Scientia Iranica E (2023) 30(5), 1796–1821

Sharif University of Technology
Scientia Iranica
Transactions E: Industrial Engineering
http://scientiairanica.sharif.edu

A stochastic mathematical programming approach to resilient supplier selection and order allocation problem: A case study of Iran Khodro supply chain

A. Bakhtiari Tavana[a], M. Rabieh[b,*], M.S. Phishvaee[c], and M. Esmaeili[a]

a. *Faculty of Management and Accounting, Allameh Tabatabaie University, Tehran, Iran.*
b. *Faculty of Management and Accounting, Shahid Beheshti University, Tehran, Iran.*
c. *School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran.*

Received 23 May 2020; received in revised form 6 April 2021; accepted 16 August 2021

KEYWORDS
Resilience;
Supplier selection;
Order allocation;
Resilient supplier;
Disruption;
Two-stage stochastic programming.

Abstract. Suppliers are one of the main sources of vulnerability in supply chains, which can lead to disruption and risk. Thus, resilient supplier selection can ensure enhanced resilience of the supply process, especially in automotive supply chains. The goal of this study is to select a set of resilient suppliers and ensure optimal demand allocation in an automotive supply chain exposed to risk. For this purpose, a bi-objective two-stage stochastic programming model is presented. In contrast to previous mathematical models, our proposed model incorporates a new objective function to consider the supplier's delivery performance as one of the criteria of resilient supplier selection. In addition, the K-means clustering method is used to cluster and decrease the number of disruption scenarios. Due to the uncertainty of demand, a chance-constrained programming approach is utilized in our proposed model. The augmented ε-constraint method is implemented to solve the presented model. Finally, sensitivity analysis is carried out to determine the effect of parameter changes on the final results. The research results indicate that contingency planning can reduce the effect of disruption risks. Further to the above, the strategy of implementing supply chain regionalization is important in reducing the effects of environmental disruption.

1. Introduction

In today's global business market, the Supplier Selection and Order Allocation (SS&OA) is an essential subject in the area of supply chains that plays a critical role in the corporate strategic success and in support of the supply chains' long-term strategy and competitiveness. In addition to cost reduction, choosing the most right suppliers can improve product quality, reduce lead times, and shortern product development time [1]. The SS&OA process is the selection of the best portfolio of suppliers that can supply high-quality products by a required time at a reasonable price, with optimal allocation of the total demand among selected suppliers to satisfy different tangible and intangible criteria [2,3].

Globalization of the activities and increased international trade have caused the breadth and complexity of supply chains to reach new markets and have increased their competitiveness. As a result of this complexity, firms have become highly vulnerable to dis-

*. *Corresponding author. Tel.: +98 21 29902263*
E-mail addresses: asma.bakhtiari@yahoo.com (A. Bakhtiari Tavana); m_rabieh@sbu.ac.ir (M. Rabieh); pishvaee@iust.ac.ir (M.S. Phishvaee); esmaeili.m.e@gmail.com (M. Esmaeili)

doi: 10.24200/sci.2021.56020.4515

ruptions of the supply chain since a firm's performance is more reliant on the actions of its supply chain [4].

In the classic SS&OA problem, traditional criteria such as cost, quality, and delivery time are taken into account. However, in today's global supply chains, disruptions and risks are numerous and continuous, and they are caused by unforeseen natural events (earthquakes, flood, hurricanes, and fires) and man-made events (transport accidents, labor strikes, deliberate sabotage, and terrorist attack) [2]. In general, the disruption is "an event that, regardless of its nature, affects negatively the supply chain companies' ability to deliver on-time" [5]. Global events such as the Thailand tsunami of 2004, the Katrina hurricane of 2005, Taiwan earthquakes of 1999, 2009 and 2010, the Icelandic volcano of 2010, Japan's 2011 earthquake, Thailand's flood of 2011, Turkey's earthquake of 2012, and terrorist attacks (New York 2001, Madrid 2004, London 2005, Mumbai 2008, Jakarta 2009) all demonstrate that supply chain management in a dynamic, unpredictable and complex environment is quite challenging. Due to these disruptions and their effect on supply chains' normal operations, stability, competitiveness, reputation, and even existence of supply chains depend on not only lower costs, higher quality, lower delivery times, and higher service levels, but also their ability to prevent and overcome various disruptions, and return to the initial or a better state after the disruption [5,6]. Thus, supply chains must be resilient. Also, a reliable level of resilience in determining supply base should be considered. For example, according to a recent survey by the World Economic Forum (2013), an important concern for more than 80% of firms is the resilience of their supply chain [7]. Resilience is a multidimensional and multidisciplinary concept and stems from different disciplines such as psychology and ecology. The first step in defining the resilience in the area of the supply chain was taken by Rice and Caniato [8]. They have defined the resilience in the supply chain as "the ability to react to unexpected disruption and restore normal supply network operations."

According to Christopher and Peck [9], the sources of the supply chain risks are divided into three levels:

1. Internal risks (process and control);
2. Risks associated with the supply chain network (demand and supply);
3. External risks (environmental).

In another categorization, the sources of supply chain risks can be classified into two kinds of operational and disruption risks. Operational risks relate to inherent uncertainties in the supply chain, such as customer demand, supply capacity, and cost uncertainty due to machine-related failures, quality problems, power outage, and key personnel absence. Disruption risks are caused by major disruptions such as natural and man-made incidents (such as floods, earthquakes, employee strikes, or terrorist attacks) [5,10]. Operational risks have medium to high probability of occurrence and their impact on performance is lower than disruption risks while disruption risks have a lower likelihood of occurrence, but a higher impact on the system [2].

Suppliers in most cases are considered as one of the unavoidable sources of external risks in supply chains. Hou et al. [11] differentiated between supply disruptions and recurrent supply uncertainties and defined supply disruptions as the sudden pause of supply process when an unforeseen event happens and makes one or more supply sources unavailable. Christopher and Lee [12] emphasized the role of suppliers in creating a resilient supply chain and the need for having a collaborative relationship with suppliers. According to them, risk reduction is possible by using suppliers with high visibility. As suppliers are one of the primary sources of vulnerability in the supply chain, selecting resilient suppliers and optimizing demand allocation can greatly enhance resilience, minimize disruptions, and reduce associated costs. Rajesh and Ravi [13] defined resilient suppliers as "suppliers who are able to provide good quality products at economy rates and flexible enough to accommodate demand fluctuations with shorter lead times over a lower ambiance of risk without compromising on safety and environment practices."

This paper intends to develop a new optimization model to select the resilient suppliers and optimally allocate the demand among the selected suppliers based on suppliers' delivery performance, reliability, and flexibility in their capacity in a real-world case study, which is inseparable from the existence of risks. For this purpose, a bi-objective integer stochastic programming model with the aim of minimizing costs and maximizing supplier delivery performance is presented in which contingency plans are included to help implement resilience strategies in order to mitigate the negative effects of disruptions. Contingency planning involves predicting potential events and identifying measures to deal with risks and disruptions of the supply chain before they occur [6].

In accordance with the base model (see, [14]), this study evaluates the strategy of regionalizing a supply chain offered by Chopra and Sodhi [15]. Selecting suppliers from multiple geographical regions can mitigate the negative effects of environmental disruptions on the supply chain. When a semi-super event occurs in a region and makes all its suppliers unavailable, the available suppliers in another region may attempt to meet the unsatisfied demand of the disrupted suppliers [15]. For example, Figure 1 shows three distinct geographic regions where some suppliers with different

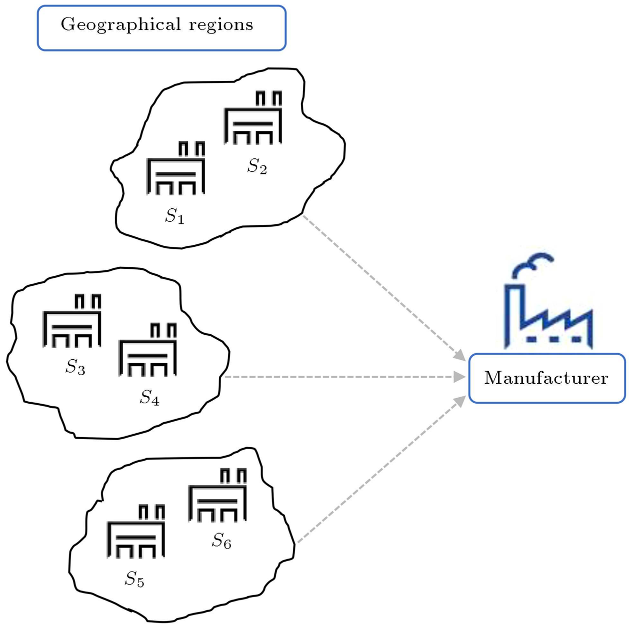

Figure 1. Supply chain regionalization.

characteristics are classified into the regions.

The remaining parts of the present study are organized in the following manner. Section 2 demonstrates a concise review of the literature. In Section 3, the problem of resilient supplier choice and order allocation and the proposed mathematical model is described. The description of chance-constrained programming and ε-constraint method is presented in Sections 4 and 5, respectively. Section 6 introduces a real case and the parameters and scenarios of the model. Section 7 presents the model's computational results. In Section 8, the sensitivity analysis of some parameters is conducted. Finally, the conclusions and directions for future work are provided in Section 9.

2. Literature review

Practitioners and academics have been aware of the need to minimize the potential impacts of disruptions by creating a resilient supply chain that is complementary to classic risk management processes. They also know one of the ways to create resilience in the supply chain is providing a resilient supply base. Therefore, various researchers have explored the area of resilient supplier choice and order allocation under risk and disruption. Berger et al. [16] first incorporated the supply disruption risk into the problem of supplier selection. They introduced three types of disruptive events that might cause supply disruption:

1. Unique events, which are associated with a single supplier and disrupt only the normal operations of a particular supplier;
2. Semi-super events, which influence a subset of suppliers (all suppliers at a location);
3. Super events, which can cause all suppliers to fail.

They modeled supply disruption only as unique events (with equal failure probabilities) and super events, applied the decision-tree approach to determine the number of suppliers, and obtained the expected total cost as the objective function. A few studies have examined the effects of environmental disruptions caused by a semi-super event in sourcing decisions. Sarkar and Mohapatra [17] considered semi-super events as supply disruption for the first time in the supplier selection problem and proposed a tabular method to determine the best size for supply base to minimize the total cost. Recently, some researchers (see, for example, [18–20, 14, and 4]) have considered the semi-super events as supply disruption in the SS&OA model. Sawik [18,19] formulated a mixed integer stochastic programming model to allocate the order and schedule customer order under disruption risk. Their model objective was either the expected worst-case cost minimization or the expected worst-case customer service level maximization. Kamalahmadi and Mellat-Parast [4,14] addressed the SS&OA problem considering supplier and environmental disruptions with the objective of minimizing expected total cost. Prasanna Venkatesan and Goh [20] presented a multi-objective mixed-integer linear programming model to choose the optimal size of the supply base and allocate the order with the aim of minimizing the expected total cost and maximizing the total purchase value. They employed the Fuzzy Analytic Hierarchy Process (FAHP) and fuzzy PROMETHEE methods to evaluate and rank suppliers.

In Table 1, some mathematical model characteristics derived from relevant articles are presented so that they can be compared with the our proposed model. As seen in Table 1, most of the SS&OA models considered a single objective function such as expected total cost or expected worst-case cost (e.g., [21]). Some authors present multi-objective programming models. For example, Torabi et al. [2] presented a bi-objective mixed possibilistic, stochastic program to select resilient suppliers under disruption and operational risks. In addition to the total cost objective function, they considered a new resilience objective function to compute the resilience level of selected suppliers and then, applied the augmented ε-constraint technique to solve their model. Lee [22] proposed a fuzzy multi-objective programming model to allocate the quantity of orders among suppliers and emergency inventory among backup suppliers. His model objectives were to minimize the total cost of ordering, rejected items, and late deliveries.

