex products and their subsystems has faced disruption and troublesome behavior in supplying goods and items. Likewise, suppliers in this area are more likely to be affected by external problems, resulting in disturbances. Selecting resilient and expedient suppliers dramatically decreases delay time and costs and contributes to the competitiveness and development of companies and organizations in this field. In this regard, this paper aims at proposing a bi-objective robust mathematical model to provide resilient supplier selection and order allocation for complex products and their 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 a supply from occurred disruptions, fortification of suppliers, using backup suppliers, and utilizing extra production capacity for suppliers, have been devised to tolerate disruptions. Meanwhile, the augmented ε-constraint method is used, ensuring optimal strong Pareto solutions and preventing weak ones for the proposed bi-objective model. 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.

1. Introduction

Due to advancements in technology, competitiveness in the market of Complex Products and their Subsystems (CoPS), and the high added value of this 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 making faster future progress. CoPS plays a vital role in the distribution of modern technology through economics and by shaping the economic, industrial and technological processes in 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,

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there are strategic products in this area, making this issue more important, such as in the aerospace industry (e.g., [2–4]), transportation (e.g., [2,3,5]), and military (e.g., [2,4,6]). 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 the resilience of suppliers in this area has not been observed. Therefore, an interesting issue can be considered 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 high levels of uncertainty and disruption by risk. CoPS suppliers are often 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 increase the ability to compete in the market during 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, and fire), cyberattacks, sanctions, disruptions in supply systems, production and distribution, and so on. Furthermore, a series of global events such as the Japanese tsunami in 2004 and 2011, hurricane Katrina in 2005, Taiwan earthquakes in 1999, 2009, and 2010, the Turkish earthquake in 2012, the flood in Thailand in 2011, terrorist attacks, disease, recession, etc. create a constantly unpredictable and changing world. Thus, these disruptions should be explored in order to discover methods of prevention [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 number of resilience strategies are virtually implemented, some of which are described below:

- Exploiting multiple sources of supply rather than using one source (e.g., [13,14]);
- Using back-up suppliers when disruptions may occur (e.g., [15,16]);
- Fortifying suppliers to cope with disruptions (e.g., [15,17]);
- Maintaining additional inventory for times when suppliers are not available (e.g., [15,18]);
- Adding extra supply/production lines to the capacities of factories (e.g., [16,19]);
- Restoring the suppliers from disruptions (e.g., [15,16,20]).
- Reducing the complexity of flow and nodes (e.g., [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 by 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 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 sustainable and resilient supply chain network and developed a multi-objective mathematical model using fuzzy programming. In their model, a case study of the plastic industry was deployed to evaluate the proposed model. Dehghani et al. [26] deployed a resilient supply chain design using different resilience strategies, including fortifying 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 number of resilience strategies to it. Torabi et al. [15] used a bi-objective mixed possibilistic scenario-based model for investigating supplier selection and order allocation under operational and disruption risks. To ameloraite the resilience level of the selected supply base, they also proposed different strategies, 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. There is also no work regarding consideration of resiliency for the supplier selection of CoPS. Likewise, the body of relevant literature regarding the use of 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 the CoPS supply chain are very scarce. Also, only a handful of studies in the literature have conducted real case studies to evaluate their models.

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

- Determining systemically the decisions of the CoPS supply chain by applying a quantitative optimization model;
- Incorporating different resilience strategies into the proposed optimization model to mitigate 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 ε-constraint method, ensuring optimal strong Pareto solutions and preventing 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 the 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 ε-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

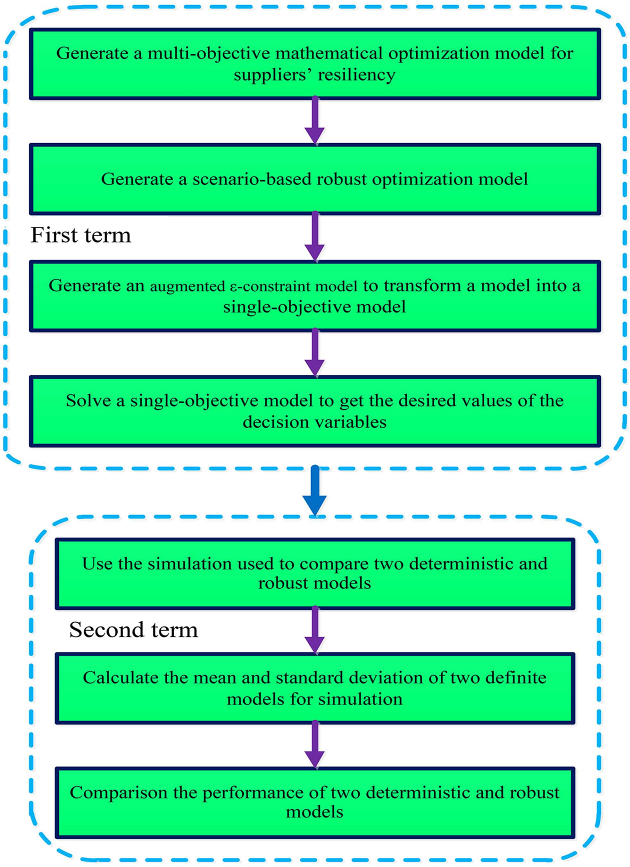

Figure 1. Structure of the methodology proposed for the paper.

for a resilience supplier selection problem. After that, a robust model is applied to cope with data uncertainty. Deploying the augmented ε-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 uncertainty is the robust optimization model. In this regard, a robust optimization method is proposed 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 to many applications, for example: logistics planning (e.g., [31]), production planning (e.g., [30]), reverse logistics (e.g., [32]), and design of a blood supply chain (e.g., [33]). In the robust optimization problem, two types of measurement are virtually taken into account. The first is solution robustness, and the second is robustness [34]. For all scenarios, solution robustness aims at finding an optimal solution, and the model robustness is intended to obtain that which is feasible for the model.

