A resilient supply portfolio considering political and disruption risks

Reza Hosnavi and Mohammad Ali Nekooie

Department of Emergency Management,
Malek Ashtar University of Technology (MUT),
Tehran, Iran
Email: ali.nekooie@gmail.com
Email: hosnavi@mut.ac.ir

Seyed Mohammad Khalili and
Ahmad Tavakoli*

Department of Management,
Ferdowsi University of Mashhad,
Mashhad, Iran
Email: m.khalili@mail.um.ac.ir
Email: tavakoli-a@um.ac.ir
*Corresponding author

Abstract: The need of accounting for resilience in global supply chains has been growing from practical and academic points of view. However, there is still the need for developing quantitative decision support models on this issue. In the present work, we propose a novel multi-objective mixed possibilistic, two-stage scenario-based stochastic programming model to handle supplier selection and order allocation problem in a global supply chain under operational and disruption risks. The model minimises cost and political risk, while, maximising resilience of the supply portfolio. Various risk mitigation approaches including: contracting with backup suppliers, fortification of suppliers and procurement of emergency inventory, are considered in the model. In addition, the proposed model determines recovery plans. Reservation level driven Tchebycheff procedure is incorporated in the solution procedure to find Pareto-optimal solutions. The validation of the model via computational experiments demonstrates the applicability of the proposed model and solution method in building a resilient supply portfolio under consideration of operational and disruption risks.

Keywords: supply chain risk/disruption management; resilient supply portfolio; mixed possibilistic two-stage stochastic programming.

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Biographical notes: Reza Hosnavi received his PhD in Industrial Engineering from Iran University of Science and Technology and is currently an Associate Professor of Department of Emergency Management, Malek Ashtar University of Technology (MUT), Tehran, Iran. His research interests include: supply chain management, project scheduling, and inventory and production planning. More specifically, he is working on supply chain risk management modelling and solution methods.

Mohammad Ali Nekooie obtained his PhD in Civil Engineering from Universiti Teknologi Malaysia (UTM), Skudai. Currently, he is an Assistant Professor of Department of Emergency Management, Malek Ashtar University of Technology (MUT), Tehran, Iran. His research interests are hydraulic, concrete, flood management, emergency management, and risk management.

Seyed Mohammad Khalili is currently a PhD student at the Department of Management Faculty of Economics and Business Administration Ferdowsi University of Mashhad, Mashhad, Iran. He has published some papers in peer-reviewed journals and conferences. His research interests include supply chain resilience and risk management in supply chain.

Ahamad Tavakoli completed his PhD in Industrial Management at Tarbiat Modares University Tehran, Iran. Currently, he is an Assistant Professor at the Department of Management Faculty of Economics and Business Administration Ferdowsi University of Mashhad, Mashhad, Iran. His research interests are production and inventory scheduling, supply chain management and quantitative methods in business.

1 Introduction

Supplier selection and order allocation (SS&OA) problem is a complex optimisation problem within supply chain management which involves multiple tangible and intangible criteria (Ho et al., 2010). In today's challenging global market, traditional criteria in SS&OA problems like cost, quality and delivery time (i.e., QCD measures) are not sufficient any more. Several events over the past decades have demonstrated it, and emphasised the existing risk is increasing in the modern fragile supply chains. Generally speaking, risks can be divided to two main groups: operational risks and disruption risks, operational risks address the inherent uncertainties of critical data such as demand-side and supply side uncertainties (Rezapour et al., 2016), and disruption risks refer to major disruptions that have significant lasting negative impacts (Tang, 2006). For instance, in early 2000 a fire at the main Philips radio-frequency chip plant disrupted the supply to Ericsson for their cellular phones. Surprisingly, this event led to exiting of Ericsson from the market of cellular phones along with an estimated $400 million revenue loss (Rice and Caniato, 2003). Other similar disruptive events in supply chains could be found in the literature (e.g., Sheffi, 2005a; Fuller, 2012), however, most of them have common properties. Disruptive events are difficult to predict, have a small probability of occurring with significant impacts on the ability of supply chains. In order to address supply risks, especially disruptive type, managers are now adopting business continuity planning (BCP) approach. BCP is an approach to optimise the ability of firms to react to unanticipated events, and keep its functionality in an acceptable range during occurrence of potential disruptions (Zsidisin et al., 2005). In other words, business continuity involves management process of identifying potential internal and external risks and their respective effects on critical business processes, in addition to developing a framework to ensure organisational resilience (Drewitt, 2013). Resilience is closely related to the capability of a system/organisation to return to a stable and predefined state after a disruption (Bhamra et al., 2011). It is important to focus on the concept of supply chain resilience in order to design and plan a system that is able to respond to changes rapidly and cost effectively (Carvalho et al., 2012; Colicchia et al., 2010). Implementation of BCPs is becoming more vital with the advent of global supply chains, since supply networks are spanned across international borders, and inevitably risk is increasing and new types of risks are emerging that should be handled by managers (Sahebjamnia et al., 2015; Faertes, 2015; Harland et al., 2003). It is essential to remind that the organisations may not have the capability to eliminate or ameliorate many of external risks in global supply chains such as political risk in key export markets (Ritchie and Brindley, 2000).

In spite of the growing number of papers in mentioned issues (Gong et al., 2014; Kim et al., 2015), there is still a lack of quantitative decision models that could be able to address resilience and political risk of global supply chains simultaneously, especially in SS&OA problems. Given its importance, this paper addresses the SS&OA problem of a manufacturer that is purchasing some critical items from global market. The manufacturer aims to prepare a supply portfolio which is resilient against plausible disruption and operational risks. Operational risk originates from inherent impreciseness in critical data, and this uncertainty is handled by introducing imprecise parameters which are formulated as possibility distributions in the form of fuzzy sets. However, disruption risks are divided to two main categories in this paper and are tackled individually. The first group of disruption risks relate to those events that has direct impact on production capacity of suppliers (e.g., natural or man-made disasters), and is considered via stochastic scenarios. Political risk is the second group of disruption risks which originate from the nature of global supply chains that requires international relations. We encounter this kind of risk by developing diversity in the supply portfolio with consideration of mutual political conflicts between countries of suppliers. As each risk is identified with two dimensions including probability and impact (Mitchell, 1995), diversity is proposed by Jansen et al. (2004) as an approach to face with this type of risk when there is no basis for predicting its probability and impact. In fact, we believe stochastic disruption scenarios can be predicted with specific probability for individual suppliers due to their specifications, but somehow it seems unrealistic or impossible for a manufacturer to provide disruption scenarios for political disruption scenarios of its supply portfolio. In this regard, a three objective mixed-possibilistic two-stage stochastic scenario-based model is developed which minimises cost, maximises resilience, and minimises political risk, simultaneously. The first stage of the model determines design related decisions which are made before realisation of scenarios, while, the second stage of the model includes recourse decisions that are specified after realisation of scenarios. To the best of our knowledge, this is the first paper in the literature which accounts for operational, disruption and political risks of supply planning problem of global supply chains simultaneously. Other contributions of the proposed model in the global supply planning problem can be listed as follows:

- addressing business continuity related concepts/measures
- considering various proactive risk mitigation actions (e.g., fortification of suppliers, providing backup suppliers, and preposition emergency inventory at suppliers), along with reactive recovery plans, simultaneously, via a two-stage modelling approach
- developing a new quantitative indicator for measuring and maximising the resilience of the supply portfolio
- using conditional value-at-risk (VaR) as the risk control method to tackle expected worst-case scenarios.

The remainder of this paper is structured as follows: the literature review is provided in the next section. Problem definition and the proposed mathematical model are elaborated in Sections 3 and 4, respectively. Solution method is developed in Section 5. Numerical experiments and managerial insights are presented in Section 6. Finally, the last section comprises conclusion highlights and future research directions.

2 Literature review

The present work aims to incorporate operational and disruption risks in a SS&OA problem in a global supply chain in order to build a resilient supply portfolio. In this regard, the relevant literature is reviewed in two separate but complementary streams: supplier selection under operational and disruption risks and resilient supply chains. At the end of this section, research gaps are discussed.

2.1 Supplier selection under operational and disruption risks

A rich body of supply chain risk management literature addresses different aspects of procurement problem under various kinds of uncertainty (e.g., Abbasi et al., 2014). Recent literature surveys such as Ho et al. (2010, 2015), Snyder et al. (2012) and Ivanov et al. (2015) have analysed new agendas in supply chain risk management filed, and all of them have emphasised the importance of supply related risks. Snyder et al. (2012) believe that these days firms are much less vertically grown, and their supply chains are increasingly global, accordingly, their suppliers are spread out throughout the world, some regions that are politically or economically unstable. Several forms of uncertainty have been discussed in the literature including: yield uncertainty, capacity uncertainty, lead time uncertainty or input cost uncertainty (Snyder et al., 2012). Bansal (2016) formulated a multi-level supply chain network with a single producer, multi distributors and multi retailers during a finite planning horizon in which the demand rate is assumed to be exponential function of time and stock is assumed to undergo deterioration. Aggarwal and Singh (2015) modelled a stochastic multi-objective supplier selection problem considering operational risks involving uncertainties-related supplier's capacity, product demand, transportation and variable costs and lead time probability distributions. Cardoso et al. (2015) modelled disruptions in a probabilistic manner, resulting in the incorporation of two sources of uncertainty. They have considered 11 indicators to assess the supply chains' resilience, which comprise network design, centralisation and operational indicators. Su and Liu (2015) developed a stochastic dynamic programming formulation to characterise how dual sourcing balances the risks and opportunities, when a company bears disruption risks and correlated operational risks. Rabbani et al. (2014) proposed a multi-objective model for the SS&OA problem under disruption risks with discount constraints. Sawik (2010, 2011b) developed supplier selection models with various assumptions, and controlled disruption risks via VaR and conditional value-at-risk (CVaR). Similarly, Meena and Sarmah (2013) studied order allocation problem under the threat of supply disruption. Berger et al. (2004) and Berger and Zeng (2006) investigated the problem of choosing from multiple identical suppliers subject to disruptions. They have concluded that typically the optimal number of suppliers is small, except in extreme cases where suppliers are very unreliable and the cost of failure is very high. Merzifonluoglu (2015) established how risk modelling can be applied to supply portfolio procurement decisions by developing mathematical models considering the risk neutral and risk averse objectives independently or simultaneously. Hosseininasab and Ahmadi (2015) introduced a two-phase supplier selection procedure which includes a primary evolution of suppliers and then feeding the results into a multi-objective portfolio optimisation problem to maximise the expected value of suppliers, and minimise their correlated risk. Fera et al. (2017) implemented a Taguchi analysis to create a decision map for identifying possible strategic decisions under different scenarios and with alternatives for order planning in the supply chains.