Many supply chain resilience studies have focused on adopting strategies that can improve the resilience of supply chains in case of disruptions. Sheffi [23]

Table 1. A review of the literature.

Author	Model description												Modelling and solution approach
		Decision variables		Risks					Resilience strategy				
	Objective function	Number of suppliers	Order allocation	Operational	Disruption				supply flexibility	pre-positioning invention	backup suppliers	protected suppliers	
					Su	Se	Uq						
							Equal	Unequal					
Berger et al. [16]	ETC	✓	–	–	✓	–	✓	–	–	–	–	–	Decision tree
Ruiz-Torres and Mahmoodi [24]	ETC	✓	–	–	✓	–	✓	✓	–	–	–	–	Decision tree
Moritz and Pibernik [25]	ETC	✓	✓	–	–	–	✓	–	✓	–	–	–	Analytical and numerical analysis
Sarkar and Mohapatra [17]	ETC	✓	–	–	✓	✓	✓	–	–	–	–	–	Decision tree /Tabular method
Sawik [21]	EWC	✓	✓	–	✓	–	–	✓	–	–	–	–	Mixed integer programming
Sawik [27]	ETC EWC	✓	✓	–	✓	–	–	✓	–	–	–	✓	Stochastic mixed integer programming
Ruiz-Torres et al. [26]	ETC	✓	✓	–	–	–	–	✓	✓	–	–	–	Decision tree/ Mathematical modeling
Sawik [18]	ETC- EWC/ ESL- EWSL	✓	✓	–	–	✓	–	✓	–	–	–	–	Stochastic mixed integer programming
Sawik [19]	EWC/EWSL	✓	✓	–	✓	✓	–	✓	–	–	–	–	Stochastic mixed integer programming
Torabi et al. [2]	ETC RE	✓	✓	✓	–	–	–	✓	–	–	✓	✓	Mixed possibilistic, two-stage stochastic programming
Prasanna Venkatesan and Goh [20]	ETC TPV	✓	✓	–	✓	✓	–	✓	✓	–	–	–	MILP/Fuzzy AHP/Fuzzy PROMETHEE
Kamalahmadi and Mellat-Parast [14]	ETC	✓	✓	–	–	✓	–	✓	✓	–	–	–	Two-stage mixed integer programming
Kamalahmadi and Mellat -Parast [4]	ETC	✓	✓	–	–	✓	–	✓	–	✓	✓	✓	Two-stage mixed integer programming

Table 1. A review of the literature (continued).

Author	Model description												Modelling and solution approach
	Objective function	Decision variables		Risks					Resilience strategy				
		Number of suppliers	Order allocation	Operational	Disruption				supply flexibility	pre-positioning invention	backup suppliers	protected suppliers	
					Su	Se	Uq						
							Equal	Unequal					
Lee [22]	TCONRI NIDL	✓	✓	–	–	–	–	✓	–	–	✓	–	Weighted additive fuzzy Modeling
Hosseini et al. [32]	GSTC	✓	✓	–	–	–	–	✓	–	–	✓	✓	Stochastic mixed integer programming
Solgi et al. [28]	ETC RE	✓	✓	✓	–	–	–	✓	–	–	✓	✓	Scenario-based robust optimization model
Sahebjamnia [33]	ETCSRP	✓	✓	✓	–	–	–	✓	–	–	–	–	Fuzzy DEMATEL/ fuzzy ANP /fuzzy mixed integer programming
Kaur and Singh [34]	TC	✓	✓	✓	–	–	–	✓	–	–	–	–	Fuzzy AHP/ TOPSIS/ DEA/MIP
Olanrewaju et al. [35]	ETC	✓	✓	✓	–	–	–	✓	–	–	–	–	Multi-stage stochastic programming
This study	ETCSDP	✓	✓	✓	–	✓	–	✓	✓	✓	–	–	Decision tree /Bi-objective integer two-stage stochastic programming /Chance constraints

Notes: Su: Super event; Se: Semi-super event; Uq: Unique event; ETC: Expected Total Cost; EWC: Expected Worst-case Cost; EWSL: Expected Worst-case Service Level; ESL: Expected Service Level; RE: Resilience objective function; TPV: Total Purchase Value; TCO: Total Cost of Ordering; NRI: Number of Rejected Items; NIDL: Number of Items Delivered Late; SDP: Supplier Delivery Performance; MINLP: Mixed-Integer Non-Linear Programming; SRP: Supplier Resilience Performance; GS: Geographical Segregation.

introduced three general ways for companies to develop resilience:

1. Creating redundancies in the supply chain, for instance, by means of holding additional inventory, investing in surplus capacity, and adopting multiple suppliers;
2. Augmenting supply chain flexibility;
3. Changing organizational culture.

Following a review of the literature, it is clear that greater attention has been paid to flexibility than redundancy. Authors such as Ruiz-Torres and Mahmoodi [24], Moritz and Pibernik [25], Ruiz-Torres et al. [26], and Kamalahmadi and Mellat-Parast [14] have incorporated only the flexibility of supplier capacity as a resilient strategy to their models. In another study, four strategies have been introduced as the most critical ones for resilience in the supply chain: increasing flexibility, adding redundancy, creating cooperative supply chain relationship, and increasing supply chain agility [6]. Kamalahmadi and Mellat-Parast [4] incorporated redundancy strategies into a SS&OA model containing pre-positioning inventory, protected suppliers, and backup suppliers. They concluded that adding redundancy could improve the responsiveness of firms to disruptions and reduce expected costs. Sawik [27] presented a mathematical programming approach to address SS&OA problem under disruption risk and developed some resilience strategies including protecting some suppliers against disruption and pre-positioning emergency inventory in protected suppliers to minimize total cost and effect of disruption risk. Sawik [27] supported the assumption that the capacity of each protected supplier remained fixed after any disruptive event. To make this assumption more real, Torabi et al. [2] assumed that the effect of disruption events on the supplier's production capacity decreased through the protection of a supplier based on the fortification level and the kind of disruptive incident. In addition to the protection of suppliers, they applied other strategies such as suppliers' business continuity plans and backup suppliers in the model of supplier selection. Lee [22] considered contracting with backup suppliers to raise the resilience of selected suppliers. In another research, Solgi et al. [28] implemented resilience strategies such as fortifying suppliers, contracting with backup suppliers, restoring supply from disruptions, and utilizing the surplus production capacity for suppliers.

As mentioned earlier, pre-positioning inventory (also named operational slack or safety stock) is usually one of the redundancy strategies that involves holding buffer stocks of raw materials or finished goods. It can be a buffer against supply disruptions and guarantees the continuity of production. On the other hand, surplus inventory is costly and reduces the quality and profitability [3,29]. In fact, pre-positioning inventory differs from existing management practices such as lean and JIT. However, from the perspective of supply chain risk management, it is necessary to maintain safety stock to overcome environmental risks [4]. In this respect, Rawls and Turnquist [30] developed a stochastic programming model that presented an emergency response to disaster threats using a pre-positioning strategy. They used the Lagrangian L-shaped method to find an optimal solution to a large-scale problem. Zheng et al. [31] considered an integrated civilian-military supply pre-positioning problem with the aim of maximizing the expected military and civilian operational efficiency and minimizing the total pre-positioning cost. They determined the locations of emergency facilities and the kinds and quantities of emergency supplies stored in each facility. To solve this model, they applied a hybrid heuristic solution method.

Generally, few quantitative models for selecting resilient supplier have addressed the impact of resilience strategies on enhancing resilience levels in the face of disruptions. This study expands upon the model proposed by Kamalahmadi and Mellat-Parast [14] by integrating pre-positioning inventory as a resilience strategy. In contrast to their model, we modified or added new constraints and objective functions, which are discussed in the following sections. Furthermore, our SS&OA problem involves multiple products. In addition, a quantitative model is implemented for solving the problem of choosing resilient suppliers and order allocation in the real world. Only a few previous studies have considered the impact of operational risk on resilient supplier selection. In this research, operational risks are addressed based on the uncertainty in demand. A chance-constrained programming approach has been utilized to face the uncertain parameter of demand for the first time in this field. In contrast to previous mathematical models, our model includes a new objective function to consider the supplier's delivery performance as one of the criteria of resilient supplier selection and the K-means clustering method is also utilized to cluster and decrease the number of disruption scenarios determined in the real case.

3. Problem description and model formulation

This section describes in detail the problem of resilient suppliers' selection and order allocation among them under disruption and operational risks, and the proposed mathematical model. Automotive supply chains are highly sensitive to disruptions. The impact of disruptive events on auto part suppliers is quite significant due to the complexity and broadness of automotive supply chains. An automobile is comprised of 20,000 pieces on average, and if one part is not available, the production of the final product will not be possible. Therefore, it is necessary that automotive supply chains be resilient in order to reduce disruptions. With this important issue in mind, the case study of the present research is the Iran Khodro supply chain. As stated earlier, our model is an expansion of Kamalahmadi and Mellat-Parast's [14] model and employs strategies that include the use of flexible capacity suppliers and pre-positioning inventory in order to effectively reduce the severity of disruptions in Sapco Company. The presented mathematical model is a integer, bi-objective, single-period, and multi-product model designed to select resilient suppliers and allocate demand among them. The objective of the model is to minimize the expected total cost while maximizing the delivery performance of the suppliers. The regional disruptions are taken into account due to the occurrence of a semi-super event that influences all suppliers in a geographical region. In the aforementioned model, operational risks are considered based on the inherent uncertainty in demand. Due to its incorporation of disruption risk scenarios, the proposed model is a two-stage stochastic model in which decisions are categorized into two groups:

1. First-stage decisions made in the event of uncertainty regarding a random scenario occurrence;
2. Second-stage decisions made after the occurrence of any scenario to mitigate the probable undesirable effects of first-stage decisions [36].

The steps in implementing the suggested model are presented in Appendix A. In the following section, some parameters and variables are defined.

3.1. Types of events

In the proposed model, two kinds of events, unique and semi-super, cause disruption risks and affect supplier operations. The first type disrupts a single supplier. The second type affects all suppliers in a particular geographical area. Accordingly, the suppliers located in various regions are distinguished by dividing them into separate sets. Thus, H^r represents the set of suppliers in region r, where $H^1 \cup H^2 \cup \ldots \cup H^r = H$. The set H is related to the set of possible suppliers. The parameters p_h and p^r correspond to the occurrence probability of unique and semi-super events in supplier h and region r, respectively, and they are determined according to experts opinions and historical data.

3.2. Scenarios and their occurrence probability

As mentioned, a scenario-based programming model is presented that contains a number of discrete scenarios. The risk of disruption is also taken into account by assigning a probability to any scenario that may happen due to the failure of suppliers or areas. In each scenario, the suppliers may be disrupted and unable to provide the allocated amount of order; therefore, the parameter $S_{s,h}$ in the model shows the delivery status of each supplier h in scenario s. Each scenario s has an occurrence likelihood of π_s, which is determined in three stages applying the decision-tree approach:

1. First step: The occurrence probability of a disruption in suppliers located in the region r in scenario s.

$$p_s^r = \prod_h \left[(1 - S_{s,h})\, p_h + S_{s,h}\, (1 - p_h) \right]. \qquad (1)$$

2. Second step: The occurrence probability of a disruption in region r and its suppliers in scenario s.

$$\pi_s^r = \begin{cases} p^r + (1 - p^r)\, p_s^r \\ \text{If all suppliers in region } r \text{ are disrupted} \\ (1 - p^r)\, p_s^r \\ \text{Otherwise} \end{cases} \qquad (2)$$

3. Third step: The occurrence probability of scenario s.

$$\pi_s = \prod_r \pi_s^r. \qquad (3)$$

For example, Figure 2 shows the decision tree and how to calculate the probability of each scenario for two regions and one supplier in each region [14].