Now, let us consider the following linear optimization model:

$$\min c^T x + d^T y, \tag{1}$$

s.t.:

$$Ax = b, \tag{2}$$

$$Bx + cy = e, \tag{3}$$

$$X, x \geq 0, \tag{4}$$

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. Eq. (2) declares the structural constraint, having constant and free coefficients for the disruption. In addition, Eq. (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 $S = \{1, 2, 3, ..., s\}$, which pictures data uncertainty. The set of parameters that is 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 that $\sum_{s=1}^{S} P_S = 1$. With regard to optimality, a robust solution is 'near' to optimal for different realizations of the scenario (i.e. solution robustness). Also, with regard to feasibility, a robust solution is 'almost' feasible for different realizations of the scenario (i.e. model robustness). It is very unlikely that a solution may be optimal as well as feasible for all scenarios. Generally, in the robust optimization model, the tradeoff between the solution and model robustness is measured and determined based on the decision maker's opinion.

For each scenario, control variable y_s is defined. That is, the objective function proposed in Eq. (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, error vector z_s is introduced to measure the infeasibility in the control constraints proposed in Eq. (7). In accordance with the mathematical model (1)–(4), the robust optimization model will be:

$$\min \sigma(x, y_1, \ldots, y_s) + \lambda \rho(z_1, z_2, \ldots, z_s), \tag{5}$$

s.t. :

$$Ax = b, \tag{6}$$

$$B_S x + C_S y_s + z_s = e_s \qquad \text{for all s} \in S, \tag{7}$$

$$x \geq 0, \quad y_s \geq 0, \qquad \text{for all s} \in S. \tag{8}$$

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 noting that parameter λ is utilized to adjust the tradeoff between solution and model robustness. For example, if $\lambda = 0$, the objective function only minimizes $\sigma(x, y_{1,...,}y_s)$ and the chance of facing an infeasible solution is high. On the other hand, if the value of λ 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 $\sigma(x, y_1, \ldots, y_s)$ and $\rho(z_1, z_2, \ldots, z_s)$, respectively. A more appropriate choice for $\sigma(x, y_{1,...,}y_s)$ is given as follows [34]:

$$\sigma(x, y_1, \ldots, y_s) = \sum_{s \in S} p_s \zeta_s + \lambda \sum_s p_s \left(\zeta_s - \sum_{s'} p_{s'} \zeta_{s'} \right)^2. \tag{9}$$

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

$$\sigma(.) = \sum_{s \in S} p_s \zeta_s + \lambda \sum_{s \in S} p_s \zeta_s \left| \zeta_s - \sum_{s' \in S} p_{s'} \zeta_{s'} \right|. \tag{10}$$

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 the above equation was also proposed by Yu and Li [31], which is given as follows:

$$\min \sum_{s \in S} p_s \xi_s + \lambda \sum_{s \in S} p_s \left[\left(\xi_s - \sum_{s' \in S} po_{s'} \xi_{s'} \right) + 2\theta_s \right], \tag{11}$$

subject to:

$$\xi_s - \sum_{s' \in S} po_{s'} \xi_{s'} + \theta_s \geq 0, \tag{12}$$

$$\theta_s \geq 0. \tag{13}$$

It should be pointed out that this formulation only needs one non-negative deviational variable per scenario. As can be perceived, if ξ_s is larger than $\sum_{s' \in S} po_{s'} \xi_{s'}$, one has θ_s=0 and the robustness of the solution will be measured by:

$$\sum_{s\in S} po_s\xi_s + \lambda \sum_{s\in S} po_s \left(\xi_s - \sum_{s'\in S} po_{s'}\xi_{s'} \right).$$

On the other hand, as $\sum_{s'\in S} po_{s'}\xi_{s'}$ is larger than ξ_s, Eq. (12) guarantees that $\theta_s = \sum_{s'\in S} po_{s'}\xi_{s'} - \xi_s$, whose solution robustness will be:

$$\sum_{s\in S} po_s\xi_s + \lambda \sum_{s\in S} po_s \left(\sum_{s'\in S} po_{s'}\xi_{s'} - \xi_s \right).$$

Indeed, the solution robustness measurement equals $\sum_{s\in S} po_s\xi_s + \lambda \sum_{s\in S} po_s \left| \xi_s - \sum_{s'\in S} po_{s'}\xi_{s'} \right|$ in both cases.