2.2 Resilient supply chains

Given the importance of accounting risk in supply chain management, resilience has emerged as a new topic in the literature, and several authors have prescribed practices to increase supply chain resilience. Resilience is defined as the ability of a system to reduce effectively both magnitude and duration of deviation from the targeted performance level (Vugrin et al., 2011). Various proactive and reactive resilience strategies (e.g., incorporating redundancy resources, implanting business continuity management systems to assure recovery of lost capacities, and improving reliability of existing facilities) have proposed in the literature to enhance supply chain resilience (Li and Savachkin, 2013; Sahebjamnia et al., 2015). Iakovou et al. (2007) referred flexible sourcing, demand-based management, strategic safety stock, supply chain visibility, and process or knowledge back-up as resilience initiatives. The most challenging issue in this issue is the trade-off between resilience and cost (Sheffi and Rice, 2005). Esmaeilikia et al. (2014) has reviewed the existing literature of supply chain planning models that involve multiple flexibility options to improve resilience, and responding to inherent operational or disruption risks. Carvalho et al. (2012) studied a supply chain redesign problem to understand how mitigation strategies affect each supply chain entity performance, and evaluating alternative scenarios to improve supply chain resilience to a disturbance. Sawik (2013) proposed a mixed integer programming approach for obtaining a resilient supply portfolio capable of supplying parts in disruption situations with prepositioning emergency inventory at protected suppliers. Sadghiani et al. (2015) developed a possibilistic scenario-based robust model by scenario generation and disruption profiling to design a robust and resilient retail network. Torabi et al. (2015) presented a bi-objective two-stage programming model that accounts for epistemic uncertainty of critical data to address SS&OA problem. Ishfaq (2012) proposed incorporating flexibility in transportation operations through the use of multiple transportation modes to improve supply chain resilience. Tang and Tomlin (2008) highlighted the power of flexibility in providing resilience in supply chains and mitigating risks. Das and Lashkari (2015) prepared risk readiness and resilience measures as well as formulating a mixed integer programming model to create risk resiliency and averting potential risks. Christopher and Peck (2004) focused on the development of a managerial agenda in management of supply chain risk, via recommendations that are drawn empirically from a number of real case industries to improve the resilience of supply chains. Khalili et al. (2016) presents a two-stage scenario-based mixed stochastic-possibilistic programming model for integrated production and distribution planning problem in a two-echelon supply chain over a midterm horizon under risk though which the resilience level of the chain is optimised based on restoration of lost capacities.

2.3 Gap analysis

The provided literature review demonstrates that although operational and disruption risks are recognised as important factors in SS&OA problem, these factors are rarely considered simultaneously in order to prepare a resilient supply portfolio, especially, very limited quantitative methods are seen in this area. Accordingly, it would be worthwhile to develop quantitative models to integrate pre-disruption risk mitigation actions and post-disruption recovery plans in SS&OA problem. On the other hand, as mentioned above, supply chain risk management in global supply chains regarding their special characteristics requires new approaches. For example, correlation of economic and geopolitical interests between involved countries in supply networks must be considered as an important factor in global supply chains. This article seeks to fill the mentioned gaps through proposing a mixed possibilistic, two-stage scenario-based stochastic programming model for a SS&OA problem in a global supply chain where operational and disruption risks are accounted concurrently. In this regard, operational risks are handled by introducing imprecise values in the form of fuzzy sets for critical data, and disruption risks are presented through stochastic scenarios. To the best of our knowledge, this the first article in the literature in which a multi-objective programming approach is used to analyse the trade-off between the following goals:

- minimising cost in the worst-case
- maximising resilience of the supply portfolio
- minimising political risk in the supply portfolio.

Furthermore, the proposed model considers various proactive risk mitigation approaches (including fortification of suppliers, prepositioning of emergency inventory at fortified suppliers, and contracting with backup suppliers), in addition to post-disruption recovery option for suppliers with BCPs to enhance resilience level of the selected supply portfolio.

3 Problem description

This paper addresses a supply planning problem where an international manufacturer assembles various types of items over a planning horizon to meet customer demands. Items are purchased from multiple global suppliers which are dispersed all over the world. The suppliers have different limited capacity and they offer different price and quality for items. Production capacities of suppliers are vulnerable to various types of disruption risks that can threaten the supply portfolio of the manufacturer. Disruptions range from natural disasters like earthquake or flood, to man-made ones such as supplier's bankruptcy or system failure. In addition, as the manufacturer deals with global suppliers, various international regulation and limitations can threaten its supply portfolio. Although international regulation and limitations seem to be as a kind of man-made disturb, but they have different aspects that should be regarded specifically. Consider the case of a qualified supplier which has enough capacity to contribute in the supply portfolio, but international limitations which happen outside the manufacturer's control confine it. This kind of risk is obviously different from other disruption risks which can decrease the production capacity of suppliers, and could be managed via various business continuity plans (Zsidisin et al., 2005).

Through a preliminary investigation on qualified suppliers, the decision maker (DM) has recognised two groups of suppliers. The first group consists of reliable suppliers which have implemented specific business continuity plans and are able to recover their capacity in the event of facing disruption risks. The second group includes unreliable suppliers which have not developed business continuity systems; however, they offer lower prices than the first group. Reliable suppliers have prepared disruption profiles consisting of disruptive events, their likelihood, impacts and estimated recovery time. Disruption profile is obtained according to the result of the 'business impact analysis' and 'risk assessment' steps of the business continuity management system (Torabi et al., 2014, 2015).

As mentioned above, qualified suppliers belong to different nationalities and political relations between their countries can influence the supply portfolio of the manufacturer. On the other hand, this kind of disruption risk is mostly unknown due to lack of information. Chuang and Ma (2013) suggested diversification as the best policy to encounter disruptive events when we have no knowledge about them. In this regard, they studied various indices to evaluate supply diversification strategy. In this paper, we propose a modification of their index to overcome mutual political conflicts between countries of suppliers and to provide a diversified supply portfolio. Details of the proposed index are elaborated in the next section.

Consequently, the manufacturer is faced with a SS&OA problem in a supply chain with disruption risks. The manufacturer has already identified a set of random disruption scenarios through a scenario-based stochastic analysis which can threaten each supplier. Each scenario is associated with an estimation of occurrence likelihood and impact. In this regard, DM has decided to focus on the following strategies to encounter disruption risks and preparing a resilient supply portfolio:

- Investing in absorptive resources to fortify suppliers against disruptions (Chen and Miller-Hooks, 2012). The manufacturer will be able to preposition emergency inventory at fortified suppliers to mitigate disruption risks (Sawik, 2013). Reliable suppliers are fortified in different levels with respective cost and reduction impact of disruption on the remained emergency inventory after disruptions (Torabi et al., 2015).

- Developing the capability of using back-up suppliers, in the event that one or some of primary suppliers are inoperable or run out of capacity (Blackhurst et al., 2005). This strategy involves making contracts with backup suppliers as a precaution action.
- Adopting a supply diversification strategy with consideration of mutual political conflicts between countries of suppliers in order to tackle the inherent political risk of the supply planning problem in the global market.

To wrap it up, DM applies all aforementioned strategies to decide which suppliers should be selected and how orders should be distributed among them to optimise cost and resilience of the selected supply portfolio in the situation of facing disruption risks.

4 Model formulation

In order to deal with the presented problem in the previous section, we apply a two-stage fuzzy-stochastic scenario-based modelling approach. Owing to inherent properties of the considered problem it is necessary to develop a modelling approach consisting of determining the design characteristics of pre-disruption precautions (i.e., in first stage of the model) and planning decisions of post-disruption actions (i.e., in second stage of the model), simultaneously. Additionally, as Klibi et al. (2010) have mentioned inherent uncertainty in demand, supply and other related data is one of the main challenges in supply chain planning problems. Therefore, it is vital to develop decision models capable of considering such uncertainty. In our model, critical parameters such as demand, defect rate, production capacity of suppliers, fortification cost, holding cost of emergency inventory at fortified suppliers and mutual political conflicts of suppliers are considered imprecise (possibilistic) due to unavailability or incompleteness of data. In this regard, we have to estimate them based on the subjective opinions of experts. Accordingly, it is assumed that suitable possibility distributions in the form of fuzzy sets based upon both available subjective and objective data of experts have been estimated for each imprecise parameter in the form of a triangular fuzzy number. For example, consider an imprecise parameter which is characterised by three prominent values n^p, n^m and n^o denoting the most pessimistic, the most likely and the most optimistic values of estimated by experts (Torabi and Hassini, 2008).