3.3. Flexibility of suppliers

In the present model, we consider that suppliers have a flexible production capacity as a disruption management strategy that permits them to deliver contingency orders in case other suppliers face disruptions. Thus, the parameter of supplier flexibility $b_{i,h}$ refers to the supplier's ability to deliver items greater than the amount allocated to it when other suppliers fail. This parameter could be measured based on suppliers' production capacity, capacity commitment to other customers, logistics capability and geographical proximity.

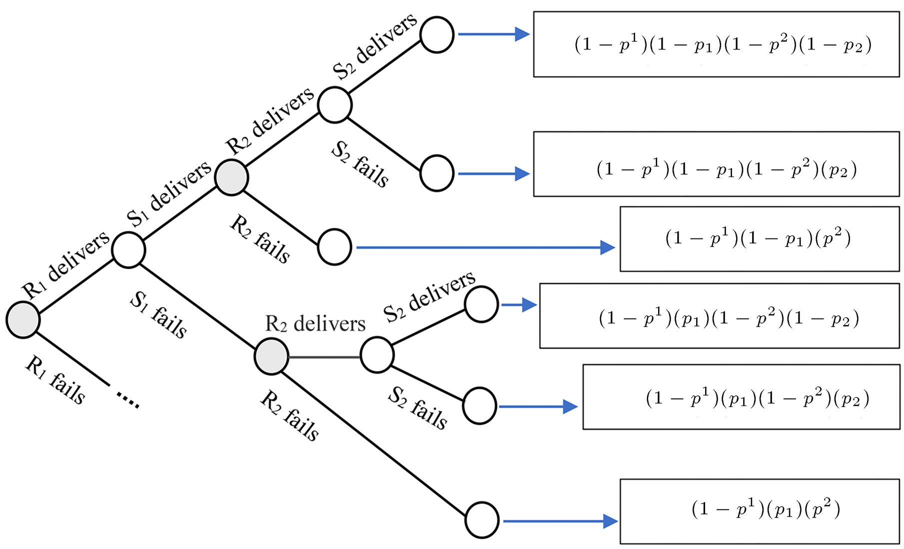

Figure 2. Decision tree related to two regions and one supplier in each region [14].

3.4. Associated costs

In the proposed two-stage stochastic planning model, costs are classified into two groups, namely first-stage costs and second-stage costs. First-stage costs involve costs that the company must pay in the first stage before becoming aware of any scenario that may occur. The second-stage costs are those that the company will incur to respond to that scenario. Table 2 provides types of costs and a brief description of each.

3.5. Pre-positioning inventory

Based on Kamalahmadi and Mellat-Parast's [4] model, to deal with disruptions, pre-positioned inventory is taken into account as a redundancy strategy according to the experts' opinions of the case study company. This type of inventory (safety stock) must be procured from suppliers and stored in warehouses prior to any potential disruption. It is then utilized to fulfill demand after the occurrence of disruptions that render suppliers unavailable. For this purpose, two parameters $y_{i,h}$ and $g_{i,s}$ are added to the model which indicate the number of parts i purchased from supplier h to be stored in warehouses and the amount of withdrawal of each part i from its inventory in warehouses in each scenario s, respectively.

3.6. Model formulation

In this section, first, assumptions and notations (including sets, indices, parameters, and variables) utilized to formulate the mathematical model are defined; then, the functions of objectives and constraints are described.

3.6.1. Assumptions of model

The following are the assumptions of our model:

1. The occurrence likelihood of unique events for suppliers located in a place is different;
2. The probability of each scenario is different and is calculated by the formula provided;
3. There is only one demand point (the buyer company);
4. Failure to satisfy the demand leads to financial loss per unit (m_i);
5. The demand for each part is uncertain and has a normal probability distribution with a specific mean and variance;
6. There is a limitation on the amount of warehouse space available for storing each part;
7. If suppliers deliver parts sooner than the programmatic delivery date, the delay is considered zero;
8. The quality of the suppliers' parts is considered acceptable by the buyer company.

3.6.2. Notations

Sets

H	Set of suppliers, $h \in H$
R	Set of regions, $r \in R$
I	Set of parts, $i \in I$
S	Set of scenarios, $s \in S$

Parameters

F_h	Fixed cost of management for supplier h
$Ca_{i,h}$	Capacity of supplier h for part i
$Cn_{i,h}$	Purchasing cost of part i from supplier h in normal conditions
$Cd_{i,h}$	Extra purchasing cost of part i from supplier h in disruption conditions when suppliers deliver parts more than its base allocation
$Tn_{i,h}$	Transportation cost of part i from supplier h in normal conditions
$Td_{i,h}$	Transportation cost of part i from supplier h in disruption conditions
Hl_i	Holding cost of part i (safety stock) in the warehouse
$b_{i,h}$	Flexibility of supplier h for part i
v_i	Warehouse capacity for holding part i
w_i	Minimum inventory required for part i that must be purchased as safety stock
m_i	Loss cost for not received part i due to supplier failure
d_i	Demand of part i for the programming period
L_h	Delay time of supplier h
Lt_h	Actual lead time of supplier h
Plt_h	Programmatic lead time of supplier h
r_h	Ratio of the delay time to programmatic lead time of supplier h
OS_h	Delivery performance score of supplier h
$S_{s,h}$	Binary parameter associated with the state of supplier h in scenario s
p_h	Occurrence probability of unique event in supplier h
p^r	Occurrence probability of semi-super event in region r
p_s^r	Occurrence probability of disruptions in suppliers positioned in region r, $h \in H^r$, in scenario s
π_s^r	Occurrence probability of disruptions in region r and its suppliers, $h \in H^r$, in scenario s
π_s	Occurrence probability of scenario s
$1-\alpha$	Confidence level

Table 2. Types of existing costs in the presented model.

Cost type	Symbol	Cost name	Description
First-stage cost	SMC	Supplier Management Cost	The cost that the company incurs to manage and maintain relations with suppliers. This cost increases with the increasing number of suppliers
	SOC	Safety stock Order Cost	The investment for purchasing safety stocks from suppliers
	STC	Safety sock Transportation Cost from suppliers to warehouses	The cost of transporting parts purchased (as a safety stock) from suppliers to the warehouse of the company
	SHC	Safety stock Holding Cost	The cost to be paid for holding safety stocks in the warehouse
Second-stage cost	OC_s	Order cost in scenario s	This cost is based on the number of parts sent from each supplier in each scenario
	TC_s	Transportation cost in scenario s	This cost for the normal allocation of available suppliers and additional allocation of them is based on the normal cost of transportation and transportation costs in disruption, respectively
	PC_s	Premium cost in scenario s	The cost that the company pays to suppliers to produce more than their normal allocation to meet the unsatisfied demand by disrupted suppliers
	LC_s	Loss cost in scenario s	This cost is calculated based on the amount of unsatisfied demand in each scenario

Decision variables of first-stage

$Z_{i,h}$ Binary variable of selecting or not selecting supplier h to supply part i

$a_{i,h}$ Number of parts i assigned to supplier h

$y_{i,h}$ Number of parts i assigned to supplier h as safety stock in the pre-disruption stage

Decision variables of second-stage

$q_{i,h,s}$ Number of parts i sent from supplier h in scenario s

$Aq_{i,h,s}$ Number of parts i sent from supplier h in scenario s being more than its base allocation

$g_{i,s}$ Number of parts i used from its safety stock in scenario s

$U_{i,s}$ Number of unsatisfied parts i in scenario s

As mentioned earlier, the decision variables of the model are classified into two stages. Figure 3 illustrates these two different stages and their relevant variables. It should be noted that the first-stage variables are determined before the occurrence of any scenario. However, the second-stage variables are determined while one of the scenarios has taken place and differs under various scenarios.

3.6.3. Objective functions

We consider two objective functions for the proposed model:

1. *Expected total cost*: The initial objective function minimizes the expected total cost which is the sum of first-stage and second-stage costs. The associated costs are calculated as follows:

$$SMC = \sum_{h\in H} F_h Z_{i,h}, \tag{4}$$

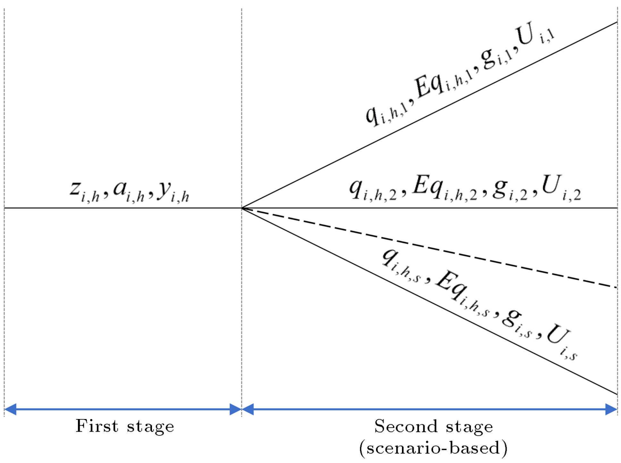

Figure 3. Illustration of two different stages and their relevant variables.

$$SOC = \sum_{i\in I}\sum_{h\in H} Cn_{i,h} y_{i,h}, \tag{5}$$

$$STC = \sum_{i\in I}\sum_{h\in H} Tn_{i,h} y_{i,h}, \tag{6}$$

$$SHC = \sum_{i\in I}\sum_{h\in H} Hl_i y_{i,h}, \tag{7}$$

$$OC_s = \sum_{i\in I}\sum_{h\in H} Cn_{i,h} q_{i,h,s}, \tag{8}$$

$$TC_S = \sum_{i\in I}\sum_{h\in H} Tn_{i,h} S_{s,h} a_{i,h} + \sum_{i\in I}\sum_{h\in H} Td_{i,h} Aq_{i,h,s}, \tag{9}$$

$$PC_s = \sum_{i\in I}\sum_{h\in H} Cd_{i,h} Aq_{i,h,s}, \tag{10}$$

$$LC_s = \sum_{i\in I} m_i U_{i,s}. \tag{11}$$

The objective function related to minimizing the expected total cost is given below:

$$\text{Min } ETC = SMC + SOC + STC + SH + \sum_{s=1}^{S} \pi_s \Big(OC_s + TC_s + PC_s + LC_s\Big). \tag{12}$$