4. Problem definition

In the concerned model, the suppliers of CoPS are divided into two groups. In accordance with 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 plan. 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. In addition, for each supplier in the second group, disruption characteristics comprise the main features of the business continuity management system. Meanwhile, the failure characteristics of each supplier include:

- Various types of disruption that can misadjust each supplier;
- The probability of occurrence of these disruptions and their impact on critical processes/operations, thus on production capacity. This subject can be specified by the results of the "business impact analysis" and "risk assessment" processes. 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 risks in supplier disruption, 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 is capable of carrying out business continuity, or incident recovery programs, and are capable of fulfilling their obligations. To create a more realistic model, it is presumed that suppliers may not use some of their production capacity after the disruptions. In real life, companies occasionally create 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 capacity. However, some disruptions may completely destroy the supplier's supply capacity. For example, incidents such as a hunger strike or a power outage for weeks that are taken into account horizons can only reduce the supplier's production capacity by 50%. Also, it is assumed that the quantity of items shipped from the supplier of the second group that is in an interrupted condition is less than a supplier being under normal conditions. Nevertheless, the major advantage of the suppliers of the 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 of suppliers does not encounter disruption, it can purchase more items from other suppliers, which are considered back-up providers. In addition, in practice, due to the likelihood that the simultaneous occurrence of several malicious events on one supplier is very low, it is assumed that in each scenario, one event happens to a supplier. In practice, those suppliers located in the same geographic regions can be affected jointly after a disruption such as an earthquake. However, this paper assumes that suppliers are scattered. Thus, a malicious event does not affect all suppliers 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 using 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 at 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 requirement;

√ Appending an extra supply for CoPS supplier 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 a single mid-term period and under any circumstances, the demand is met. However, the costs are paid by manufacturers for the products delivered. Meanwhile, it is presumed that the total defective volume of each item bought by the manufacturer should not exceed a predetermined value. Additionally, under normal conditions, the number of suppliers must be less than a predetermined bound. It is noted that one of the main challenges in supply chain planning is that the supply data and demand are hemmed in by uncertainty. Accordingly, to cope with the uncertainty, a scenario-based model proposed by Mulvey et al. [34] is deployed 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 include order cost (FO_s), purchase cost (PO_S), shipping cost (TO_s), backup supplier cost (BO_s), strengthening cost (FFO_S), inventory cost (IO_s), the cost of purchasing from backup suppliers (ppo_s), shipping cost of backup supplier (TTO_s), inventory cost to strengthen the supplier (IIO_s), expected cost of ordering the undelivered items (UCO_s), and extra factory production capacity cost (AO_s). The description and formulation of these components are given below:

Order cost:

$$Fo_s = \sum_{i \in v} f_i \, z_i, \tag{14}$$

Purchase cost:

$$PO_S = \sum_{i \in v} \sum_{k \in k} \tilde{p}_{ik} x_{ik}, \tag{15}$$

Shipping cost:

$$TO_s = \sum_{i \in v} \sum_{k \in k} g_{ik} x_{ik}, \tag{16}$$

Backup supplier cost:

$$BO_s = \sum_{i \in v} \tilde{f}_i \, z'_i, \tag{17}$$

Strengthening cost:

$$FFO_S = \sum_{i \in J} \sum_{u \in U} F\tilde{R}_{iu} y_{iu}, \tag{18}$$

Inventory cost:

$$IO_s = \sum_{i \in J} \sum_{K \in K} \tilde{h}_{ik} w_{ik}, \tag{19}$$

The cost of purchasing from backup supplier:

$$ppo_s = \sum_{i \in v_s} \sum_{k \in k} \tilde{p}'_{ik} q'_{iks}, \tag{20}$$

Shipping cost of backup supplier:

$$TTO_s = \sum_{i \in v} \sum_{k \in k} g'_{ik} q'_{iks}, \tag{21}$$

Inventory cost to strengthen the supplier:

$$IIO_s = \sum_{i \in J} \sum_{K \in K} \tilde{p}_{ik} q_{iks}, \tag{22}$$

Expected cost of ordering the undelivered items:

$$UCO_s = -\sum_{i \in \bar{V}_S} \sum_{K \in K} \tilde{P}_{ik} (x_{ik} - x'_{iks}), \tag{23}$$

The cost of factories' extra production capacity:

$$AO_s = \sum_{m \in M} e_m E_{ms}. \tag{24}$$

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

$$\begin{aligned} \min obj = & \sum_{s \in S} PO_s (Fo_s + PO_S + TO_s + BO_s \\ & + FFO_S + IO_s + ppo_s + TTO_s + IIO_s \\ & + UCO_s + AO_s) + \lambda \sum_{s \in S} po_s \\ & \begin{bmatrix} (Fo_s + PO_S + TO_s + BO_s + FFO_S + IO_s \\ +ppo_s + TTO_s + IIO_s + UCO_s + AO_s) \\ -\sum_{s' \in S} po_{s'} (Fo_{s'} + PO_{s'} + TO_{s'} + BO_{s'} \\ +FFO_{s'} + IO_{s'} + ppo_{s'} \\ +TTO_{s'} + IIO_{s'} + UCO_{s'} + AO_s) + 2\theta_s \end{bmatrix} \\ & + \psi \sum_{t \in T} \sum_{s \in S} po_s \tau_t^s. \end{aligned} \tag{25}$$

The first two parts of the above objective function are 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 model feasibility, aimed at measuring the robustness of the model.