To put it briefly, the addressed problem of this paper includes considering disruption risks via stochastic scenarios, and at the same time encountering operational risks through possibility distributions for imprecise parameters. Each scenario represents a disruption risk including disrupted suppliers who are faced with a specific disruptive event. Also, possibilistic parameters are used in response to operational risks according to aforementioned description about ambiguous data of the problem. It is worth noticing that two-stage stochastic programming is one of the most acceptable approaches to deal with two-stage decision problems (Torabi et al., 2015). In order to develop a stochastic optimisation model, first a set of disruption scenarios are identified. Then, an initial decision is made in the first stage (i.e., before any scenario realisation). In the second stage of the model, recourse actions (i.e., second stage variables) are taken in order to compensate for the decision made in the first stage (Falasca and Zobel, 2011). Generally, since some parameters and variables of the model are defined scenario-based, a solution is sought which is immunised against all possible scenarios, however, the solution may not be optimal in general for the individual scenarios (Birge and Louveaux, 1997). A general discussion of stochastic programming models can be found in Kall and Wallace (1994). Accordingly, this paper presents a flexible multi-objective mixed possibilistic, two-stage stochastic program with recourse to handle the considered SS&OA problem under operational and disruption risks, simultaneously. Design decisions of the first stage of model include determining primary suppliers, backup suppliers, order quantity from each supplier as well as fortification decision of suppliers and allocation of emergency inventory among fortified suppliers. Furthermore, recourse decisions of the second stage of the model encompasses determining the required extra items which must be ordered from main or backup suppliers, as well as determining how to use prepositioned emergency inventories of selective fortified suppliers, and providing recovery plan of lost capacities at post-event phase. The model aims to achieve the minimum worst-case cost of ordering, purchasing, transportation, shortage, suppliers' fortification and emergency inventory prepositioning. At the same time, the model optimises the resilience of the provided supply portfolio quantitatively with consideration of mutual political conflicts between countries of suppliers in order to face the inherent political risk of supply planning in the global market. In other words, the presented model not only mitigates catastrophic risks by taking plausible supply disruption scenarios into account, but also reduces supply disruption probability by considering political dimension of procurement problem. In addition to implicit assumptions mentioned former, the following explicit assumptions are considered in the mathematical modelling.

- It is assumed that backup suppliers provide items with higher cost in disruption situations. Each random scenario might be occurred independently with a given likelihood.
- Suppliers have limited capacities that might be lost partially or completely due to disruption scenario realisation, and reliable suppliers are able to restore their lost capacities.
- Incurred shortage due to realisation of each disruption scenario is considered as lost sales
- Pre-positioning of emergency inventory in reliable suppliers is done in pre-disruption situation. If this inventory is used in a scenario realisation, then it must be replenished in that scenario to bounce back the system to its initial state for the next period.

Notations (i.e., sets, indices, parameters and variables) used for modelling are listed in Table 1. Please note that each parameter with the tilde sign (~) shows an imprecise parameter associated with a triangular fuzzy number.

Table 1 List of notations

Sets	*Description*
I	Set of suppliers
$J \subset I$	Set of reliable suppliers
K	Set of items
E_i	Set of possible fortification levels of reliable supplier i ($i \in J$)
L_{is}	Set of possible recovery levels of reliable supplier i ($i \in J$) after the realisation of disruption scenario s ($s \in S$)
S	Set of disruption scenarios through which lost production capacity of suppliers are decreased
Indices	*Description*
i	Index of suppliers ($i \in I$)
k	Index of items ($k \in K$)
e	Index of possible fortification levels of reliable suppliers ($e \in E_i$; $i \in J$)
l	Index of possible recovery levels of reliable suppliers ($l \in L_{is}$; $i \in J$; $s \in S$)
s	Index of disruption scenarios ($s \in S$)
Parameters	*Description*
A_i	fixed cost of ordering from supplier i (\$)
P_{ik}	Unit cost of purchasing and shipping item k from supplier i (\$/unit of item)
P'_{ik}	Unit cost of purchasing and shipping item k from backup supplier i (\$/unit of item)
SC_k	Unit cost of shortage of item k
D_k	Demand of item k
$\tilde{\theta}_{ik}$	Defect rate of supplier i for item k
CO_i	Fixed cost of contracting with backup supplier i (\$)
FC_{ik}	Fixed cost of fortifying reliable supplier i ($i \in J$) at level l (\$)
HC_{ik}	Unit cost of holding item k at reliable supplier i ($i \in J$) (\$/unit of item)
RC_{ik}	Unit cost of replenishing item k at reliable supplier i ($i \in J$) (\$/unit of item)
P_s	Disruption likelihood of scenario s
γ	Confidence level in calculating *CVaR* (i.e., first objective function)
Ca_l	Production capacity of supplier i (unit of item)
CaP_l	Storage capacity of reliable supplier i ($i \in J$) for prepositioning emergency inventory (unit of item)
δ_{is}	Amount of production capacity of supplier i that remains available after the realisation of disruption scenario s (as a percentile of its respective original value)

Table 1 List of notations (continued)

Parameters	*Description*
ε_{ils}	Amount of production capacity of reliable supplier i ($i \in J$) that is retrieved due to recovery at level l after the realisation of disruption scenario s (as a percentile of its respective original value)
η_{ies}	Amount of increase in remaining production capacity of reliable supplier i ($i \in J$) due to fortification at level e if disruption scenario s is realised (as a percentile of its respective original value)
ψ_{ll}	Mutual political conflicts between countries of supplier i and supplier i'
α	Feasibility degree
M	A very big number
Decision variables	*Description*
z_i	Binary variable that takes 1 if supplier i is chosen as a primary supplier in the supply portfolio; 0, otherwise
y_i	Binary variable that takes 1 if contract is arranged with supplier i as a backup supplier in the supply portfolio; 0, otherwise
x_{ik}	amount of item k that is purchased from supplier i
v_i	Fraction of total demand for all items that is purchased from supplier i
Re_{ils}	Binary variable that takes 1 if reliable supplier i ($i \in J$) is fortified at level e; 0, otherwise
f_{ie}	Binary variable that takes 1 if disrupted and reliable supplier i ($i \in J$) recovers its production capacity to level l after the realisation of disruption scenario s; 0, otherwise
EI_{ik}	Amount of emergency inventory of item k that is preposition at reliable supplier i ($i \in J$)
x'_{iks}	Amount of item k that is purchased from supplier i after the realisation of disruption scenario s
xb'_{iks}	Amount of item k that is purchased from backup supplier i after the realisation of disruption scenario s
xs'_{ks}	Amount of shortage of item k after the realisation of disruption scenario s
EI'_{iks}	Amount of emergency inventory of item k that is used from prepositioned inventory at reliable supplier i ($i \in J$) after the realisation of disruption scenario s
δ_{is}	Amount of production capacity of reliable supplier i ($i \in J$) that remains available after the realisation of disruption scenario s due to providing any fortification level (as a percentile of its respective original value)
VaR	Value-at-risk variable for the first objective function
TC_s	Auxiliary variable for calculating the amount by which total cost (i.e., the first objective value) exceeds VaR after the realisation of disruption scenario s

4.1 First objective function: expected worst-case cost

The first objective function of the proposed model includes two main parts. The first part is associated with the design related costs (*DC*), and includes ordering, purchasing and transportation cost of sending items from primary suppliers, plus contracting cost with backup suppliers, fortification cost of reliable suppliers and holding cost of prepositioning emergency inventory at fortified suppliers. It should be clarified that the fortification cost relates to the investment of improving infrastructure, e.g., buying enough spare power generators or renovation of supplier's building (Torabi et al., 2015), and preparing capacity storage at reliable suppliers. Fortification of suppliers increases the remained production capacity of disrupted suppliers (as a percentile of its respective original value).

$$DC = \sum_{i \in I} A_i z_i + \sum_{i \in I} \sum_{k \in K} P_{ik} x_{ik} + \sum_{i \in I} Co_i y_i + \sum_{i \in J} \sum_{e \in E} FC_{ie} f_{ie} + \sum_{i \in J} \sum_{k} HC_{ik} EI_{ik} \tag{1}$$

The second part is associated with the plan related costs (PC) for each scenario, and encompasses shortage cost, purchasing and transportation cost of sending items from backup suppliers, plus purchasing and transportation cost of sending prepositioned items at fortified suppliers, in addition to cost of replenishing used prepositioned inventory. Notably, consider that the manufacturer will not pay for the ordered but not delivered items due to realisation of disruption risks, so this part is subtracted form the first objective function.

$$\begin{aligned} PC_s = & \sum_{k \in K} SC_k xs'_{ks} + \sum_{i \in I} \sum_{k \in K} P'_{ik} xb'_{iks} + \sum_{i \in J} \sum_{k \in K} \left(RC_{ik} + P_{ik} \right) EI'_{iks} - \sum_{i \in J} \sum_{e \in E} FC_{ie} f_{ie} \\ & + \sum_{i \in J} \sum_{k \in K} P_{ik} \left(x_{ik} - x'_{iks} \right) \end{aligned} \tag{2}$$

Using expected value is the common approach to account for incurred costs over all scenarios. Pettit (2008) has criticised traditional risk management approaches due to their deficiency in characterising low-probability-high-consequence events, and has emphasised that considering worst-case is essential in modern risk management. Supply chain disruptions are mostly underestimated by managers due to their small probability of occurrence (Lim et al., 2010). In modern risk management approaches, it is vital to prepare yourself for extreme events, because we have learnt from the past that maximum loss of catastrophic events are significantly greater than mean or median of their loss (Grossi and Kunreuther, 2005; Kelle et al., 2014; Olson and Wu, 2013). However, Haimes (2004) has declared catastrophic risks can be mitigated significantly by a small raise in cost to improve structure. In this regard, we can invest in some precaution options (i.e., first stage variables) to alleviate catastrophic risks of the considered supply planning problem. To consider worst-case (i.e., catastrophic events) in our model quantitatively, we apply VaR and CVaR. These methods have been used extensively in financial engineering (Uryasev, 2000; Rockafellar and Uryasev, 2002). However, there are some other issues in which VaR and CVaR could be used in, for instance, Manavizadeh et al. (2017) utilised the concept of VaR to evaluate the amount of risk in multi project selection. VaR is the acceptable loss level above which DM wants to minimise the number of realisation of scenarios and *CVaR* is a weighted average of losses that exceed *VaR* (Sawik, 2011a). A detailed description about *CVaR* is introduced in Appendix A.