2. *Supplier delivery performance*: The supplier delivery performance is taken into account in this model as one of the criteria for selecting the resilient supplier. Obviously, if the supplier's lead time is long, it creates a critical path in the supply network and eventually, the likelihood of the company's vulnerability increases against disruptions. Therefore, a new objective function is added to the model that maximizes the delivery performance score of suppliers and is calculated according to suppliers' actual lead time, programmatic lead time, and delay time given below:

$$\text{Max } SDP = \sum_{i\in I}\sum_{h\in H}\sum_{s\in S} \pi_s \Big(Os_h . q_{i,h,s}\Big), \tag{13}$$

$$L_h = Lt_h - Plt_h, \tag{14}$$

$$r_h = L_h / Plt_h, \tag{15}$$

$$Os_h = 100 - (r_h \times 100). \tag{16}$$

3.6.4. Constraints

$$P\left(\sum_{h\in H} a_{i,h} = d_i\right) \geq 1 - \alpha, \tag{17}$$

$$a_{i,h}\left(1+b_{i,h}\right) \leq Z_{i,h} Ca_{i,h} \qquad \forall h \in H,\ i \in I, \tag{18}$$

$$a_{i,h} \geq 0.1 d_i Z_{i,h} \qquad \forall h \in H,\ i \in I, \tag{19}$$

$$q_{i,h,s} \leq a_{i,h}\left(1+b_{i,h}\right) S_{s,h} \qquad \forall i \in I,\ h \in H,\ s \in S, \tag{20}$$

$$q_{i,h,s} \geq a_{i,h} S_{s,h} \qquad \forall i \in I,\ h \in H,\ s \in S, \tag{21}$$

$$Aq_{i,h,s} = (q_{i,h,s} - a_{i,h}) S_{s,h} \qquad \forall i \in I,\ h \in H,\ s \in S, \tag{22}$$

$$\sum_{h \in H} y_{i,h} \leq v_i \qquad \forall i \in I, \tag{23}$$

$$\sum_{h \in H} y_{i,h} \geq w_i \qquad \forall i \in I, \tag{24}$$

$$y_{i,h} \leq Z_{i,h}\left(ca_{i,h} - a_{i,h}\right) \qquad \forall i \in I,\ h \in H, \tag{25}$$

$$g_{i,s} \leq \sum_{h \in H} a_{i,h}\left(1 - S_{s,h}\right) \qquad \forall i \in I,\ s \in S, \tag{26}$$

$$g_{i,s} \leq \sum_{h \in H} y_{i,h} \qquad \forall i \in I,\ s \in S, \tag{27}$$

$$P\left(U_{i,s} + \sum_{h \in H} q_{i,h,s} + g_{i,s} = d_i\right) \geq 1 - \alpha \qquad \forall i \in I, s \in S, \tag{28}$$

$$z_{i,h} = \{0, 1\} \qquad \forall h \in H, \tag{29}$$

$$a_{i,h}, q_{i,h,s}, Aq_{i,h,s}, U_{i,s}, y_{i,h}, g_{i,s} \geq 0, \quad integer\ \forall i \in I,\ h \in H,\ s \in S. \tag{30}$$

Constraint (17) ensures that at least $1-\alpha$, the demand for each part, will be allocated to selected suppliers. Constraint (18) indicates the utilization limit of supplier's capacity in order to respond to additional orders during the disruption. Constraint (19) prevents selecting suppliers with a very low order quantity and accordingly, the amount of each supplier allocation should be 10% of the demand for each part. Constraints (20) and (21) represent the upper and lower limits of the number of parts to be sent from each supplier in each scenario. Constraint (22) calculates the number of additional parts satisfied by available suppliers in different scenarios. According to Constraint (23), the safety stock quantity of each part must be equal to or less than the warehouse capacity. Constraint (24) indicates the minimum safety stock of each part which should be allocated to suppliers and stored in the warehouse. Constraint (25) indicates that the amount of safety stock allocated to each supplier for every part must be less than or equal to the supplier's available capacity, which is calculated as the difference between the supplier's overall capacity and its allocation. According to Constraint (26), the safety stock of each part is used only in disruption conditions. It also limits the extent of using safety stock to the allocation of disrupted suppliers in a particular scenario. Constraint (27) ensures that the usage quantity of safety stock of each part must be less than its total inventory in the warehouse. Constraint (28) indicates the amount of unsatisfied demand for each part in each scenario. Finally, Constraints (29) and (30) relate to the type of decision variables.

4. The proposed chance-constrained programming approach

In the present study, due to the inherent demand uncertainty, chance-constrained programming for fixing the demand has been used. Chance-constrained programming is a method that deals with optimization problems in which some of the parameters are non-deterministic and include chance constraints that should be satisfied with the minimum confidence level [37]. One of the advantages of chance-constrained programming is that decision-makers can control the satisfaction level of chance constraints [38]. In the presented model, Constraints (17) and (28) are chance constraints realized with the probability of at least $1-\alpha$ ($0 \leq \alpha < 1$). The chance constraint $P(\sum_{h \in H} a_{i,h} = d_i) \geq 1-\alpha$ is converted into deterministic constraint as follows [39].

Random variable d_i (demand for each part) is assumed to have a normal distribution with mean $E(d_i)$ and standard deviation $\sigma(d_i)$ and in order to check the normal distribution of demand data, Kolmogorov-Smirnov test was utilized in the SPSS 24.0 software package. The results of the test confirm the normality of demand data.

$$\sum_{h \in H} a_{i,h} \leq E\left(d_i\right) - Z_{1-\alpha}.\sigma\left(d_i\right). \tag{31}$$

Similarly, other chance constraints (constraint of unsatisfied demand) become deterministic as follows:

$$U_{i,s} + \sum_{h \in H} q_{i,h,s} + g_{i,s} \leq E\left(d_i\right) - Z_{1-\alpha}.\sigma\left(d_i\right). \tag{32}$$

The confidence level $(1-\alpha)$ is considered 0.95 and the corresponding value for the standard normal distribution function can be found in the table of values (Ref. [39] for further study).

5. The augmented ε-constraint method

The literature has discussed several techniques for solving multi-objective programming models, including the weighted sum method, goal programming, ε-constraint methods, and fuzzy programming methods. In the present study, due to the multi-objective nature of the proposed stochastic programming model, the augmented ε-constraint method is used to solve the model. One advantage of the ε-constraint method is that it changes the original feasible area and provides non-extreme efficient solutions. This method, unlike the weighted sum method, is utilized in multi-objective integer and mixed integer programming. The scale limitation of objective functions does not have much effect on the results. Also, in the ε-constraint method, we can control the generated efficient solutions by correctly setting the network points in each range of the objective function [40,41]. This method is a modified version of the overall ε-constraint method, which provides Pareto optimal solutions and avoids inefficient solutions [2,41]. In this method, the most important objective function is considered to be the principal objective function, and the rest of the objective functions are added to the model as a limitation [41,42] (refer to Refs. [40,41] for further study).

5.1. Selection of the best pareto solution

After determining the set of optimal Pareto solutions, a fuzzy approach can be used to facilitate the decision-making process to select the best Pareto optimal response and to determine its degree of optimality. In this fuzzy method, assuming the k Pareto optimal solution, the membership function $\mu_{\mathrm{i}}^{\mathrm{k}}$ denotes the optimality degree for the objective function i in the Pareto solution k and is calculated using the following formula:

1. For minimizing the objective function, we have:

$$\mu_i^k = \begin{cases} 1 & f_i^k(x) \leq l_i \\ \frac{u_i - f_i^k(x)}{u_i - l_i} & l_i < f_i^k(x) \leq u_i \\ 0 & f_i^k(x) > u_i \end{cases} \tag{33}$$

2. For maximizing the objective function, we have:

$$\mu_i^k = \begin{cases} 0 & f_i^k(x) \leq l_i \\ \frac{f_i^k(x) - l_i}{u_i - l_i} & l_i < f_i^k(x) \leq u_i \\ 1 & f_i^k(x) > u_i \end{cases} \tag{34}$$

In these formulas, l_i and u_i represent the lower and upper limits of objective function f_i, respectively, and $f_i^k(x)$ expresses the value of the objective function i in the optimal Pareto solution k, so that $f_i^k(x) \in [l_i, u_i]$.

After determining the weight vector for each objective function by the decision maker (w_i), which represents the relative value of the objective function i, the total value of the membership function of the Pareto solution $k(\mu_k)$ can be calculated using the following equation:

$$\mu_k = \frac{\sum_{i=1}^{m} w_i . \mu_i^k}{\sum_{i=1}^{m} w_i}. \tag{35}$$

The solution with the highest value of μ_k is chosen as the best Pareto solution [42].

6. Case study

As mentioned earlier, the case study for the present study is the Iran Khodro supply chain, with Sapco Company responsible for managing the parts supply system in this supply chain. The responsibilities of this Company comprise technical designing and supplying parts required for Iran Khodro production lines. The area where the Sapco Company operates is subject to wide and various disruptions (such as natural disasters, fluctuations of the exchange rate and prices, supplier interruptions, limited capacity of suppliers, low quality and high prices of suppliers' products, inflexibility of suppliers, etc.), which can reduce customer satisfaction, competitiveness, and ultimately, the company's profitability. This company often enjoys plenty of sources for supplying the same parts. One of the reasons for this issue is the uncertainties and risks involved in the performance and behavior of the suppliers that complicate single sourcing. In this context, one of the most significant ways to achieve the company's goals is to determine the optimal number of resilient suppliers and appropriate allocation of orders between selected suppliers that are able to meet and respond to the company's demand in the event of disruption. Also, a numerical example is presented in Appendix B to demonstrate the applicability of the proposed model for the real case.

6.1. Model data and parameters

For this study, 18 types of parts required by Sapco Company were selected to be supplied by 15 different suppliers. Among all the parts of a car, very important parts were also chosen. Table 3 lists the selected parts and suppliers of each part and different regions. As for multiple sourcing of the company and the regionalization of the supply chain, in order to reduce the impacts of environmental disruptions, the 15 selected suppliers are positioned in different cities. Other parameters required for the model (including the related costs, supplier capacity, warehouse capacity, demand, event probability, and flexibility rate) were determined using organizational documentation.

6.2. Model scenarios

In the proposed model, scenarios are determined based on the binary parameter ($S_{s,h}$) that represents the status of suppliers when disruption occurs. If the number of suppliers is n, the number of disruption scenarios is

Table 3. Suppliers related to each part and geographic location of selected suppliers.

	Suppliers														
Parts	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	⊙	⊙	⊙	⊙	–	–	–	–	–	–	–	–	–	–	–
2	⊙	⊙	⊙	–	⊙	–	–	–	–	–	–	–	–	–	–
3	–	⊙	⊙	⊙	⊙	–	–	–	–	–	–	–	–	–	–
4	⊙	⊙	⊙	⊙	⊙	–	–	–	–	–	–	–	–	–	–
5	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙	–	–	–	–	–
6	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙	–	–	–	–	–
7	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙	–	–	–	–	–
8	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙	–	–	–	–	–
9	⊙	⊙	–	–	⊙	–	–	–	–	–	–	–	–	–	–
10	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙	–	–	–	–	–
11	–	–	–	–	–	–	–	–	–	–	⊙	⊙	⊙	–	⊙
12	–	–	–	–	–	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙
13	–	–	–	–	–	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙
14	–	–	–	–	–	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙
15	–	–	–	–	–	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙
16	–	–	–	–	–	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙
17	–	–	–	–	–	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙
18	–	–	–	–	–	–	–	–	–	–	⊙	⊙	⊙	⊙	⊙
Regions	Garmsar	Takestan	Savadkuh	Saveh	Saveh	Esfahan	Eshtehard	Tehran	Saveh	Esfahan	Takestan	Tehran	Tehran	Tehran	Tehran

equal to $2n$. The number of these disruption scenarios increases exponentially upon increase in the number of suppliers, and it is difficult or impossible to solve the model with a huge number of scenarios. Therefore, the K-means clustering method is used to reduce the occurrence probability for scenarios. K-means technique is a relatively common clustering method due to its simple implementation, broad application of large data sets, and high efficiency. In this method, first, k samples are randomly selected from all the samples which are known as the representation of k cluster and are sometimes taken as the center of the cluster. Using criteria such as Euclidean distance, the similarity between each of the remaining samples and the k representation is calculated, and the sample is assigned to the cluster that has the nearest center. Subsequently, for each cluster, a new center is selected by computing the average among cluster members. This process is repeated until achieving convergence (such as fixing members of the clusters or minimizing the error function) [43].

The disruption scenarios in Sapco Company were identified based on historical data and the allocation of each part to different suppliers (whose number was 400) was taken into account. Then, before solving the presented model, similar scenarios were clustered using K-means clustering method in SPSS 24.0 software package. The number of clusters was equal to 10. Finally, from each cluster, scenarios with higher importance and occurrence probability were selected. All scenarios considered in the presented model are presented reported in Appendix C. For example, in Scenario 5, all suppliers are available and able to supply orders, except Suppliers 1 and 2 who have been disrupted.