4.1.2. Second objective function

Figure 2 indicates the recovery process in the proposed

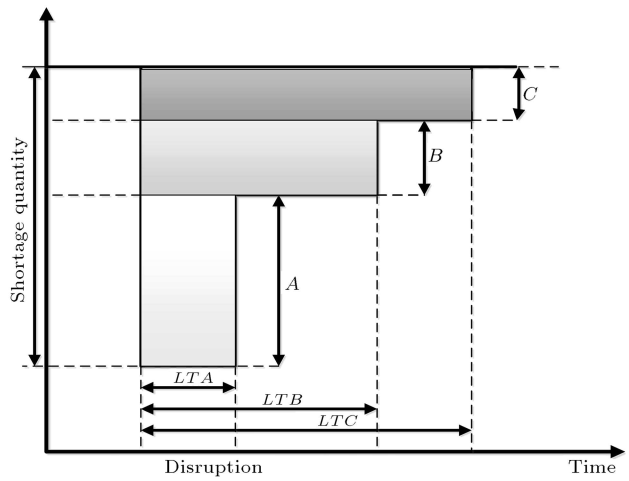

Figure 2. Supply disruption recovery process [15].

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 at which the pertaining resilience strategies are received, are denoted by LTA, LTB and LTC, respectively.

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

$$A * LTA + B * LTB + C * LTC.$$

It is noted that in this relation, resilience strategies, such as inventory prediction and contracting with a backup provider, by which items are received by customers, are taken into account. To calculate the loss of resilience, a quantitative measure is given, as follows:

$$RE' = \sum_{s\in S} P_S \Bigg[\sum_{i\in V_s}\sum_{k\in k} LT'_i q'_{iks} + \sum_{i\in j}\sum_{k\in K} LT_i q_{iks} + \sum_{i\in J\cap \bar{V}_s}\sum_{k\in K} \Bigg((x'_{iks} - \theta_{ie_is} x_{ik}) \Big(LT_i + \sum_{l\in L_{ie}} RT^l_{ie_ie} RL^l_{ie_is} \Big) \Bigg) \Bigg]. \tag{26}$$

The first and second parts of Eq. (26) calculate the amount of bought items from the suppliers and the predetermined inventory multiplied by their arrival times. The third term also considers the amount of items provided by the second type of supplier after disruption.

As mentioned before, Eq. (26) computes the loss of resilience. However, to directly obtain the normalized resilience level, the following formula can be used:

$$RE = 1 - \frac{RE'}{Q.T^*}, \tag{27}$$

where Q represents the quantity of required items for the manufacturer.

4.1.3. Model constraints

$$\sum_{i\in V_s} (x_{ik} + q'_{iks}) + \sum_{i\in \bar{V}_s} x'_{iks} + \sum_{i\in J} q_{iks} \geq \tilde{d}_k \quad \forall s \in S, k \in K, \tag{28}$$

$$\sum_{k\in K} a_{ik}(x_{ik} + q'_{iks}) \leq Ca_i \qquad \forall s \in S,\ k \in K, \tag{29}$$

$$\sum_{k\in K} a_{ik} x'_{iks} \leq \theta_{ie_is} \qquad \forall s \in S, \quad i \in I \cap \bar{V}_s \tag{30}$$

$$\sum_{k\in K} a_{ik} x'_{iks} \leq \Bigg[(\theta_{ie_is} + \beta_{ie_isu} y_{iu}) \Big(1 - \sum_{l\in L_{ie}} RL^l_{ie_is} \Big) + \sum_{l\in L_{ie}} CL^l{}_{ie_is} RL^l{}_{ie_is} \Bigg] Ca_i \quad \forall s\in S, \quad i \in J \cap \bar{V}s, \tag{31}$$

$$\theta_{ie_is} x_{ik} \leq x'_{iks} \qquad \forall s \in S, \quad i \in \bar{V}_s, \quad k \in K, \tag{32}$$

$$\sum_{k\in K} b_{ik} w_{ik} \leq Sc_i \sum_{u\in U} y_{iu} \qquad \forall i \in J, \quad s \in S, \tag{33}$$

$$\sum_{i\in V_s} \tilde{\varphi}_{ik}(x_{ik} + q'_{iks}) + \sum_{i\in V_s} \tilde{\varphi}_{ik} x'_{iks} + \sum_{i\in J} \tilde{\varphi}_{ik} q_{iks} \leq R_k \Bigg[\sum_{i\in V_s} (x_{ik} + q'_{iks}) + \sum_{i\in \bar{V}_s} x'_{iks} + \sum_{i\in J} q_{iks} \Bigg] \quad \forall s \in S, \quad k \in K, \tag{34}$$

$$\sum_{u\in U} y_{iu} \qquad \forall i \in J, \tag{35}$$

$$q_{iks} \leq w_{ik} \qquad \forall s \in S, k \in K, \quad i \in J, \tag{36}$$

$$\sum_{k\in K} x_{ik} \leq M.z_i \qquad \forall i \in V, \tag{37}$$

$$x'_{iks} \leq x_{ik} \qquad \forall i \in \bar{V}_s, \quad k \in K, \quad s \in S, \tag{38}$$