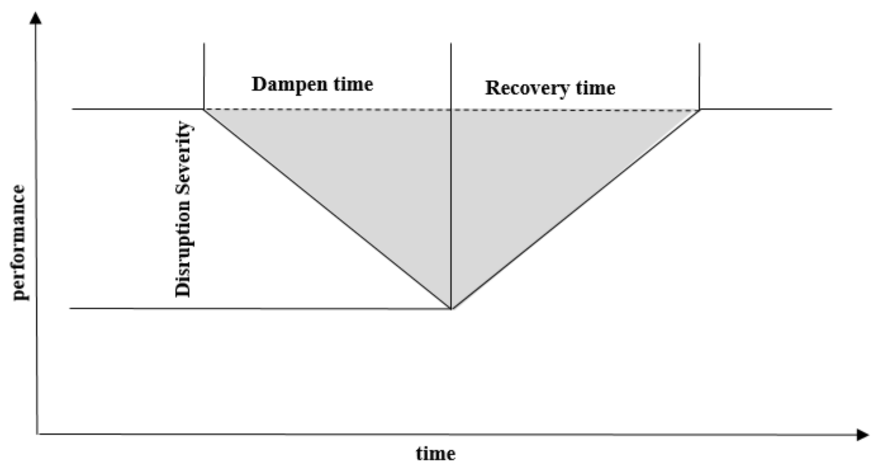
Accordingly, the first objective function of the proposed model minimises expected worst-case cost of the supply plan. The expected worst-case cost is minimised using CVaR as follows:

$$MinCVaR = Var + \left(\frac{1}{1-\gamma} \times \sum_{s \in S} p_s TC_s \right) \tag{3}$$

4.2 Second objective function: resilience of the supply portfolio

Increasing confidence and conferring the resilience ability to the supply chain is one of the ways to deal with supply chain disruption risks. Resilience capabilities of a resilient supply chain enable it to react to the negative consequences of unexpected events, and to return quickly to its initial state or even to a new better state after being affected by the disruptions (Nyoman Pujawan and Geraldin, 2009). In order to assess the supply chain resilience quantitatively, we should design indexes to be optimised during the planning horizon. An initial attempt to assess supply chain resilience originates from the concept 'resilience triangle', Figure 1, which represents the loss of functionality from disruption and performance evolution along the time (Sheffi, 2005b; Bruneau et al., 2003). The depth of the triangle shows the magnitude of disruption, and the length of the triangle represents the recovery time. Accordingly, the smaller the triangle is, the more resilient the supply chain is.

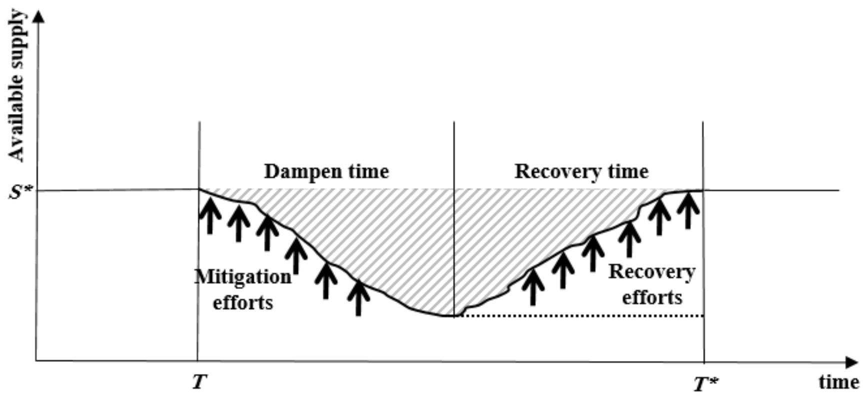
Figure 1 'Resilience triangle'



Source: Adapted from Carvalho et al. (2014)

In this approach, it is vital to use a reasonable criterion which should be optimised according to the considered supply planning problem. As mentioned above, the manufacturer mitigates disruption risks by prepositioning of emergency inventory at fortified suppliers as well as contracting with some back-up suppliers as counter measures against disruption risks. Also, the manufacturer can select reliable suppliers that have developed recovery plans to react to disruption risks. From a resilience perspective, it is important to analyse the supply portfolio in a specific time period, for example between T and T^* in which the supply plan is affected due to realisation of a disruption scenario. Suppose that the available supply is measured between T and T^*, a curve is generated with the available supply along time (S_t) (see Figure 2). The total available supply portfolio in the case of no disruption is given by S^*. When suppliers are affected by the disruption risk, a triangle pattern emerged showing the loss of total available supply. Nevertheless, some time after occurrences of the disruption risk the total available supply is bounced back to the initial state (S^*).

Figure 2 'Resilience triangle' pattern of the supply portfolio along time



As shown in Figure 2, risk mitigation actions reduce the potential risk of lack of available supply, while recovery efforts of reliable suppliers bounce back available supply to its initial value. An estimation of the triangle area can be computed based on straight line approximations between the available supply values for consecutive time periods (Suwanruji and Enns, 2004). Accordingly, the resilience index of the supply portfolio (R) is computed in equation (4):

$$R = 1 - \frac{\int_T^{T^*} \left(S^* - S_t \right) \partial t}{S^* \times (T^* - T)} \cong 1 - \frac{\sum_T^{T^*} \left(S^* - S_t \right)}{S^* \times (T^* - T)} \tag{4}$$

The range of resilience index of the supply portfolio (R) is from 0 to 1. The value of 0 for the resilience index means that the supply portfolio has no resilience capability (i.e., the available supply is null during the period time between T and T^*), while the value of 1 for the resilience index implies that the supply portfolio has enough resilience capability and is able to sustain in the event of facing the disruption risk (i.e., the available supply is equal to S* during the period time between T and T^*).

As we can infer from equation (4) maximisation of resilience implies that the available supply (S_t) should be as equal as possible to its initial value (S^*). From another point of view S^* in equation (4) can be considered as the total loss of supply (TLS) due to occurrence of disruptions, and (S_t) can be regarded as the provided supply by risk mitigation and recovery actions (RMRA). Note that some of the lost supply is retrieved through recovery efforts of reliable suppliers that have faced disruption risks. Consequently, maximisation of resilience in this regard as the second objective function of the model is presented in equation (5). Respective notations are presented in Table 1.

$$MaxR = 1 - \frac{TLS - RMRA}{TLS} \tag{5}$$

Or:

$$MaxR = 1 - \frac{RMRA}{TLS} \tag{6}$$

where:

$$RMRA = \sum_{i \in I} Ca_i y_i + \sum_{i \in J} \sum_{k \in K} EI_{ik} + \sum_{s \in S} \sum_{i \in J} \sum_{l \in L_{is}} P_s \left[\left(\left(1 - \delta'_{is} \right) \varepsilon_{ils} Ca_i \right) Re_{ils} \right] \tag{7}$$

$$TLS = \sum_{s \in S} \sum_{i \in I} P_s \left(\left(1 - \delta_{is} \right) Ca_i \right) \tag{8}$$

Note that the last term in equation (7) is nonlinear. Linearisation of this equation is presented in Appendix B.

4.3 *Third objective function: political risk of the supply portfolio*

The third objective function of the presented model minimises the potential political risk of supply disruption. The political-related supply risk has been studied in various studies (Chuang and Ma, 2013; Erdmann and Graedel, 2011). In this regard, most of researchers have focused on political instability of countries and mutual political conflicts between them in supply planning problem. On the other hand, recent studies have investigated that diversity strategies are being employed into this field. Diversified systems are able to return to the steady state faster after disturbances because there are multiple species to substitute one other (Smith, 1996). The diversity of interacting components (i.e., countries of suppliers and their political relations) is helpful to mitigate political aspect of risks in supply planning problem. Diversity indices have been developed widely in various fields and most of them are similar in calculation method (Rosenzweig, 1995). Chuang and Ma (2013) developed a modification of Herfindahl-Hirschman index (Hirschman, 1980; Herfindahl, 1950), and applied this index, equation (9), to an energy supply planning problem.

$$Min \left\{ \sum_{i=1}^{n} v_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=i+1}^{n} v_i v_j \sigma_{ij} \right\} \tag{9}$$

where v_i is the share of asset *i*, σ_i is the variance of asset *i*, and σ_{ij} is the covariance of asset *i* and *j*. This index is developed based on mean-variance-portfolio (MVP) theory (Markowitz, 1952) which minimises the risk of a portfolio composed of n assets. Inspiring by this index we propose the following index, i.e., equation (10), to overcome mutual political conflicts between countries of suppliers and to provide a diversified supply portfolio. Respective notations are presented in Table 1.

$$MinPR = \sum_{i \in I} \Psi_i v_i + \sum_{i \in I} \sum_{\prec i' \in I} \Psi_{ii'} \left| v_i - v_{i'} \right| \tag{10}$$

As we can see in equation (10), the first term considers the political conflicts between the country of manufacturer and countries of suppliers. In this way, the share of the supplier in the supply portfolio increases with lower political conflicts between the country of manufacturer and the country of supplier (i.e.). The second term in equation (10) corresponds to the political conflicts between countries of suppliers (i.e.). Our model tries to equalise the shares of suppliers in the supply portfolio which belongs to countries that have higher political conflicts between each other. Conversely, the model attempts to make a significant difference between shares of the suppliers in the supply portfolio which belongs to countries that have lower political conflicts between each other. This approach relates to the phenomena in political relations that if a country decides to stop its trade relations with the country of manufacturer, its allies may follow the same way, while countries with high political conflicts mostly select different ways in this situation. In this regard the presented model diversifies the supply portfolio with the aim of equalising the share of suppliers which have higher political conflicts and making significant disparity between the shares of suppliers with lower political conflicts. Mutual political conflicts are considered imprecise (fuzzy) in the model due to lack of historical data, and subjective nature of this parameter. The value of this parameter can be derived from worldwide governance indicators (WGI) of the dataset of World Bank (Bank, 2015), or another dataset provided by Gartzke and Jo (2006) which is created based on the relation of votes of all countries that are members of the United Nations (UN). This parameter takes positive values, and the higher values indicate higher political conflicts between countries. Note that the second term in equation (10) is nonlinear. This equation can be easily converted to linear form which is reported in Appendix C.