7. Computational results for the case study

As already mentioned, the augmented ε-constraint

Table 4. Values of objective functions and the membership degree for different Pareto points

Pareto points	Objective functions		Membership degree (μ_k)
	Expected total cost	Supplier delivery performance	
1	1555085000	3142772.59	0.8797
2	1555255000	3193961.21	0.8918
3	1555413000	3244735.75	0.9037
4	1555575000	3295717.33	0.9157
5	1555773000	3346698.91	0.9278
6	1556111000	3397680.49	0.9398
7	1556463000	3448663.06	0.9518
8	1557233000	3499643.94	0.9637
9	1559236000	3550625.23	0.9756
10	1563428000	3601606.81	0.9873
11	1581396000	3652588.39	0.9979

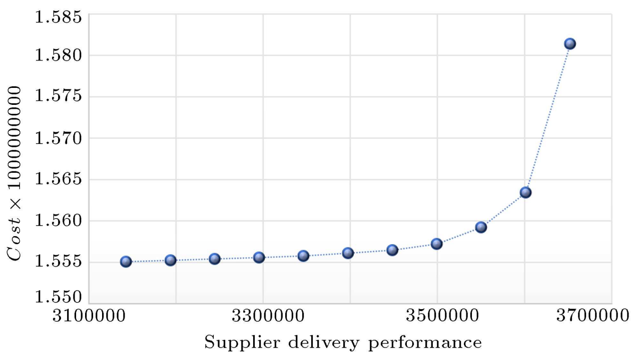

Figure 4. Pareto chart for two objective functions.

method is used for solving the proposed model. The mathematical model was coded in GAMS 24.1.3 on a personal computer with Intel Core i5 CPU and 4 GB of RAM. The input data of the model was recalled from EXCEL software. The number of constraints and variables of the model was 36312 and 24738, respectively. In the augmented ε-constraint method, the cost objective function was taken into account as the main objective and the objective function of the supplier delivery performance was considered as a constraint. After solving the model using the GAMS software, the optimal Pareto solutions were obtained, which are shown in Table 4. Pareto chart for these solutions can be observed in Figure 4. In order to choose the best Pareto optimal solution, the total value of the membership function for each Pareto point was obtained. In order to calculate the total membership function (μ_k) value, the weight of the first and second objective functions was considered 0.4 and 0.6, respectively, according to the opinion of the experts of Sapco Company. Finally, with respect to the values obtained for the membership function, the Pareto point 11, which has the highest value of (μ_k), was selected as the best Pareto optimal solution to the problem of choosing the resilient supplier and demand allocation.

Based on the Pareto point 11 as the best Pareto optimal solution, the optimal values of demand allocation to different suppliers for each part were determined, which are reported in Appendix D. Given that the objective function related to the supplier delivery performance was of greater importance and weight than the cost objective function, the supplier delivery performance criteria were prioritized compared to reliability and cost criteria and the suppliers with less delivery performance score than other suppliers were not allocated. The results indicate that at the Pareto point 11, the size of the supply base decreased because of the selection of suppliers with high delivery performance. However, due to the occurrence likelihood of the disruptions, the loss cost and, consequently, the total cost increased. In other words, selection of fewer suppliers with high delivery performance in comparison to the selection of a large set of suppliers with low delivery performance reduces delay time and increases the loss cost and thus, the total cost. Therefore, the balance between delivery performance and costs must be considered.

The order value of safety stock from different suppliers for each part is reported in Appendix D. The results indicate that the cost criterion holds greater weight in allocating required safety stock to suppliers, meaning that suppliers with lower purchasing cost were selected for supplying emergency inventory. In other words, the reliability, flexibility, and supplier delivery performance criteria are much less important than the cost criterion in providing safety stocks since the supply of safety stock is a process that may occur only once during the period.

In general, if disruption occurs at one or more suppliers and regions, the company may adjust the allocation amount of disrupted suppliers to the available suppliers based on the flexibility rate and their delivery performance score, or use the safety stock in warehouses (which is purchased and stored before the occurrence of any disruption scenario). For example, the value of second-stage variables for some scenarios are presented in Appendix E. Since the objective function related to supplier delivery performance is more important, during a supply disruption, the allocation amount of disrupted suppliers has been adjusted to the available suppliers and their flexible capacity was utilized to compensate for any parts not supplied by the disrupted suppliers. Then, in case of failing to satisfy the demand fully, the safety stock was used. Also, according to the results, it can be seen that among available suppliers, those with higher delivery performance scores and those with higher flexibility rates were selected to meet the unsatisfied demand. In other words, when allocating additional parts to available suppliers, the supplier delivery performance is prioritized to its flexibility rate. In the case of the same delivery performance score and flexibility rate of suppliers, the cost index in selecting the available suppliers is determinative.

Based on the table presented in Appendix E, it can be seen in Scenario 24 that Suppliers 6 and 10 (located in the same region) are disrupted and will be unable to supply parts. Therefore, their allocation has been switched to Suppliers 7 and 9 whose geographic location is different. It should be noted that if all these suppliers are located in a region, all of them are affected by regional disruptions and the order allocated to them cannot be met. Thus, the importance of regionalizing the supply chain and selecting suppliers from different regions in order to respond to disruptions can be seen and confirmed.

8. Sensitivity analysis

In this section, in order to understand the behavior of the model in various conditions and also to increase the reliability of the results, the effect of changes in several parameters on the results of the mathematical model was investigated and the best Pareto optimal solution (Pareto point 11) was selected for sensitivity analysis. Each time, one of the objective functions was considered the most important objective function, while the other was treated as a constraint (with a constant value assumed for it). The model was then solved, and new values of the decision variables and objective functions were obtained. Sensitivity analysis of selected parameters and the results are presented in the following.

8.1. Score of supplier delivery performance

This section examines how the supplier delivery performance score affects the final result of the supplier choice and order allocation. For this purpose, the Supplier 1 with a low score in the delivery performance was selected. According to Figure 5, values 10, 53, 90,

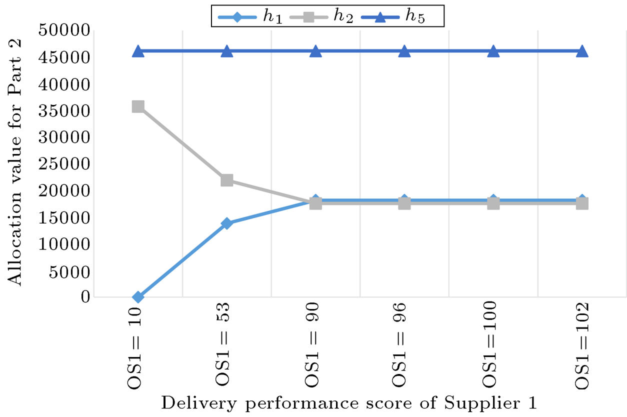

Figure 5. Effect of supplier delivery performance 1 on suppliers' allocation for Part 2.

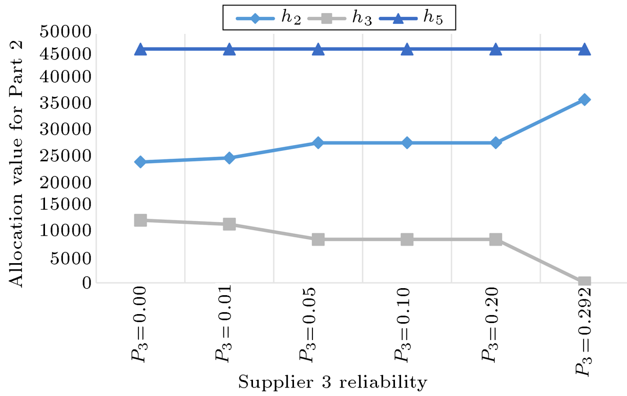

Figure 6. Effect of Supplier 3 reliability on the suppliers' allocation for the Part 2 (objective: minimization of cost).

96, 100, and 102 were considered for this parameter, and then, the sensitivity analysis at Pareto point 11 was carried out with the aim of maximizing the delivery performance of the suppliers. The results indicate that by increasing the delivery performance score of Supplier 1, the demand was allocated to it so that the allocation amount of Supplier 2 with a less delivery performance score than Supplier 5 could be reduced and the allocation amount of the Supplier 1 increased. According to Figure 5, the allocation of this supplier increased as long as its delivery performance score remained equal to 90, and from this level onwards, its allocation value was kept fixed. It was also observed that by increasing the delivery performance of Supplier 1, the value of the delivery performance objective function and, also, the loss cost increased. The reason for the increase in loss costs is that the Supplier 1 is less reliable than other suppliers and therefore, has a higher likelihood of failure. As a result, the existence of this supplier in the supply base has led to an increase in shortages and associated costs.

8.2. Supplier reliability

In order to investigate the effect of supplier reliability on their allocation amount, Supplier 3 with the highest

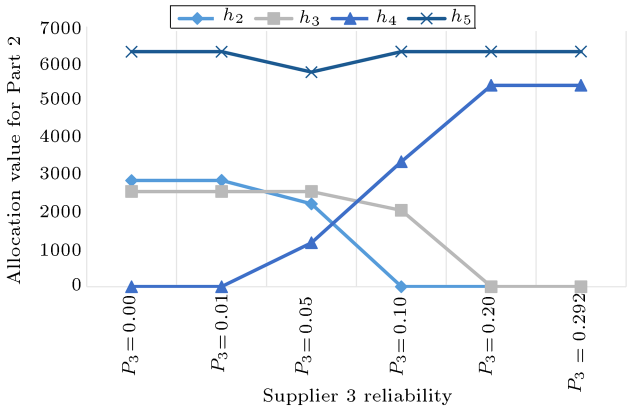

Figure 7. Effect of Supplier 3 reliability on suppliers' allocation for Part 4 (objective: minimization of cost).

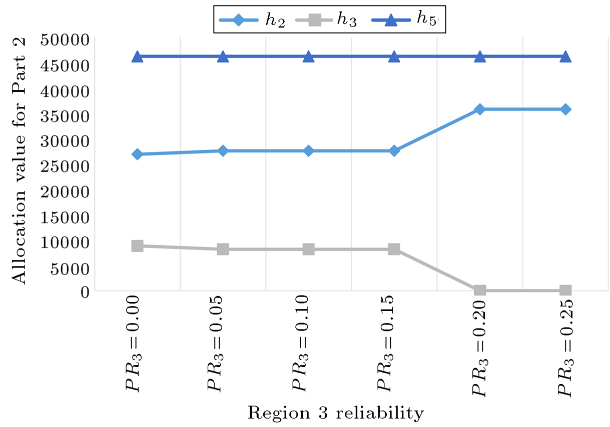

Figure 8. Effect of Region 3 reliability on suppliers' allocation for Part 2 (objective: minimization of cost).

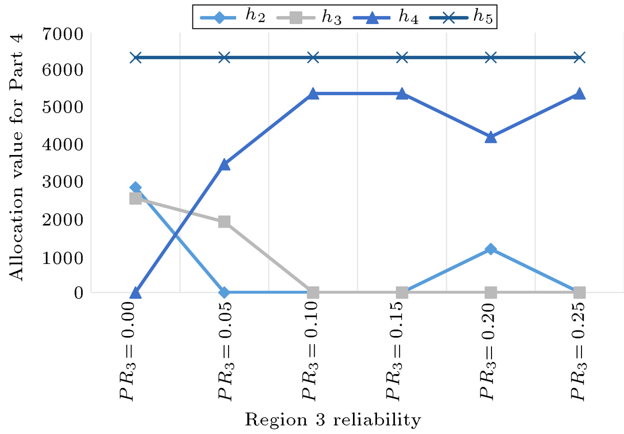

Figure 9. Effect of Region 3 reliability on suppliers' allocation for Part 4 (objective: minimization of cost).

probability of the disruptive event (0.292) among the suppliers was selected and for the reliability of this supplier, the values 0, 0.01, 0.05, 0.1, 0.2, and 0.292 were considered. The results of any change in the reliability were investigated for Parts 2 and 4, as can be seen in Figures 6 and 7. In the best Pareto optimal solution, assuming the cost objective function as the main objective and the objective function of the supply delivery performance as a constraint, the sensitivity analysis was conducted. It can be observed that upon reducing the failure probability of Supplier 3 (the one in the optimal solution was not selected due to its low reliability), it was placed at the supply base. The allocation of Supplier 2 for Part 2 (which is more probable to fail than the other suppliers) was reduced and allocated to Supplier 3.