$$q'_{iks} \leq M.z'_i \qquad \forall i \in V, \quad k \in K, \quad s \in S, \tag{39}$$

$$q'_{iks} = 0 \qquad \forall s \in S, \quad k \in K, \quad i \in \bar{V}_s, \tag{40}$$

$$\sum_{i\in V} z_i \leq n, \tag{41}$$

$$\sum_{l\in L_{ie_is}} RL^l{}_{ie_is} \leq 1 \qquad \forall s \in S, \quad i \in J, \quad \cap \bar{V}_s, \tag{42}$$

$$E_m \leq k_m, \qquad m \in M, \tag{43}$$

$$P_{ms} \leq (1-v_{ms})(w_m+E_m) \quad \forall m \in M, \quad \forall s \in S, \tag{44}$$

$$\begin{aligned} &Fo_s + PO_S + TO_s + BO_s + FFO_S + IO_s + ppo_s \\ &\quad + TTO_s + IIO_s + UCO_s + AO_s) \\ &\quad - \sum_{s' \in S} po_{s'}(Fo_{s'} + PO_{s'} + TO_{s'} + BO_{s'} \\ &\quad + FFO_{s'} + IO_{s'} + ppo_{s'} + TTO_{s'} + IIO_{s'} \\ &\quad + UCO_{s'} + AO_s) + \theta_s \geq 0 \qquad \forall s \in S, \end{aligned} \tag{45}$$

$$x_{ik}, x'_{iks}, w_{ik}, q_{iks}, q'_{iks} \geq 0$$

$$\forall i \in V,\ k \in K,\ s \in S \tag{46}$$

$$y_{iu} \in \{0,1\} \qquad \forall i \in J, \quad u \in U, \tag{47}$$

$$z_i,\ z'_i \quad \in \{0,1\} \qquad \forall i \in V, \tag{48}$$

$$RL^l{}_{ie_{is}} \in \{0,1\} \quad \forall i \in J, \quad s \in S, \quad l \in L_{ie_{is}}. \tag{49}$$

Constraint (28) ensures the demand for builders under any scenario. Constraint (29) ensures that the total ordered amount given to a main or backup undisrupted supplier is smaller than the supplier's production capacity. Constraint (30) restricts the purchasing amount of the first group to limit suppliers to the available capacity after the disruption. Constraint (31) limits the amount purchased from the second group's disrupted suppliers after disruption, considering their recovery and strengthening levels, to their available production capacity. This constraint is nonlinear. Constraint (32) 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 the supplier's residual capacity percentage after the disruption occurrence. Constraint (33) presents inventories that are stored to strengthen suppliers and the amount of available inventory. Constraint (34) guarantees the expected defective rate of each item purchased proportional to a maximum acceptable defective rate. Constraint (35) states that the second category supplier can be strengthened at a certain level. Constraint (36) limits the delivery amount of items from a preset amount to the amount provided in the previous step. Constraint (37) 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 (38) 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 under normal circumstances. Constraint (39) ensures that if the contract is not set with the supplier as the backup supplier, the amount of each item purchased from them is zero. Constraint (40) ensures that disrupted suppliers under any scenario cannot be used as back-up suppliers under this scenario. Constraint (41) states that the total number of main suppliers in a normal situation (i.e. the pre-event stage) should be less than the maximum number in a normal situation, in accordance with supply chain principles. Constraint (42) indicates that each supplier of the second group under disruption can recover at the highest rate of recovery in each scenario. Constraint (43) represents the maximum capacity of factory production. Constraint (44) indicates the capacity limitation of the primary supplier of the plant. Constraint (45) shows the auxiliary equation defined in Eq. (12). Constraints (46)–(49) show the type of decision variables. Also, the probability of occurrence of each scenario can be calculated as follows:

$$p_s = \left[\prod_{i \in V_S} \left(1 - \sum_{e \in E_i} \pi_{ie} \right) \right]. \tag{50}$$

Also, Constraints (27) and (31) are nonlinear, which, according to Torabi et al. [15] become linear.

5. Augmented ε-constraint method

In solving a multi-objective problem, methods that produce Pareto solutions are sought. 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 [36]. In interactive approaches, the decision maker aims at achieving the desired solutions interactively [37]. The main weakness of this approach is that it cannot provide an image of the Pareto 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 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-mention discussion, the third method will be used in this article. The ε-constraint method is a famous posterior method used to find optimal Pareto solutions for multi-objective problems. In this method, an objective function will be optimized and the rest will be added as constraints as shown below:

$$M \text{ in } f_1(x), \tag{51}$$

$$f_q(x) \le r_q; \qquad \forall q = 2..., q, \tag{52}$$

$$x \in X, \tag{53}$$

where x is the decision variable's vector, X is feasible availability and $f_1(x)$, $f_2(x)$, $\cdots$, $f_q(x)$ are the objective functions that must be minimized. By parametric changes in the right of the objective functions, being in the constraints, the Pareto solution will be obtained [38]. To this end, the range of each ε 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 ε are obtained by spilling the obtained ranges to the n_q interval, as follows [39]:

$$rangrp = f_q^{\max} - f_q^{\min},$$

$$\varepsilon_p^l = f_q^{\max} - (rangr_p)/n_q * k,$$

$$\forall p \neq 1, \qquad k = 0, 1, \qquad n_q = 1, \tag{54}$$

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

$$\begin{aligned} \min\ & \theta_1\ f_1(x) - rangr_{q1} * \delta * (\beta_2\ jl_2/(rangr_2) \\ & +\beta_3 jl_3/(rangr_3) + ... + \beta_q jl_q/(rangr_q) \\ & +... + \beta_q jl_p/(rangr_q)) \\ \text{s.t.}:\ & \\ & f_q(x) + \beta jl_q = r_{(q)}, \quad \forall q = 2..., q, \\ & x \in X; \quad jl_q \in R^+, \end{aligned} \tag{55}$$

where δ is a very small number (between 10^{-6} and 10^{-3}), β_q is the priority value of the objective function of qth, and jl_p is the shortage variable of the relevant constraint. Note that the complementary term of $\beta_q \frac{jl_q}{rangr_q}$ will ensure that only the efficient solution is obtained for the vector ε.

6. Case study

Choosing a resilient and appropriate supplier in the CoPS supply chain is one of the most important dictates in this area, and its literature needs to be enriched due to important and strategic products, such as 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 aerospace and the 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 reports 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 is coded in GAMS software, and a CPLEX solver is used to solve it. Meanwhile, all computational experiments are performed using a laptop with Intel R Pentium R T 4500, 2.5 GHz and 4 GB of RAM. To this end, for the concerned case study, 10 suppliers are considered. In addition, three scenarios encompassing low, medium and high demand for delivery components are considered. The objective is to make tactical, strategic, and operational decisions to ensure their optimality.

The solutions are obtained by solving the objective functions using the augmented ε constraint method. This approach is a famous method belonging to the 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 a pessimistic scenario (i.e., scenario 1), a higher number of delivery components is needed, whist in optimistic scenarios (i.e., scenario 3), a lesser number is applied. Another appealing result is that suppliers 1, 3, 5, and 6 are more suitable for supplying items under any scenario. Conversely, supplier 10 is selected only for the low scenario and is not chosen in other scenarios.

In the next step, a tradeoff between the solution robustness and model robustness is obtained by changing risk aversion, Ψ. A risk averse decision maker tends to choose high values of Ψ, 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 Ψ. Thus, the value of Ψ can be changed to obtain tradeoffs between demand fulfillment and costs. Figure 4 shows the trade-off between solution robustness and model robustness according to the variations in risk aversion. What is clear from this figure is that the large amounts of this weight increase costs, which reflect solution robustness, while reducing the under-fulfillment of demand representing model robustness. Given these observations, it can be deduced

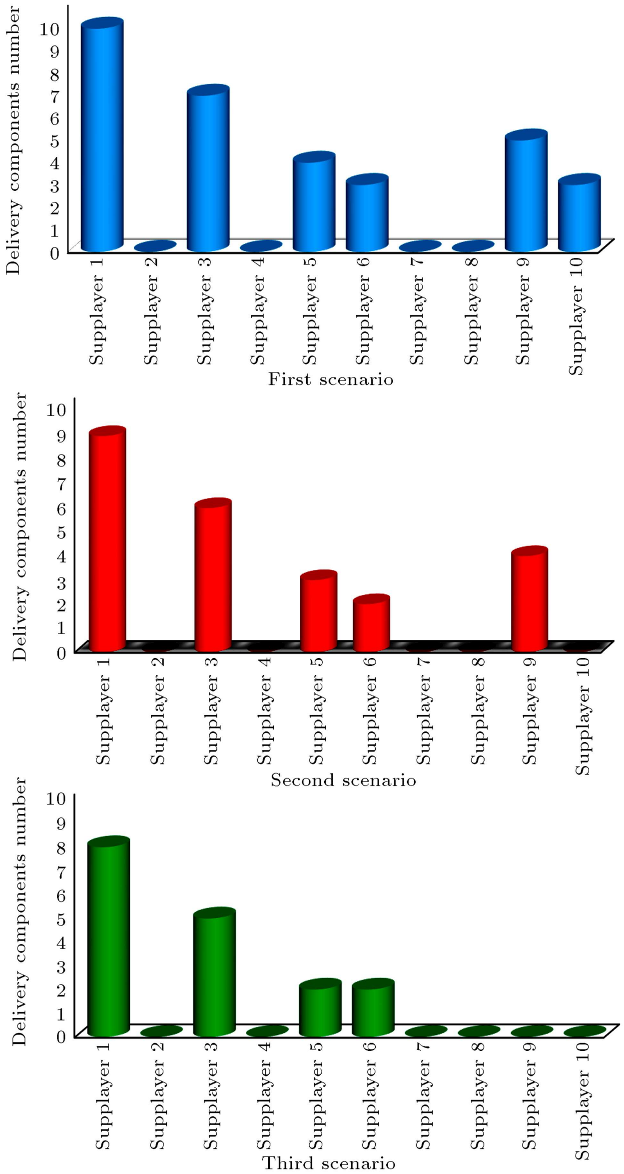

Figure 3. Scenarios used based on the number of delivery components by suppliers for CoPS.