4.4 Functional and operational constraints

$$x_{ik} \le Mz; \quad \forall i \in I, k \in K \tag{11}$$

$$xb'_{iks} \le My_i; \quad \forall i \in I, k \in K, s \in S \tag{12}$$

$$y_i + z_i \le 1; \quad \forall i \in I \tag{13}$$

$$xs'_{ks} = \tilde{D}_k - \left\{ \sum_{i \in I} \left(1 - \tilde{\theta}_{ik}\right)\left(x'_{iks} + xb'_{iks} + EI'_{iks}\right) \right\}; \quad \forall k \in K, s \in S \tag{14}$$

$$\sum_{k \in K} x_{ik} \le \tilde{C}a_i; \quad \forall i \in I \tag{15}$$

$$\sum_{k \in K} \left(x_{ik} + EI_{ik}\right) \le \tilde{C}a_i; \quad \forall i \in J \tag{16}$$

$$EI_{ik} \le Mz_i \in J, k \in K \tag{17}$$

$$\sum_{k \in K} EI_{ik} \le \tilde{C}aP_i; \quad \forall i \in J \tag{18}$$

$$EI'_{iks} \le EI_{ik}; \quad \forall i \in J, k \in K, s \in S \tag{19}$$

$$\sum_{k \in K} \left(x'_{iks} + xb'_{iks} \right) \leq \delta_{is} \widetilde{Ca}_i; \quad \forall i \in I, s \in S \tag{20}$$

$$\sum_{k \in K} \left(x'_{iks} + xb'_{iks} \right) \leq \delta'_{is} \widetilde{Ca}_i + \sum_{l \in L_{is}} \left[\left(1 - \delta'_{is}\right) \left(\varepsilon_{ils} \widetilde{Ca}_i \right) Re_{ils} \right] \tag{21}$$

$$\delta'_{is} = \delta_{is} + \sum_{e \in E_i} f_{ie} \eta_{ies}; \quad \forall i \in J, s \in S \tag{22}$$

$$\sum_{e \in E_i} f_{ie} \leq 1; \quad \forall i \in J \tag{23}$$

$$\sum_{l \in L_{is}} Re_{ils} \leq 1; \quad \forall i \in J, s \in S \tag{24}$$

$$x'_{iks} \leq x_{ik}; \quad \forall i \in I, k \in K, s \in S \tag{25}$$

$$\upsilon_i \cong \frac{\sum_k \left(x_{ik} + EI_{ik} \right) + \sum_{s \in S} \sum_{k \in KP_s} xb'_{iks}}{\sum_k \tilde{D}_k}; \quad \forall i \in I \tag{26}$$

$$z_i, y_i \in \{0, 1\}; \quad \forall i \in I, l \in L, s \in S \tag{27}$$

$$Re_{ils} \in \{0, 1\}; \quad \forall i \in I, l \in L, s \in S \tag{28}$$

$$\nu_i \geq 0; \quad \forall i \in I \tag{29}$$

$$f_{ie} \geq 0; \quad \forall i \in I, e \in E \tag{30}$$

$$x_{ik}, EI_{ik} \geq 0; \quad \forall i \in I, k \in K \tag{31}$$

$$x'_{iks}, xb'_{iks}, EI'_{iks} \geq 0; \quad \forall i \in I, k \in K, s \in S \tag{32}$$

$$xs'_{ks} \geq 0; \quad \forall k \in K, s \in S \tag{33}$$

$$\delta'_{is} \geq 0; \quad \forall i \in I, s \in S \tag{34}$$

$$TC_S \geq 0; \quad \forall s \in S \tag{35}$$

Constraints (11) and (12) guarantee that items could be purchased from suppliers which are chosen as primary or backup suppliers. Constraint (13) controls the role of each supplier in the supply portfolio (primary or backup supplier).Constraint (14) determines shortage of item *k* under each disruption scenario. Constraint (15) and (16) ensures that the total amount of purchased items from each supplier to be smaller or equal to supplier's production capacity. As we can see in constant (16), some of production capacity of reliable suppliers can be used to provide emergency inventory. Constraint (17) limits prepositioning emergency inventory only in reliable suppliers that are chosen as primary supplier. Constraint (18) controls storage capacity of reliable supplies for prepositioning emergency inventory. Constraint (19) represents that the amount of products that are used after realisation of each disruption scenario is smaller or equal to the amount of prepositioned inventory in pre-disruption situation. Constraints (20) and

(21) limit purchasing quantity of items after realisation of disruption scenarios, however, consider that constraint (21) accounts for fortification and recovery of reliable suppliers. Note that the last term in the right side of constraint (21) is nonlinear; hence, linearisation procedure of this term is presented in Appendix B. Constraint (22) shows that the remained production capacity of reliable suppliers after realisation of disruptions can be improved by fortifying them. Constraint (23) says fortification of reliable suppliers is mostly allowed with one level. Constraint (24) represents that disrupted and reliable suppliers can be recovered at most in a specific recovery level after realisation of disruption scenarios. Constraint (25) ensures the amount of items purchased from each supplier after realisation of disruption scenarios must be smaller than or equal to its value in pre-disruption situation. Constraint (26) approximately estimates the supply portfolio of the supply plan. It should be noted that this constraint is ambiguous because the exact amount of items that are purchased from each supplier is determined after realisation of disruption scenarios. Constraints (27)-(35) define the type of decision variables.

5 Solution procedure

In order to develop the solution procedure of the proposed multi-objective mixed possibilistic scenario-based two-stage stochastic model, we have to consider the following issues:

- disruption scenarios may result in reduction of production capacity of suppliers, hence, there might be many scenarios in the model that should be reduced to a reasonable range
- the original possibilistic model must be converted to an equivalent parametric crisp model through an efficient method to reduce the number of crisp models that should be solved
- the resulting crisp model is still multi-objective; therefore, an efficient method should be used to find their compromise solutions.

Regarding the aforementioned points we propose the following solution algorithm that is summarised in Figure 3. Details of the main steps are clarified hereafter.

5.1 Reducing the number of disruption scenarios

The literature of supply chain risk management has emphasised that disruption scenarios should be reduced to a reasonable range (Pettit, 2008; Grossi and Kunreuther, 2005; Olson and Wu, 2013). In this regard, many approaches have been developed by researchers. Shapiro (2007) has suggested sampling as a technique to tackle the problem of scenario reduction in risk management. Novak and Kravanja (1999) have proposed a heuristic approach to reduce the dimension of stochastic scenario-based optimisation problems by determining a subset of the feasible space of random parameters. Sadghiani et al. (2015) have used a method developed by Karuppiah et al. (2010), which is built based on an idea similar to the approach of Novak and Kravanja (1999). In this approach, a subset of scenarios is selected with the optimal objective value of the reduced problem, then the optimal objective of the full scenario problem is decreased. Torabi et al. (2015) have used a fuzzy clustering approach to handle the problem of reducing the number of scenarios.

As we know, each disruption scenario is addressed based on two dimensions, the likelihood and the impact of disaster. Risk classification models based on likelihood and impact are introduced by Haimes (2011) and DoD (2000). Various combinations of likelihood and impact build up the 'risk matrix' which addresses different regions for prioritising scenarios from high priority to low priority (DoD, 2000). A sample of 'risk matrix' is depicted in Figure 4. This matrix shows each disruption scenario that is located in high priority region (i.e., based on its likelihood and impact) should be considered as a critical scenario.

Figure 3 The proposed solution algorithm

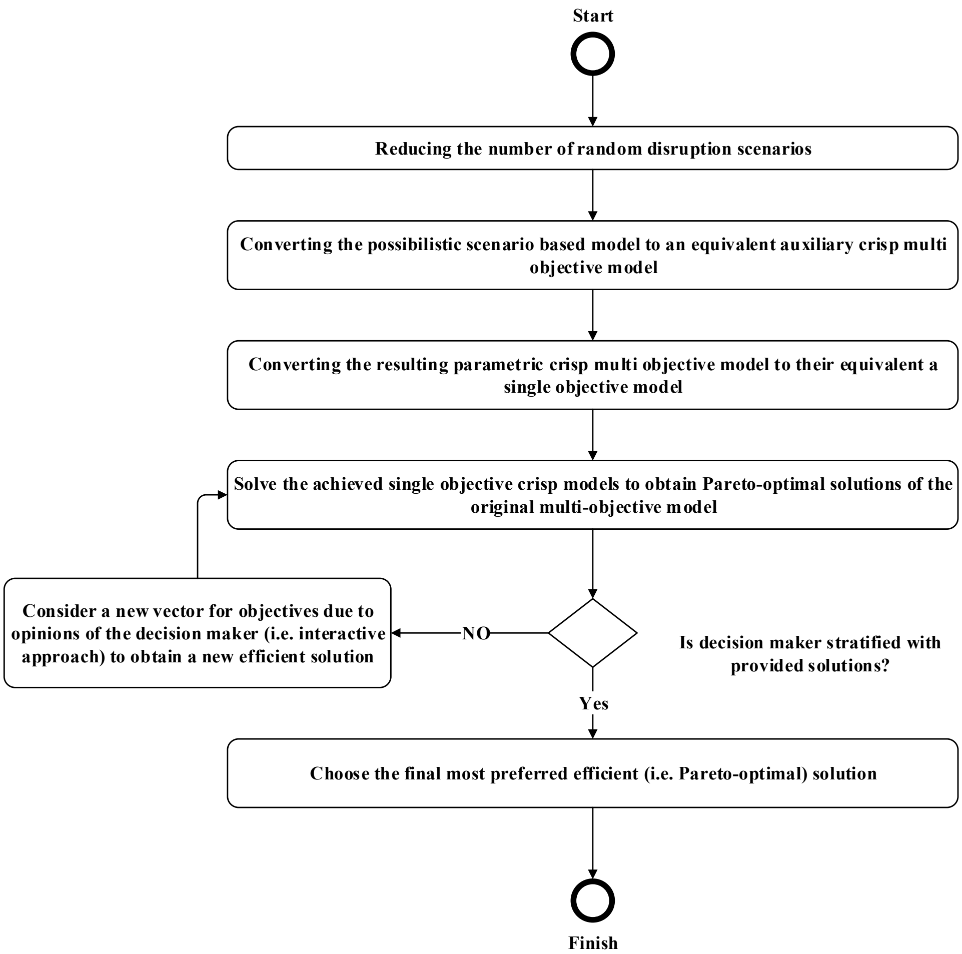
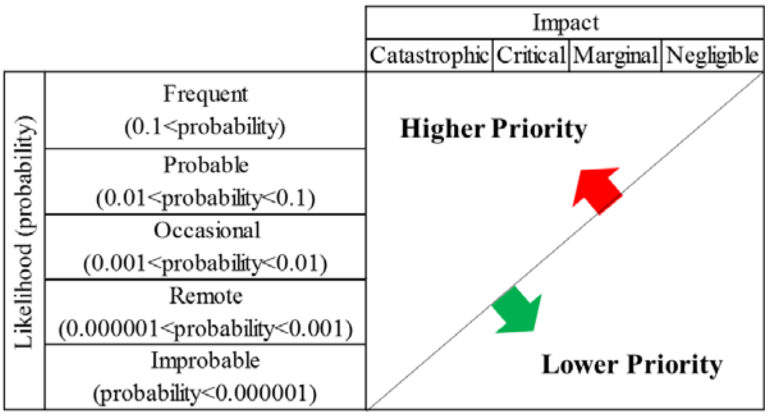