Also, for Part 4 which was initially allocated to Suppliers 4 and 5, increasing the reliability of Supplier 3 will result in the supply being shared among Suppliers 2, 3, and 5. In other words, the Supplier 4 is removed and its allocation is transferred to Suppliers 2 and 3. By selecting Supplier 2 in the supply base (having a high failure probability and lower cost), the balance between reliability and cost is achieved. Also, between Suppliers 4 and 5, Supplier 5 with a high delivery performance and less reliability than Supplier 4 remains in the supply base. In addition, by selecting Supplier 3 (with a lower delivery performance and more reliability than Supplier 5), a balance between delivery performance score and reliability is established. When the objective function of supplier delivery performance is considered the most important, the corresponding parameter change resulted in an infeasible region for the problem. However, when the reliability of Supplier 3 was set to 0.2, an optimal solution was obtained, and Supplier 3 was selected for supplying Part 4.

8.3. Regions' reliability

In this section, the behavior of the model is analyzed when the occurrence probability of semi-super events for regions changes. The reliability of Region 3 varies from 0 to 0.25. When the goal is to maximize the supplier delivery performance and the reliability of Region 3 is set to 0, 0.05, or 0.1, the problem remains infeasible. However, if the reliability value of 0.15 is assigned to Region 3, Supplier 3 located in the third region will be selected to supply Part 4. Also, if the failure probability of this region exceeds 0.15, Supplier 3 will not be selected. When considering the cost objective function as the main objective, as shown in Figures 8 and 9, an increase in the reliability of Region 3 results in the third supplier being included in the supply base to supply Parts 2 and 4. By considering the reliability of zero ($p_r = 0$) for the third region, Supplier 3 located in this region and Supplier 2 are selected to supply Part 4 and Supplier 4 is removed from the supply base. The choice of Supplier 2 implies making a balance between reliability, risk, and cost due to the lower cost of this supplier. Also, when the failure probability of Supplier 3's region is less than or equal to the reliability of other regions, Supplier 3 is selected despite its low reliability. This indicates a trade-off

Table 5. Comparison of the loss cost in the condition of existence and lack of flexibility in the suppliers' capacity.

Objective	Loss cost	
	Main model	Eliminating suppliers' flexibility
Minimization of cost	14709690	18554010
Maximization of supplier delivery performance	14709760	19230240

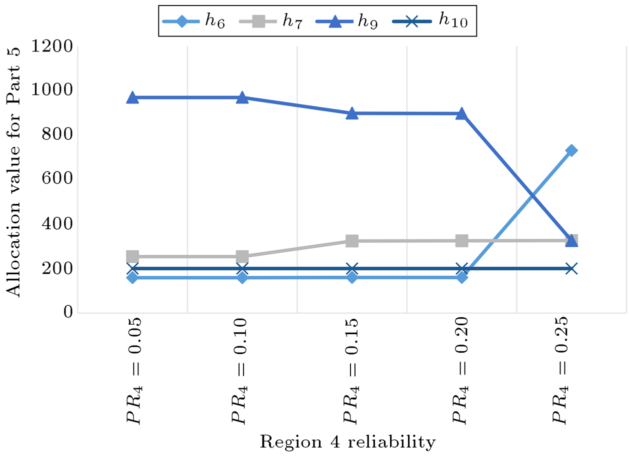

Figure 10. Effect of Region 4 reliability on suppliers' allocation for Part 5 (objective: maximization of delivery performance).

between the reliability of the region and the reliability of the supplier.

In the next step, the effect of region reliability on the results was investigated by selecting Region 4, where Suppliers 4, 5, and 9 are located. The range of change in the reliability of this region ranges from 0.05 to 0.25. The results of sensitivity analysis with regard to the delivery performance of the supplier as the objective function are presented in Figure 10. Accordingly, when the reliability of Region 4 varies from 0.05 to 0.25, the allocation of Supplier 9 for Part 5 is reduced and added to the allocation of Suppliers 6 and 7. Although Suppliers 6 and 10 are in the same region, the allocation of Supplier 9 shifts to Supplier 6 since it has a lower failure probability than Supplier (10). Supplier 9 remains in the supply base due to the high delivery performance and high reliability, and only its allocation is reduced.

8.4. Suppliers' flexibility

In this section, the effect of changing the supplier's flexibility parameter on their selection and allocation is examined. For this purpose, the flexibility rate of Supplier 4 for Part 3 was considered at five levels of 0.1, 0.2, 0.4, 0.6, 0.8, and 1. After solving the model with the aim of maximizing the delivery performance, it can be seen that upon increasing the flexibility of Supplier 4, the demand allocated to it for Part 3 decreases. Therefore, when a supplier has a very flexible capacity, the most appropriate strategy is to reserve its flexible capacity for disruptions. The findings demonstrate that enhancing the flexibility of certain suppliers does not lead to a shift in their allocation, as there are sufficient safety stocks available for those specific parts.

Also, to examine the effect of supplier flexibility on results, it was assumed that the flexibility of all suppliers was zero. Therefore, the only action during contingency planning under disruption is to use safety stock to obviate the shortage. In this case, when the objective is to minimize costs, all suppliers will be selected to prevent the shortage during the disruption and in each scenario, the number of additional parts sent from the available suppliers is zero. In addition, according to Table 5, the cost of loss increases to its previous value. Upon maximizing the supplier delivery performance as the primary objective, the elimination of flexibility across all suppliers results in the selection of only those with high delivery performance scores. As compared to the cost objective function, a smaller number of suppliers are chosen, which in turn leads to higher loss costs.

8.5. Minimum safety stock

In this section, the effect of changing the parameter w_i (minimum required safety stock) on the results is investigated. When the value of this parameter is reduced by 50%, the loss cost rises relative to the main model and the total cost decreases. Therefore, while the total cost decreases due to lower purchasing and holding costs of safety stocks, the loss cost increases as a result of the limited use of suppliers' flexible capacity and the incomplete compensation for shortages through supplier flexibility. In general, the appropriate strategy for contingency planning is the simultaneous use of the suppliers' flexible capacity and safety stock. Therefore, complete elimination of safety stocks from the view of supply chain risk management is not logical since there is the occurrence likelihood of environmental risks in the supply chain and all suppliers of a region are affected. Therefore, in such a situation, the most appropriate action is to use safety stock.

9. Conclusions and future works

In today's changing business environment, the automotive supply chain as one of the most critical and complex supply chains may be exposed to various types of risks and disruptions, and suppliers as the main source of external risks can cause a broad range of disruptions. Therefore, it is essential to consider approaches that reduce the severity of the potential effects of these disruptions and revert them to the initial state. In this research, the problem of choosing resilient suppliers and order allocation in the Iran-Khodro supply chain (Sapco Company) was studied. First, the present structure of the supplier selection in the case study company was investigated by interviewing relevant experts, and the criteria for selecting the supplier were appointed according to the conditions of the resilience. Then, the mathematical model for choosing resilient supplier was designed with the purpose of minimizing total costs and maximizing the supplier's delivery performance (in order to reduce the delay time in the process of supplying parts). In this proposed model, disruption and operational risks were considered. Also, the presented model included contingency plans to support the implementation of resilience strategies in order to reduce the negative impact of disruptions. Then, after determining the disruption scenarios in the company and reducing the number of them through K-means clustering method and collecting input data and model parameters, the model was solved by utilizing the augmented ε-constraint method. The mathematical model of the present study was a stochastic (scenario-based), integer, bi-objective, single-period, and multi-product model. In addition, the chance-constrained programming approach was applied due to the uncertainty in demand for parts.

The regionalization of the supply chain was considered as a way of reducing the impact of environmental disruptions. Our results supported regionalizing the supply chain by selecting multiple suppliers from various regions.

By examining the results, it can be seen that due to the occurrence likelihood of disruptions in the suppliers or regions (occurrences such as natural disasters, economic crises, bankruptcies, employee strikes, disruptions in transportation, etc.) and as a result of disruptions in procurement processes, the implementation of contingency planning should be considered to reduce the effects of these disruptions. The contingency plan suggested in this study includes transferring the order allocation of disrupted suppliers to the available suppliers based on their flexibility level and their delivery performance, as well as the purchasing and storing of additional inventory as safety stock. As previously noted, the sensitivity analysis of the flexibility and minimum safety stock parameters indicates that the utilization of safety stocks should be accompanied by flexibility in supplier capacity. Otherwise, the loss cost will exceed previous levels. It is often believed that pre-positioning inventory (safety stock) can mitigate disruptions and associated shortages, but at the same time, it may increase costs and reduce profitability. However, in addition to supply disruptions, there is a probability of environmental disruptions occurring in the supply chain. Thus, it is necessary to maintain safety stock to mitigate the risks associated with such disruptions. The results also show that allocating fewer orders to suppliers with high flexibility and reserving their flexible capacity can help reduce the effects of disruptions. In general, it can be stated that for supplier selection in a normal situation, delivery performance, reliability, and cost criteria are important. However, in a disruptive situation, when ordering additional parts from the available supplier, flexibility rate and delivery performance criteria should be prioritized. In other words, when supplying additional parts to compensate for shortages, among suppliers with similar flexible capacities, those with higher delivery performances should be selected. In addition, the results of the present study indicate that the flexibility, delivery performance, and reliability of suppliers and regions, as well as achieving a balance between these criteria, should be considered as important determinants in developing contingency plans for selecting resilient suppliers and allocating orders. Finally, the results of this research can help the managers of Sapco Company and also other managers and researchers to design resilient supply chains to respond to disruptions effectively.

The directions worth considering in future research are as follows:

1. Designing a mathematical model in a multi-period mode and considering the time dimension;
2. Considering the uncertainty of other parameters of the model including capacity, cost, etc;
3. Using other resilience strategies in choosing resilient suppliers, including the adoption of backup suppliers, protection of suppliers, etc;
4. Considering dependent disruption events where a disrupted supplier can affect other suppliers that depend on it.

References

1. Mendoza, A. and Ventura, J.A. "Analytical models for supplier selection and order quantity allocation", *Applied Mathematical Modelling*, **36**(8), pp. 3826–3835 (2012).
2. Torabi, S.A., Baghersad, M., and Mansouri, S.A. "Resilient supplier selection and order allocation under operational and disruption risks", *Transportation Research Part E: Logistics and Transportation Review*, **79**, pp. 22–48 (2015).
3. Hosseini, S. and Al Khaled, A. "A hybrid ensemble and AHP approach for resilient supplier selection",

Journal of Intelligent Manufacturing, **30**(1), pp. 207–228 (2019).