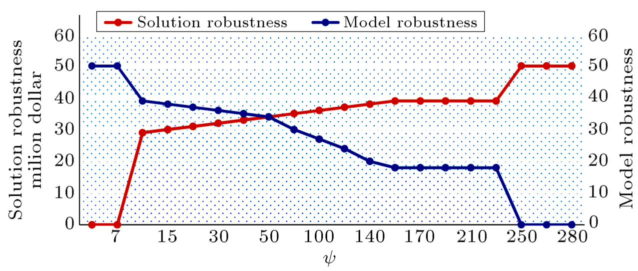

Figure 4. A tradeoff between the solution and model robustness.

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 Ψ. 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 equilibrium with a constant value. Certainly, according to the decision maker's goals and particular model conditions, other values may be selected for Ψ. In the next step, the effects of resilient strategies on total costs are analyzed. 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, total expected costs are calculated by applying different resilient strategies. The relevant results are illustrated in Figure 5.

As shown in Figure 5, all resilient strategies are effective in reducing the overall cost of the supply chain in the 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 decisions 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 Models (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 whose compact forms are proposed as follows.

$$\min Ob\, j_1 = f_{real}x^* + c_{real}y + vS,$$

$$Ay + S \geq D_{real},$$

$$By \leq 0,$$

$$Dy = 0,$$

$$Ny \leq Ex^*,$$

$$S \geq 0, \tag{56}$$

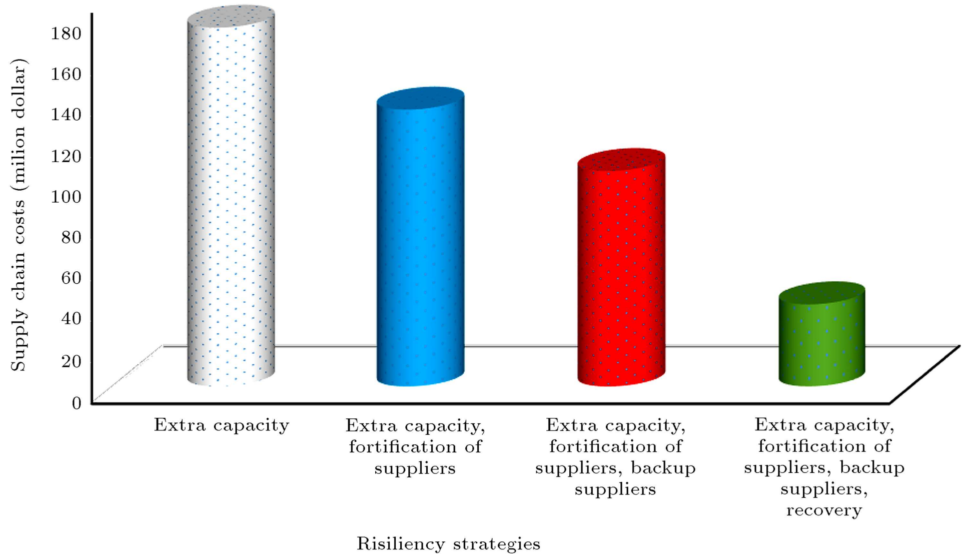

Figure 5. Costs performance considering different resilient strategies.

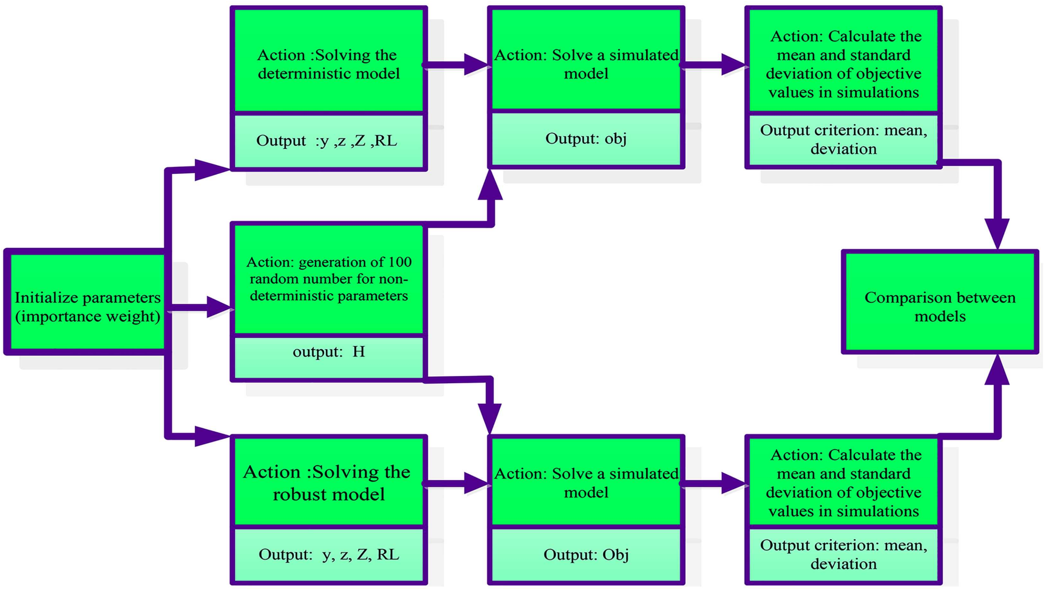

Figure 6. The evaluation approach to compare the robust optimization model with the deployed average model.

where f_{real} and c_{real} vectors represent simulated values for the objective function coefficients. Vectors x^* and y^*, respectively, are the binary and continuous variables derived from robust and deterministic models. Likewise, A, B, D and N are the technical coefficients of the constraints. D_{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, which is $\Psi = 250$, the robust model and the deterministic model have almost the same performance in both of these criteria. When Ψ equals 250 or more, the 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 the deterministic model. More precisely, the robust model is able to provide a stable structure for a CoPS supplier supply chain.