Figure 4 A sample of 'risk matrix' (see online version for colours)



Source: Adapted from DoD (2000)

In the addressed problem of this paper, the manufacturer has prepared a set of disruption risk scenarios, and has implemented a risk-filtering approach based on 'risk matrix' to exploit critical scenarios.

5.2 *Finding the equivalent single objective model via reservation level driven Tchebycheff procedure*

There are various scalarising methods for solving multiple objective programs. Among available multiple objective program approaches, epsilon-constraint method and Tchebycheff-based approaches are frequently applied. Tchebycheff metric-based approaches have become popular in multiple objective decision making situations. These approaches systematically reduce the set of non-dominated solutions which remain available for identification and selection. Reservation level driven Tchebycheff procedure (RLTP) is known as a common and strong algorithm in the literature of Tchebycheff metric based approaches for generating non-dominated solutions (Reeves and MacLeod, 1999). We can see RLTP matches the case of this paper; because, through an interactive procedure DM is able make decisions about tradeoffs between cost, political risk, and resilience. In fact, reservation levels (RLs) for objective space reduction are determined based upon DM opinions. RLTP produces only Pareto-optimal solutions and can solve mixed integer multi-objective models with non-convex solution space. This method is introduced in what follows.

As RLTP method is an interactive approach, first, we should specify the number of solutions for presenting to the DM in each iteration. Consider this parameter is shown by P. Now suppose we have K objective functions ($f_i(x)$) where ($P \geq K$). Next we have to compute a reference vector called z^{**} as:

$$z_i^{**} = \max[f_i(x)] + \varepsilon_i; \quad i = 1, \ldots, K \tag{36}$$

$$x \in S \tag{37}$$

where S is the solution space, and ϵ_i is a small positive scalar for each objective function i. For the first iteration, we set $RL_i = -\infty$, $i = 1, \ldots, K$, where RL_i is the RL for the i^{th} objective function. Next, a group of $2P$ dispersed weight vectors is generated as:

$$A_j = [\lambda_i \in R^k / \lambda_i \in (0,1)]; \quad (j = 1, \ldots, 2P) \tag{38}$$

$$\sum_{i=1}^{K} \lambda_i = 1 \tag{39}$$

where R^k is the objective function k space. Then, the associated Tchebycheff program for each weight vector is solved, and the P most different resulting objective vector is selected for presenting to the DM. This procedure is shown in Figure 5. It should be mentioned that ρ, in this procedure is a small positive scalar which is recommended to take from 0.0001 to 0.01. Also, α is a free of sign variable.

Figure 5 Pseudo code of RLTP

While $(j \leq 2P)$

solve

$z_j = Min\ [\alpha - \rho \sum_i z_i]$

$ST.\ \alpha \geq \lambda_i \left(z_i^{**} - z_i\right);\ i = 1, \ldots, k$

$f_i(x) = z_i;\ i = 1, \ldots, k$

$z_i \geq RL_i;\ i = 1, \ldots, k$

$x \epsilon S$

End While

While $(k \leq 2P)$

While $(j \leq 2P)$

$d_{kj} = \left| z_k - z_j \right|$

End While

End While

Sort $[d_{kj}]$

If DM is not satisfied with the results, the current solutions are partitioned into more preferred and less preferred solutions, and RLs are adjusted. RLs should be revised by DM to reduce the objective space for which they must be set less than or equal to the worst value for that objective among the current more preferred solutions. Yet, at least one RL must be set greater than an objective value of current less preferred solutions in order to reduce the objective space. Next another group of 2P dispersed weight vectors is generated, and the algorithm is iterated. The algorithm stops whenever DM is satisfied with the provided solution. Interested readers for more details about RLTP are referred to Reeves and MacLeod (1999).

5.3 Handing the ambiguousness of the model

Several methods are proposed to find the equivalent crisp counterpart of a possibilistic mathematical model relying on the possibility theory (Zadeh, 1978; Dubois and Prade, 1988). For instance, LH method is developed by Lai and Hwang (1992), however, this approach has difficulties in implementation, and implies some restrictive assumptions. In this paper, a possibilistic programming method adopted by Jiménez et al. (2007) and Parra et al. (2005) is applied to deal with the existing ambiguousness in the proposed model, and defuzzifying the possibilistic model into its crisp counterpart. It should be mentioned that this method has lots of advantages, like computational efficiency and ease of use in real cases, e.g., Pishvaee and Torabi (2010) and Torabi and Amiri (2012). A brief description of this method based on Jiménez et al. (2007) and Parra et al. (2005) is presented in Appendix E.

6 Experiments

In this section properties of the considered problem are derived, and applicability of the proposed model in real cases is evaluated. In addition, different managerial insights are discussed at the end of this section. Consider that each imprecise parameter of the model is produced by an appropriate possibility distribution in the form of a symmetric fuzzy triangular number based on LH method (Lai and Hwang, 1992). In this regard, the most likely value for each fuzzy triangular parameter (e.g., n^m) is generated randomly based on uniform distributions. The most pessimistic (n^p) and the most optimistic (n^o) values of this parameter are calculated by a symmetrical spreads as (n^p = 0.8 nm) and (n^o = 1.2 n^m), respectively. Feasibility degree for possibilistic constraints is set (0.8). The resulting crisp model of the solution method is coded in GAMS 23.5/CPLEX 12.2 optimisation software package, and experiments are done on a PC with Intel Core i7 processor running at 2 GHz with 4 GB RAM. Table 2 represents RLTP parameters that are used in numerical experiments.

Table 2 RLTP parameters

ρ	*Weight of objective functions* (λ_i)			*The number of presented non-dominated solution*
	First objective function (λ_1)	*Second objective function* (λ_2)	*Third objective function* (λ_3)	
0.01	0.4	0.3	0.3	10

6.1 Numerical example

The considered example in this section is inspired by a real case in Iran; however, due to difficulties of gathering data in developing countries, some of parameters are set randomly. To this end, suppose the manufacturer wants to supply four critical items from global market. The manufacturer has recognised six prequalified suppliers belonging to six different countries (including South Korea, Russian Federation, China, Sweden, Australia and India), which are able to deliver all of needed items. The manufacturer has implemented the first step of solution procedure, and reduced plausible disruptive events of the supply plan. In this regard, three states of loss in production capacity of suppliers (including minor, moderate and major disruption) are considered. Major disruptions in each supplier individually, and moderate disruptions in two suppliers concurrently are considered as reasonable causes of disruptions in supply portfolio. Indeed, other combinations of losses are supposed negligible. Characteristics of disruptive events in each supplier, and the resulting 21 disruptive events with their likelihood are shown in Table 3 and Table 4, respectively. It should be noted as disruptive events occur independently, likelihood of disruption scenarios is calculated as:

$$p_s = \left[\prod_{i \in \text{Disruped suppliers}} \pi_{is} \right] \left[\prod_{i' \in \text{Undisrupted suppliers}} \pi'_{is} \right] \tag{40}$$

where π_{is} is the occurrence likelihood of disruption scenario s in supplier i. As mentioned above, major disruption in suppliers individually, and moderate disruptions in two suppliers concurrently are set as disruption scenarios. Therefore, likelihood of each scenario can be calculated from equation (40). For instance consider disruption scenario 20 in Table 4, the likelihood of these scenarios is computed as:

$$P_{20} = [0.14 \times 0.14][0.42 \times 0.35 \times 0.71 \times 0.49] = 0.0010 \tag{41}$$

It assumed two of four suppliers have deployed business continunity management systems with fortification and recovery plans. Details of other scenario-based parameters and uniform distributions to generate imprecise and crisp parameters for the considered case are reported in Appendix D. Also, another important parameter of the model which is the mutual political conflicts between countries of suppliers (i.e.) is adapted by Gartzke and Jo (2006). As mentioned above, considered case is a manufacturer in Iran, hence, mutual political conflicts between Iran and six countries of suppliers, and mutual political conflicts among these six countries are gathered. It should be mentioned that this parameter is originally based on affinity of countries' votes in United Nations General Assembly (UNGA), and ranges from –1 (least similar interests) to 1 (most similar interests). However, in order to avoid negative coefficients in the third objective function of our model, original correlations are subtracted from 1, and the results are reported in Table 5. Hence, ranges from 0–2 as lowest to highest mutual political conflicts.