4. Kamalahmadi, M. and Mellat-Parast, M. "An assessment of supply chain disruption mitigation strategies", *International Journal of Production Economics*, **184**, pp. 210–230 (2017).
5. Carvalho, H., Maleki, M., and Cruz-Machado, V. "The links between supply chain disturbances and resilience strategies", *International Journal of Agile Systems and Management*, **5**(3), pp. 203–234 (2012).
6. Tukamuhabwa, B.R., Stevenson, M., Busby, J., et al. "Supply chain resilience: definition, review and theoretical foundations for further study", *International Journal of Production Research*, **53**(18), pp. 5592–5623 (2015).
7. Soni, U., Jain, V., and Kumar, S. "Measuring supply chain resilience using a deterministic modeling approach", *Computers & Industrial Engineering*, **74**, pp. 11–25 (2014).
8. Rice, J.B. and Caniato, F. "Building a secure and resilient supply network", *Supply Chain Management Review*, **7**, pp. 22–30 (2003).
9. Christopher, M. and Peck, H. "Building the resilient supply chain", *The International Journal of Logistics Management*, **15**(2), pp. 1–14 (2004).
10. Jabbarzadeh, A., Fahimnia, B., Sheu, J.B., et al. "Designing a supply chain resilient to major disruptions and supply/demand interruptions", *Transportation Research Part B: Methodological*, **94**, pp. 121–149 (2016).
11. Hou, J., Zeng, A.Z., and Zhao, L. "Coordination with a backup supplier through buy-back contract under supply disruption", *Transportation Research Part E: Logistics and Transportation Review*, **46**(6), pp. 881–895 (2010).
12. Christopher, M. and Lee, H. "Mitigating supply chain risk through improved confidence", *International Journal of Physical Distribution & Logistics Management*, **34**(5), pp. 388–396 (2004).
13. Rajesh, R. and Ravi, V. "Supplier selection in resilient supply chains: a grey relational analysis approach", *Journal of Cleaner Production*, **86**, pp. 343–359 (2015).
14. Kamalahmadi, M. and Mellat-Parast, M. "Developing a resilient supply chain through supplier flexibility and reliability assessment", *International Journal of Production Research*, **54**(1), pp. 302–32 (2016).
15. Chopra, S. and Sodhi, M. "Reducing the risk of supply chain disruptions", *MIT Sloan Management Review*, **55**(3), pp. 72–80 (2014).
16. Berger, P.D., Gerstenfeld, A., and Zeng, A.Z. "How many suppliers are best? A decision-analysis approach", *Omega*, **32**(1), pp. 9–15 (2004).
17. Sarkar, A. and Mohapatra, P.K. "Determining the optimal size of supply base with the consideration of risks of supply disruptions", *International Journal of Production Economics*, **119**(1), pp. 122–135 (2009).
18. Sawik, T. "On the robust decision-making in a supply chain under disruption risks", *International Journal of Production Research*, **52**(22), pp. 6760–6781 (2014).
19. Sawik, T. "Optimization of cost and service level in the presence of supply chain disruption risks: Single vs. multiple sourcing", *Computers & Operations Research*, **51**, pp. 11–20 (2014).
20. PrasannaVenkatesan, S. and Goh, M. "Multi-objective supplier selection and order allocation under disruption risk", *Transportation Research Part E: Logistics and Transportation Review*, **95**, pp. 124–142 (2016).
21. Sawik, T. "Selection of supply portfolio under disruption risks", *Omega*, **39**(2), pp. 194–208 (2011).
22. Lee, S.H. "A fuzzy multi-objective programming approach for determination of resilient supply portfolio under supply failure risks", *Journal of Purchasing and Supply Management*, **23**(3), pp. 211–220 (2017).
23. Sheffi, Y. "Building a resilient supply chain", *Harvard Business Review*, **1**, pp. 1–11 (2005).
24. Ruiz-Torres, A.J. and Mahmoodi, F. "A supplier allocation model considering delivery failure, maintenance and supplier cycle costs", *International Journal of Production Economics*, **103**(2), pp. 755–766 (2006).
25. Moritz, S. and Pibernik, R. "The optimal number of suppliers in the presence of volume discounts and different compensation potentials-an analytical and numerical analysis", *European Business School Research*, (2008).
26. Ruiz-Torres, A.J., Mahmoodi, F., and Zeng, A.Z. "Supplier selection model with contingency planning-for supplier failures", *Computers & Industrial Engineering*, **66**(2), pp. 374–382 (2013).
27. Sawik, T. "Selection of resilient supply portfolio under disruption risks", *Omega*, **41**(2), pp. 259–269 (2013).
28. Solgi, O., Gheidar-Kheljani, J., Dehghani, E., et al. "Resilient supplier selection in complex product and its subsystems' supply chain under uncertainty and risk disruption: A case study for satellite components", *Scientia Iranica*, **28**(3), pp. 1802–1816 (2019).
29. Sheffi, Y. "Preparing for the big one [supply chain management]", *Manufacturing Engineer*, **84**, pp. 12–15 (2005).
30. Rawls, C.G. and Turnquist, M.A. "Pre-positioning of emergency supplies for disaster response", *Transportation Research Part B: Methodological*, **44**(4), pp. 521–534 (2010).
31. Zheng, Y.J., Wang, Y., Ling, H.F., et al. "Integrated civilian-military pre-positioning of emergency supplies: A multi-objective optimization approach", *Applied Soft Computing*, **58**, pp. 732–741 (2017).
32. Hosseini, S., Morshedlou, N., Ivanov, D., et al. "Resilient supplier selection and optimal order allocation under disruption risks", *International Journal of Production Economics*, **213**, pp. 124–137 (2019).

33. Sahebjamnia, N. "Resilience supplier selection and order allocation under uncertainty", *Scientia Iranica*, **27**(1), pp. 411–426 (2018). https://doi.org/10.24200/sci.2018.5547.1337

34. Kaur, H. and Singh, S.P. "Multi-stage hybrid model for supplier selection and order allocation considering disruption risks and disruptive technologies", *International Journal of Production Economics*, **231**, 107830 (2021).

35. Olanrewaju, O.G., Dong, Z.S. and Hu, S. "Supplier selection decision making in disaster response", *Computers & Industrial Engineering*, **143**, 106412 (2020).

36. Falasca, M. and Zobel, C.W. "A two-stage procurement model for humanitarian relief supply chains", *Journal of Humanitarian Logistics and Supply Chain Management*, **1**(2), pp. 151–169 (2011).

37. Zhalechian, M., Tavakkoli-Moghaddam, R., and Rahimi, Y. "A self-adaptive evolutionary algorithm for a fuzzy multi-objective hub location problem: An integration of responsiveness and social responsibility", *Engineering Applications of Artificial Intelligence*, **62**, pp. 1–16 (2017).

38. Zhalechian, M., Torabi, S.A., and Mohammadi, M. "Hub-and-spoke network design under operational and disruption risks", *Transportation Research Part E: Logistics and Transportation Review*, **109**, pp. 20–43 (2018).

39. Mir Hasani, S.A. and Hooshmand Khaligh, F., *Stochastic Programming*, 2th Edn., pp. 149–153, Amirkabir University of Technology Publications, Tehran (2015).

40. Mavrotas, G. "Effective implementation of ε-constraint method in multi-objective mathematical programming problems", *Applied Mathematics and Computation*, **213**, pp. 455–465 (2009).

41. Felfel, H., Ayadi, O., and Masmoudi, F. "A decision-making approach for a multi-objective multisite supply network planning problem", *International Journal of Computer Integrated Manufacturing*, **29**(7), pp. 754–767 (2016).

42. Balaman, Ş.Y., Matopoulos, A., Wright, D.G., et al. "Integrated optimization of sustainable supply chains and transportation networks for multi technology bio-based production: A decision support system based on fuzzy ε-constraint method", *Journal of Cleaner Production*, **172**, pp. 2594–2617 (2018).

43. Yu, H., Wen, G., Gan, J., et al. "Self-paced learning for K-means clustering algorithm", *Pattern Recognition Letters*, **132**, pp. 69–75 (2020).

Appendix A

The steps in implementing the suggested model are shown in Figure A.1.

Appendix B

The parameters and optimal solutions of numerical example are shown in Tables B.1 to B.5.

Appendix C

Defined disruption scenarios and their occurrence probability are shown in Table C.1.

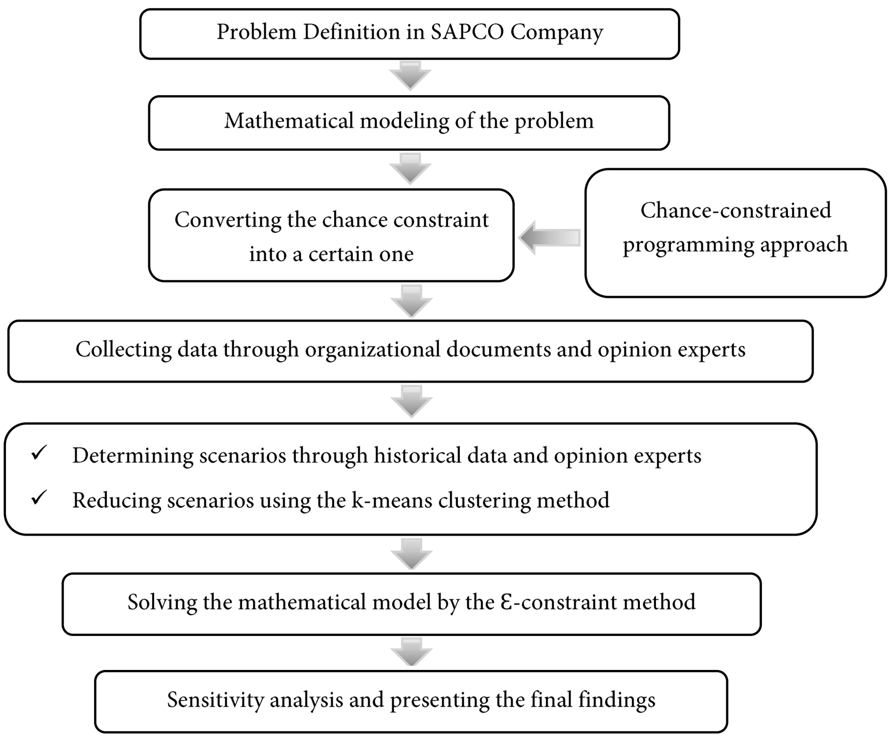

Figure A.1. Steps of implementing the presented model.

Table B.1. The parameters of numerical example.

Part code	Holding cost (Hl_i)	Loss cost (m_i)	Demand of part (d_i)	Warehouse capacity (v_i)	Minimum inventory required (w_i)	Supplier code	Flexibility of supplier ($b_{i,h}$)	Capacity of supplier ($Ca_{i,h}$)	Purchasing cost ($Cn_{i,h}$)	Transportation cost ($Tn_{i,h}$)
1	56000	84900	475	4410	250	1	0.2	3000	25000	105
1						2	0.3	4000	26000	280
1						3	0.4	5000	27000	380
1						4	0.5	6000	28000	400
2	52500	78800	495	4410	252	1	0.2	3200	25100	102
2						2	0.3	4100	26280	285
2						3	0.4	5500	27250	385
2						4	0.5	6100	28250	405
3	48000	72700	371	4410	255	1	0.2	3100	25220	106
3						2	0.3	4200	26250	282
3						3	0.4	5100	27260	380
3						4	0.5	6200	28240	400
4	44000	66700	475	4410	320	1	0.2	3500	25120	105
4						2	0.3	4000	26240	282
4						3	0.42	5200	27230	385
4						4	0.5	6000	28240	400
5	121000	181000	305	2604	200	1	0.19	3200	25300	108
5						2	0.32	4400	26640	250
5						3	0.4	5000	27630	382
5						4	0.5	6200	28640	410

Table B.2. The parameters of numerical example.

Regions (p^r)	Region 1 (0.010)		Region 2 (0.015)	
Suppliers	1	2	3	4
p_h	0.042	0.039	0.035	0.03
Os_h	21	25.65	26.25	28.75
F_h	3000	3000	3000	3000

Table B.3. The optimal solutions of numerical example.

		Supplier code						Supplier code				
	Part code	1	2	3	4		Part code	1	2	3	4	
$a_{i,h}$	1	–	174	–	301	$y_{i,h}$	1		–	250	–	–
	2	–	187	–	308		2		–	252	–	–
	3	–	90	–	281		3		–	255	–	–
	4	–	120	–	354		4		–	320	–	–
	5	31	53	–	221		5		200	–	–	–

Table B.4. Values of objective functions for different Pareto points.