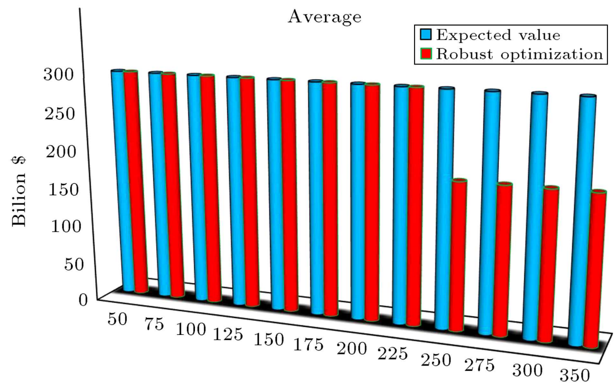

Figure 7. Average performance of robust optimization and expected value of the model with Ψ changes.

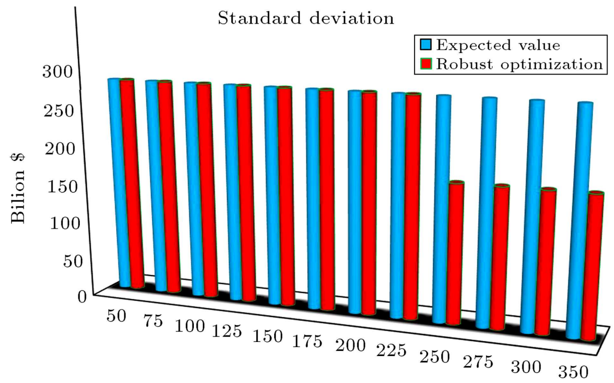

Figure 8. Standard deviation performance of robust optimization and expected value of the model with Ψ changes.

7. Conclusions

The eventual goal of each problem in the evaluation and selection of CoPS suppliers is choosing 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 suppliers, using backup suppliers, and utilizing extra production capacity for suppliers, have been applied to tolerate disruptions. To solve the proposed bi-objective model, the augmented ε-constraint method is proposed, which ensures strong Pareto solutions and prevents weak solutions. Also, to examine the effectiveness and desirability of the optimization model, a case study is discussed, through 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 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. Conversely, supplier 3 is selected only for the low scenario and is not chosen in other scenarios. Also, by changing the value of ψ the trade-off between the 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 could be an interesting avenue for the proposed model. Also, given the complex nature of the proposed model, future research may be aimed at proposing an exact solution procedure, such as Benders algorithm, to solve it.

Nomenclature

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 $E_i \subset E$
K	Outsourcing items set
S	Set of disrupted scenarios ($\lvert S\rvert$ shows the total number of scenarios)
$\bar{V}_S$	A set of affected suppliers by disruption under the scenario
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_{ie}	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 strengthening 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
I	Recovery Level Index for second category suppliers
m	Factory numbers

Parameters

$\tilde{d}_k$	Request item k on the decision horizon
$\tilde{A}_i$	Order fixed cost from supplier i as a main supplier
$\tilde{f}_i$	Contract fixed price with supplier i as a backup supplier
$\tilde{p}_{ik}$	Purchase and shipping unit price of k from supplier i
$\tilde{p}'_{ik}$	Purchase and shipping unit price K from backup supplier "i"
FR_{iu}	The strengthening cost of i at the u level
$\tilde{h}_{ik}$	The cost of the inventory required unit for item k from 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
$\tilde{\varphi}_{ik}$	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
π_{ie}	Disruption risk for supplier "i"
p_s	Scenario occurrence probability
θ_{ie}	Residual capacity of supplier "i" after disruption "e"
B_{ieu}	Increased residual capacity of supplier "i"
$RT^l{}_{ie}$	Recovery time of supplier "i" after 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 a normal situation in order to ignore 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 supplier "i" ($i \in v$) under the disruption
z_i	If the contract is provided with the supplier i ($i \in v$) 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 ($i \in v$) 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 is equal to 1 and otherwise equals 0
w_{ik}	Preset amount of item "k" to strengthen supplier i
x'_{iks}	The amount of "k" item that the manufacturer receives from supplier "i" after disruption in scenario s
q_{iks}	The amount of "k" item used from the proposed inventory in supplier i, at failure and disruption under scenario "s" stages
q'_{iks}	The amount of "k" purchasing from the "i" ($i \in v$) backup supplier in the disruption under scenario s
$RL^l{}_{ie_{is}}$	1, if disrupted supplier $i(i_2J)$ is recovered at level l after event eis ($e_{is}2E_i$) at post-disruption stage under scenario s; 0, otherwise
E_{ms}	Extra production capacity for the "m" factory
p_{ms}	"m" factory production capacity under "s" scenario

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