Figure 6 Resulted supply plan for the considered case (see online version for colours)

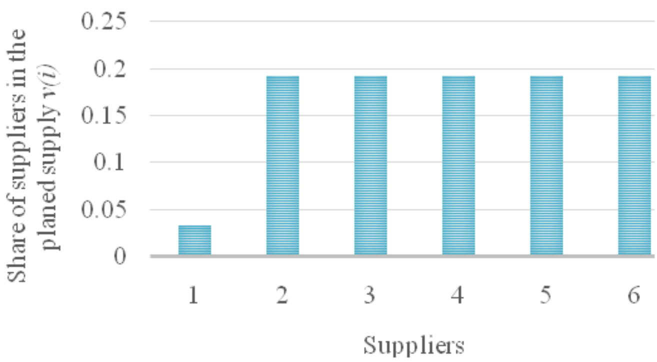


Table 3 Characteristics of disruptive events in each supplier

State of disruption	*Supplier 1*				*Supplier 2*				*Supplier 3*			
	*ND**	*Minor*	*Moderate*	*Major*	*ND**	*Minor*	*Moderate*	*Major*	*ND**	*Minor*	*Moderate*	*Major*
Amount of loss in production capacity	0%	Lower than 30%	Between 30% and 70%	Over 70%	0%	Lower than 30%	Between 30% and 70%	Over 70%	0%	Lower than 30%	Between 30% and 70%	Over 70%
Likelihood of disruption	0.42	0.34	0.15	0.09	0.35	0.31	0.19	0.15	0.71	0.14	0.09	0.06
State of disruption	*Supplier 4*				*Supplier 5*				*Supplier 6*			
	*ND**	*Minor*	*Moderate*	*Major*	*ND**	*Minor*	*Moderate*	*Major*	*ND**	*Minor*	*Moderate*	*Major*
Amount of loss in production capacity	0%	Lower than 30%	Between 30% and 70%	Over 70%	0%	Lower than 30%	Between 30% and 70%	Over 70%	0%	Lower than 30%	Between 30% and 70%	Over 70%
Likelihood of disruption	0.51	0.24	0.14	0.11	0.49	0.32	0.15	0.04	0.46	0.31	0.14	0.09
State of disruption	ND*	Minor	Moderate	Major	ND*	Minor	Moderate	Major	ND*	Minor	Moderate	Major

Note: * ND: no disruption.

Table 4 Plausible disruptive events of the supply portfolio

Disruption scenarios	*Disrupted supplier (s)*	*Undisrupted supplier (s)*	*Likelihood of disruption scenarios*
1	1	2, 3, 4, 5, 6	0.0026
2	2	1, 3, 4, 5, 6	0.0051
3	3	1, 2, 4, 5, 6	0.0010
4	4	1, 2, 3, 5, 6	0.0026
5	5	1, 2, 3, 4, 6	0.0010
6	6	1, 2, 3, 4, 5	0.0023
7	1, 2	3, 4, 5, 6	0.0023
8	1, 3	2, 4, 5, 6	0.0005
9	1, 4	2, 3, 5, 6	0.0012
10	1, 5	2, 3, 4, 6	0.0013
11	1, 6	2, 3, 4, 5	0.0013
12	2, 3	1, 4, 5, 6	0.0008
13	2, 4	1, 3, 5, 6	0.0018
14	2, 5	1, 3, 4, 6	0.0020
15	2, 6	1, 3, 4, 5	0.0020
16	3, 4	1, 2, 5, 6	0.0004
17	3, 5	1, 2, 4, 6	0.0005
18	3, 6	1, 2, 4, 5	0.0005
19	4, 5	1, 2, 3, 6	0.0010
20	4, 6	1, 2, 3, 5	0.0010
21	5, 6	1, 2, 3, 4	0.0011

Table 5 Mutual political conflicts between countries of suppliers in 2011

Suppliers	*Supplier 1*	*Supplier 2*	*Supplier 3*	*Supplier 4*	*Supplier 5*	*Supplier 6*
Countries	*South Korea*	*Russian Federation*	*China*	*Sweden*	*Australia*	*India*
Iran	0.7000	0.0909	0	0.7907	1.0667	0.1702
South Korea	-	0.5000	0.5116	0	0.1364	0.5000
Russian Federation	-	-	0.0400	0.5909	0.7143	0.1304
China	-	-	-	0.5778	0.8333	0.1132
Sweden	-	-	-	-	0.1304	0.6190
Australia	-	-	-	-	-	0.8085

Table 6 Results of the computational experiment for the considered case

*First OFV**	*Second OFV**	*Third OFV**	*RLTP method OFV**	*No** constraints*	*No** continuous variables*	*No** binary variables*	*CPU time (seconds)*
1,638,331.694	0.567	0.433	0.118058	3,550	2,593	390	0.503

Notes: *Objective function value, **number of.

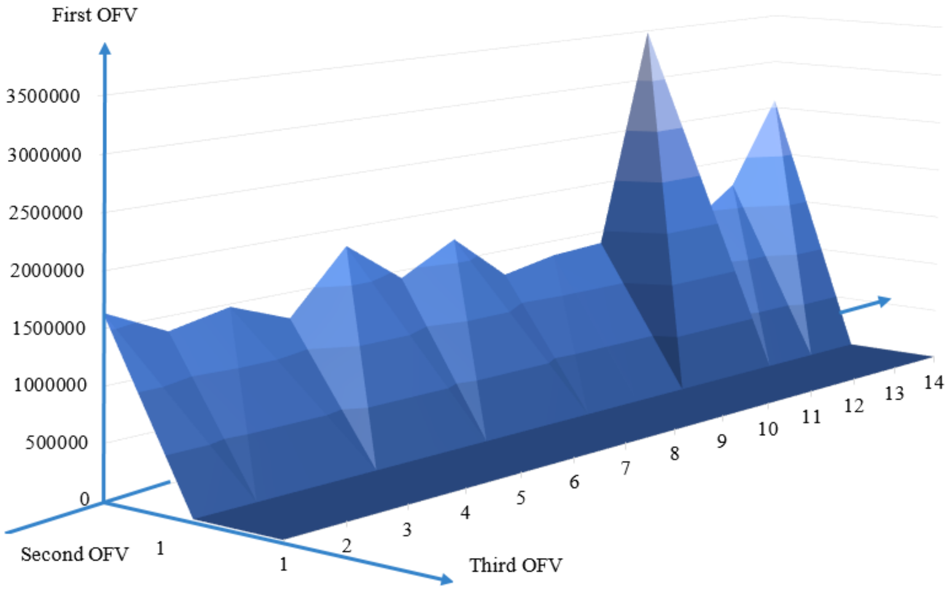
Table 7 Resulted Pareto-optimal solutions for the considered case

Solution	*Weight of objective functions* (λ_i)			*First OFV**	*Second OFV**	*Third OFV**	*RLTP method OFV**
	λ_1	λ_2	λ_3				
1	0.4	0.3	0.3	1,638,331.694	0.567	0.433	0.118058
2	0.43	0.47	0.10	1,364,701.611	0.905	0.444	0.038876
3	0.45	0.35	0.20	1,474,777.175	0.753	0.433	0.082491
4	0.94	0.03	0.03	1,260,481.053	0.402	0.598	0.006927
5	0.36	0.24	0.40	1,831,623.398	0.279	0.433	0.156754
6	0.51	0.31	0.18	1,427,426.036	0.747	0.436	0.070094
7	0.24	0.55	0.21	1,705,240.361	0.835	0.433	0.081113
8	0.78	0.20	0.02	1,257,497.676	0.935	0.650	0.008817
9	0.76	0.09	0.16	1,354,038.507	0.200	0.450	0.057859
10	0.65	0.18	0.17	1,383,709.440	0.571	0.454	0.065241
11	0.10	0.48	0.42	3,485,010.898	0.621	0.433	0.155468
12	0.43	0.56	0.01	1,384,664.058	0.888	0.467	0.044395
13	0.50	0.44	0.06	1,729,327.481	0.548	0.433	0.186235
14	0.18	0.37	0.45	2,575,053.029	0.474	0.433	0.174331

Note: *Objective function value.

Results of the computational experiments for the considered case are presented in Table 6. Also, portfolio variable of the resulted supply plan is presented in Figure 6. In addition, Pareto-optimal front of the presented model for the considered case is reported in Table 7, and illustrated Figure 7.

Figure 7 Resulted Pareto-optimal front for the considered case (see online version for colours)



6.2 Managerial insights

This section verifies managerial insights of the proposed model. In this regard, consider the proposed case in the previous subsection. We highlight three points about the presented model in what follows.

6.2.1 Inspecting impacts of the fuzziness and the confidence level of the DM on the first objective function

As mentioned former, *CVaR* as the first objective function of the proposed model, i.e., equation (3), controls the worst-case disruption scenarios, and γ as the confidence level parameter is decided by the DM. In the other hand, the presented model encompasses ambiguity of the input data through possibility theory, and α is another parameter that is set by the DM to control the fuzziness of the case. Sensitive analysis on these two parameters is done for the original case of the pervious subsection, and the results are shown in Table 8. As we can see in this table, more confidence level costs more. This fact is obviously inferred by comparison of columns of Table 8. In other words, the more risk averse the DM is, the higher costs is incurred. For example, consider the second and the third columns of the first row, improving 1% of confidence level (0.93 – 0.92 = 0.01), costs (2,018,398.827 – 1,795,683.606 = 222,715.221). On the other hand, comparison of rows of Table 8 shows that relaxation of constraints (i.e., expanding solution space), and acceptance of more ambiguity, positively impacts on the results, however, note that this trend negatively affects certainty of solutions.

Table 8 Comparison of results due to different confidence levels versus different feasibility degrees

	$\gamma = 0.85$	$\gamma = 0.92$	$\gamma = 0.93$
		*First OFV**	
$\alpha = 0.95$	1,649,861.768	1,795,683.606	2,018,398.827
$\alpha = 0.9$	1,646,057.231	1,744,886.998	1,935,756.242
$\alpha = 0.7$	1,630,446.867	1,656,356.123	1,711,850.458

Note: *Objective function value.

6.2.2 Inspecting risk reduction of the second objective function

In order to verify risk reduction impact of the second objective function on plausible worst-cases in the considered supply planning problem, the following two cases are considered:

1 The original model with the objective of optimising only *CVaR*, i.e., equation (3).

2 The original model with the objective of optimising *CVaR*, i.e., equation (3), and *R*, i.e., equation (6), simultaneously.