Pareto points	Objective functions	
	Expected total cost	Supplier delivery performance
1	162663500	45718.92
2	162821900	46859.21
3	163123200	48000.57
4	163451500	49139.82
5	163805900	50280.1
6	164230400	51420.39
7	164727000	52560.68
8	165438300	53700.99
9	166260900	54841.27
10	167400900	55981.56
11	169315500	57121.85

Table B.5. The optimal solutions of numerical example.

Part code	Supplier code	Scenario 1	Scenario 2				Scenario 3				Scenario 4			
		$q_{i,h,s}$	$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$	$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$	$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$
1	2	174	0	0	250	225	174	0	0	0	0	0	24	0
	4	301	0	0			301	0			451	150		
2	2	187	0	0	252	243	187	0	0	0	0	0	33	0
	4	308	0	0			308	0			462	154		
3	2	90	0	0	255	116	90	0	0	0	0	0	0	0
	4	281	0	0			281	0			371	90		
4	2	120	0	0	320	155	120	0	0	0	0	0	0	0
	4	354	0	0			354	0			475	120		
5	1	31	0	0	200	105	0	0	0	0	31	0	0	0
	2	53	0	0			53	0			0	0		
	4	221	0	0			221	31			274	53		

Part code	Supplier code	Scenario 5				Scenario 6				Scenario 7			
		$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$	$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$	$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$
1	2	226	52	249	0	0	0	250	225	225	51	250	0
	4	0	0			0	0			0	0		
2	2	243	56	252	0	0	0	252	243	243	56	252	0
	4	0	0			0	0			0	0		
3	2	116	26	255	0	0	0	255	116	116	26	255	0
	4	0	0			0	0			0	0		
4	2	156	36	318	0	0	0	320	155	155	34	320	0
	4	0	0			0	0			0	0		
5	1	36	5	200	0	36	5	200	105	0	0	200	36
	2	69	16			0	0			69	16		
	4	0	0			0	0			0	0		

Part code	Supplier code	Scenario 8				Scenario 9			
		$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$	$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$
1	2	0	0	24	0	0	0	24	0
	4	451	150			451	150		
2	2	0	0	34	0	0	0	33	0
	4	461	153			462	154		
3	2	0	0	0	0	0	0	0	0
	4	371	90			371	90		
4	2	0	0	0	0	0	0	0	0
	4	475	120			475	120		
5	1	0	0	1	0	31	0	5	0
	2	0	0			0	0		
	4	304	83			269	48		

Table C.1. Defined disruption scenarios and their occurrence probability.

Scenario	Occurrence probability (π_s)	Suppliers														
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	0.10334	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	0.09127	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
3	0.03052	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
4	0.01968	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
5	0.00609	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
6	0.00124	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1
7	0.00004	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1
8	0.00075	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1
9	0.00101	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1
10	3.0517E-6	1	0	1	0	0	1	1	1	1	1	1	1	1	1	1
11	2.687E-6	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
12	0.00049	1	1	1	1	1	1	1	1	1	1	0	1	0	0	1
13	0.00099	1	0	1	1	1	1	1	1	1	1	1	0	0	1	1
14	0.00004	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1
15	0.00002	0	1	1	1	1	0	1	1	1	1	0	1	1	1	1
16	0.00001	1	1	1	0	1	1	1	1	0	1	1	0	1	0	1
17	2.794E-6	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1
18	0.00117	1	0	1	1	1	1	0	1	1	1	0	0	1	1	1
19	0.00031	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
20	0.00057	1	1	1	0	1	1	1	1	0	1	1	1	0	1	0
21	1.598E-6	1	0	1	0	1	1	1	1	0	1	0	1	1	0	1
22	2.97E-6	1	1	1	0	1	1	1	1	0	1	0	0	0	1	1
23	3.7012E-8	1	0	1	1	0	1	1	1	1	0	0	1	1	1	0
24	4.725E-9	0	1	1	1	0	0	1	1	1	0	0	1	1	1	0
25	0.00458	0	0	0	0	1	1	1	0	0	1	1	1	0	1	1
26	5.225E-9	0	0	0	0	0	1	1	1	0	1	1	1	1	0	1
27	2.549E-6	1	0	1	0	1	1	0	1	0	1	0	0	1	0	1
28	0.00104	0	0	0	0	1	1	0	0	1	1	0	0	1	1	1
29	5.657E-7	1	0	1	0	0	1	1	1	0	0	1	1	0	0	0
30	8.0501E-9	0	0	1	1	0	1	0	1	1	0	0	0	1	1	0
31	1.755E-10	1	0	0	1	0	1	1	0	1	0	1	0	1	0	0
32	9.353E-9	1	1	1	0	1	0	0	0	0	0	1	1	0	1	0
33	8.743E-11	0	0	0	0	0	1	1	1	0	0	1	1	1	0	0
34	7.802E-7	0	0	0	0	0	1	1	0	1	0	1	1	0	1	0
35	9.282E-7	1	0	1	0	1	1	0	1	0	1	0	0	0	0	0
36	6.178E-13	1	0	0	0	1	0	0	0	0	0	1	1	0	0	1
37	1.852E-13	1	1	0	0	1	0	0	0	0	0	1	0	0	0	1
38	1.266E-7	0	0	1	0	1	1	0	1	0	1	0	0	0	0	0
39	6.244E-7	0	0	0	0	1	1	1	0	0	0	1	0	0	0	0
40	2.727E-14	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1

Table D.1. Allocation value of each part to different suppliers in the best Pareto optimal solution ($a_{i,h}$).

	Supplier code														
Part code	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	–	6947	–	7500	–	–	–	–	–	–	–	–	–	–	–
2	–	35752	–	–	46153	–	–	–	–	–	–	–	–	–	–
3	–	19305	–	26666	20869	–	–	–	–	–	–	–	–	–	–
4	–	–	–	5364	6333	–	–	–	–	–	–	–	–	–	–
5	–	–	–	–	–	159	254	–	969	200	–	–	–	–	–
6	–	–	–	–	–	166	316	–	969	200	–	–	–	–	–
7	–	–	–	–	–	–	124	–	912	200	–	–	–	–	–
8	–	–	–	–	–	159	254	–	969	200	–	–	–	–	–
9	–	1090	–	–	9804	–	–	–	–	–	–	–	–	–	–
10	–	–	–	–	–	102	117	–	225	572	–	–	–	–	–
11	–	–	–	–	–	–	–	–	–	–	102	15	15	–	15
12	–	–	–	–	–	–	–	–	–	–	93	17	17	17	17
13	–	–	–	–	–	–	–	–	–	–	137	–	20	–	–
14	–	–	–	–	–	–	–	–	–	–	184	31	31	31	31
15	–	–	–	–	–	–	–	–	–	–	189	33	33	33	33
16	–	–	–	–	–	–	–	–	–	–	189	33	33	33	33
17	–	–	–	–	–	–	–	–	–	–	141	–	35	–	–
18	–	–	–	–	–	–	–	–	–	–	141	–	35	–	–

Table D.2. Order optimal value of safety stock for each part ($y_{i,h}$).

	Supplier code														
Part code	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	–	–	–	300	–	–	–	–	–	–	–	–	–	–	–
2	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
3	–	1000	–	–	–	–	–	–	–	–	–	–	–	–	–
4	–	–	–	1269	1267	–	–	–	–	–	–	–	–	–	–
5	–	–	–	–	–	–	840	–	–	–	–	–	–	–	–
6	–	–	–	–	–	–	549	–	–	–	–	–	–	–	–
7	–	–	–	–	–	–	840	–	–	–	–	–	–	–	–
8	–	–	–	–	–	–	801	–	291	–	–	–	–	–	–
9	–	–	–	–	1464	–	–	–	–	–	–	–	–	–	–
10	–	–	–	–	–	363	131	–	23	172	–	–	–	–	–
11	–	–	–	–	–	–	–	–	–	–	298	232	385	–	385
12	–	–	–	–	–	–	–	–	–	–	157	144	233	233	233
13	–	–	–	–	–	–	–	–	–	–	133	–	–	–	–
14	–	–	–	–	–	–	–	–	–	–	176	237	329	329	329
15	–	–	–	–	–	–	–	–	–	–	131	274	287	287	287
16	–	–	–	–	–	–	–	–	–	–	151	262	307	307	307
17	–	–	–	–	–	–	–	–	–	–	–	–	160	–	–
18	–	–	–	–	–	–	–	–	–	–	–	–	136	–	–

Appendix D

Table D.1. Allocation value of each part to different suppliers in the best Pareto optimal solution ($a_{i,h}$).

Table D.2. Order optimal value of safety stock for each part ($y_{i,h}$).

Appendix E

The optimal value of second stage variables for some parts in scenarios 1, 20, and 24 are shown in Table E.1.

Biographies

Asma Bakhtiari Tavana received her MSc and BSc degrees in Industrial Management from University of Shahid Beheshti in Tehran province. She is a PhD student in the same field (production and operation) at the Department of Industrial Management Allameh

Table E.1. The optimal value of second stage variables for some parts in scenarios 1, 20, and 24.

Part code	Supplier code	Scenario 1	Scenario 20				Scenario 24			
		$q_{i,h,s}$	$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$	$q_{i,h,s}$	$Aq_{i,h,s}$	$g_{i,s}$	$U_{i,s}$
2	2	35752	35752	0	0	0	50052	14300	4600	27253
	5	46153	46153	0			0	0		
3	2	19305	19305	0	0	0	27027	7722	1000	6814
	4	26666	26666	0			31999	5333		
	5	20869	20869	0			0	0		
6	6	166	182	16	0	0	0	0	0	0
	7	316	0	0			323	76		
	9	969	1259	290			1259	290		
	10	200	210	10			0	0		
9	2	1090	1090	0	0	0	1417	327	1464	8013
	5	9804	9804	0			0	0		
10	6	102	102	0	0	0	0	0	641	0
	7	117	0	0			128	11		
	9	225	225	0			247	22		
	10	572	689	117			0	0		
12	11	93	110	17	0	0	0	0	96	0
	12	17	0	0			22	5		
	13	17	17	0			20	3		
	14	17	17	0			23	6		
	15	17	17	0			0	0		
14	11	184	215	31	0	0	0	0	200	0
	12	31	0	0			34	3		
	13	31	31	0			37	6		
	14	31	31	0			37	6		
	15	31	31	0			0	0		
16	11	189	222	33	0	0	0	0	201	0
	12	33	0	0			39	6		
	13	33	33	0			42	9		
	14	33	33	0			39	6		
	15	33	33	0			0	0		
18	11	141	141	0	0	0	0	0	133	0
	13	35	35	0			43	8		

Tabataba'i University, Tehran. Her research interests are in the field of supply chain management, resiliency and sustainability in the supply chain, and project management.

Masood Rabieh received his PhD from Tarbiat Modaress University, Iran. He is an Assistant Professor at the Department of Industrial Management at Shahid Beheshti University, Iran. His research interests include operations research, system dynamics & systems thinking, supply chain management, and project management.

Mir Saman Phishvaee received his PhD in Industrial Engineering from the University of Tehran and now, he is an Assistant Professor at Iran University of Science and Technology (IUST). He has published many papers in various journals such as Omega, Transportation Research: Part E (TR-E), Computers & Operations Research (COR), and Computers & Industrial Engineering (CAIE) as well as several book chapters under Springer-Verlag in the area of supply chain management. His research areas are supply chain management, robust optimization, and system dynamics.

Mahdi Esmaeili is a PhD student in Industrial Management (production and operation) at the Department of Industrial Management Allameh Tabataba'i University, Tehran, Iran. He is the Head of Logistics Engineering in Supplying Automative Part Co., Iran. His research interests include logistics, supply chain management, transportation, and lean production.