We solved these two versions of the original model and details of results including: first objective function value, i.e., *CVaR*, second objective function value, i.e., *R*, *DC*, i.e., equation (1), *TLS*, i.e., equation (8), and *RMRA*, i.e., equation (7) are reported in Table 9. Based on the results, we can infer that a little improvement in *DC* by 3.4% (i.e., from 2,456,679.105 to 2,540,292.758) can improve the resilience of the supply plan by 29.215% (i.e., from 0 to 0.29215). Also, this result has mentioned by Haimes (2004) which emphasised that catastrophic risks can be mitigated significantly via a small raise in cost of improving structure.

Table 9 Summary of computation results for the considered cases

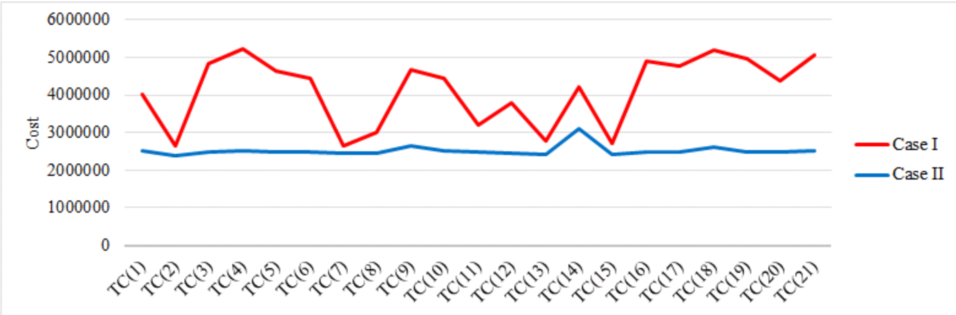
	CVaR	*DC*	*R*	*TLS*	*RMRA*
Case I	809,731.492	2,456,679.105	0	1,746.005	0
Case II	1,239,607.48	2,540,292.758	0.29215	1,746.005	510.096

Table 10 Summary of computation results for TC_s for the considered cases

TC_s	*Case I*	*Case II*	*Likelihood of disruption scenarios*
TC_1	4,009,787.9	2,504,796.2	0.0026
TC_2	2,640,182.2	2,375,388.3	0.0051
TC_3	4,818,528.3	2,491,760.0	0.0010
TC_4	5,229,545.8	2,516,341.2	0.0026
TC_5	4,639,225.9	2,482,694.3	0.0010
TC_6	4,458,786.6	2,490,087.8	0.0023
TC_7	2,651,718.9	2,435,698.6	0.0023
TC_8	2,995,084.9	2,441,121.0	0.0005
TC_9	4,671,116.0	2,651,082.2	0.0012
TC_{10}	4,438,861.6	2,520,383.7	0.0013
TC_{11}	3,190,155.1	2,469,048.2	0.0013
TC_{12}	3,800,685.6	2,447,553.4	0.0008
TC_{13}	2,765,920.1	2,404,250.3	0.0018
TC_{14}	4,198,417.5	3,118,843.4	0.0020
TC_{15}	2,703,520.1	2,410,235.5	0.0020
TC_{16}	4,895,995.4	2,486,615.3	0.0004
TC_{17}	4,767,377.3	2,485,561.3	0.0005
TC_{18}	5,200,308.8	2,617,321.9	0.0005
TC_{19}	4,952,030.8	2,492,022.3	0.0010
TC_{20}	4,372,063.6	2,477,419.7	0.0010
TC_{21}	5,046,923.2	2,502,224.4	0.0011
Average	4,116,487.41	2,515,259.48	–
Max	5,229,545.80	3,118,843.40	–

It is worth investigating how the resilience indicator of the second objective function reduces massive disruption risks of the planned supply portfolio. In this regard, we should remind some properties of *CVaR* method which minimises the average incurred cost of those massive disruption scenarios exceeding *VaR*. In the presented model, we account this value for each scenario by TC_s. The results of this variable for the mentioned cases are reported in Table 10 and depicted in Figure 8. As we can see, improving resilience of the supply plan through investigating in *RMRA* significantly reduces *TC* values, and implies that the resilient supply plan is able to react to massive disruption risks effectively. The most massive disruption in case I relates to disruption scenario 4 with likelihood of 0.0026, where reliable supplier 4 loses its production capacity completely. However, in case II, we can see the average of massive disruptions (i.e., *TC*) is declined, and also the maximum of them is decreased (from 5,229,545.8 in case I to 3,118,843.4 in case II at scenario 14 with likelihood of 0.0020 which is lower than its respective value in case I, i.e., 0.0026).

Figure 8 Comparison of resulted TC_s values for the considered cases (see online version for colours)



6.2.3 *Inspecting diversity impact of the third objective function*

In order to verify diversity impact of the third objective function on the planned supply base, the following two cases are considered:

1. The original model with the objective of optimising only *CVaR*, i.e., equation (3).
2. The original model with the objective of optimising *CVaR*, i.e., equation (3), and *PR*, i.e., equation (10), simultaneously.

We solved these two versions of the original model and the resulted supply portfolio, in addition to their objective function values, is shown in Table 11. It is shown that the case II has got lower value for political risk of supply which verifies the significant impact of third objective function on mitigation of political risk. Also, the resulted supply portfolios for these two cases are depicted in Figure 9 and Figure 10.

Table 11 Summary of computation results for the considered cases

	v_i						*CVaR*	*PR*
	Supplier 1	*Supplier 2*	*Supplier 3*	*Supplier 4*	*Supplier 5*	*Supplier 6*		
Case I	0.199	0.004	0.193	0.211	0.207	0.186	809,731.492	0.816
Case II	0.005	0.2	0.197	0.202	0.202	0.193	1,082,815.57	0.450

Developing a precise index clarifies diversity impact of the third objective function on the supply base. To this end, we propose the following diversity index (*DI*):

$$DI = \sum_{i} \sum_{i \prec j} \left(v_i - v_j\right)^2 \tag{42}$$

where $(v_i - v_j)$ is the difference of shares of supplier *i* and supplier *j* in the supply base. The resulted *DI* for case I is 0.192551, and for case II is 0.188064. As we can see, case II has lower value for *DI* which implies the disparities between shares of suppliers are reduced, and the supply plan is more diversified. As discussed in Subsection 4.3, the provided diversification relates to mutual political conflicts of countries of suppliers, and a more diversified supply portfolio reduces political risk in the considered supply planning problem.

Figure 9 Resulted supply plan for the case I (see online version for colours)

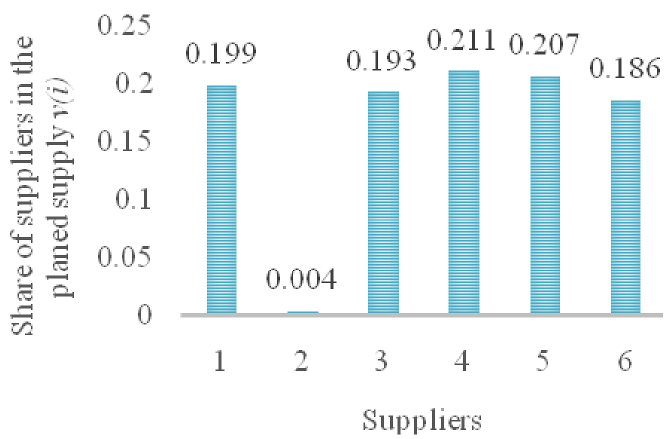
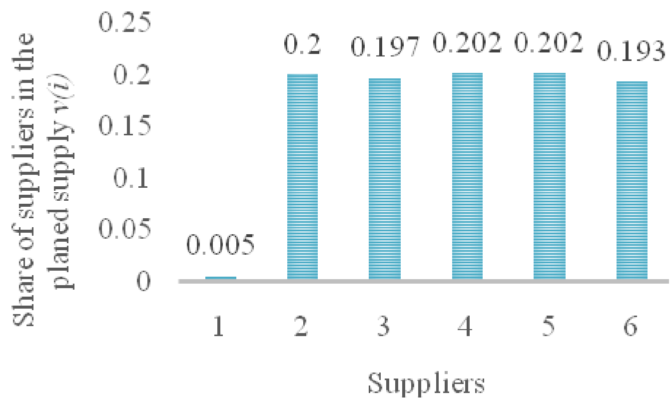


Figure 10 Resulted supply plan for the case II (see online version for colours)



7 Concluding remarks and future research

Organisations all over the word have well recognised that supply chains are operating in an increasingly global, complex and risky environment. Economic or political crises, natural disasters, terrorist attacks, strikes, unreliable logistics and so on can severely impact the core business of supply chains. In this situation, this article addressed a novel multi-objective mixed possibilistic, two-stage scenario-based stochastic programming model to handle the SS&OA problem in a global supply chain under operational and disruption risks. Disruption risks are considered via stochastic scenarios, and operational risks are encountered through possibility distributions for imprecise parameters. The proposed model optimises cost, resilience and political risk of the selected supply portfolio quantitatively. Risk mitigation decisions (e.g., fortification of suppliers, prepositioning emergency inventory among fortified suppliers and selection of backup suppliers) are determined in the first stage of model, while, recovery plans are established in the second stage of the model. Pareto-optimal (compromise) solutions of the presented model are achieved through a comprehensive solution algorithm. Computational experiments validated the applicability of the presented approach of this article, and emphasised that the proposed indicators for optimisation of resilience and political risk have significant impacts on the selection of supply portfolio in a SS&OA problem. Possible future research avenues are listed below:

- Development of multi-dimension resilience indicators which account for political risks as well as other types of risks.
- Owing to the prevalence of environmental issues, consideration of sustainable risk-averse approaches that account for both the environmental factors and disruption risks involved in a SS&OA could be a promising future research, e.g., see Seddighi and Ahmadi-Javid (2015).
- Applying clustering approaches for the sake of reducing the number of scenarios to a reasonable range.
- Adjustment of the presented SS&OA model for multi period situations.
- Development of multi-objective meta-heuristic algorithms would be another promising future research direction to solve the proposed model more efficiently in large-scale cases.

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Appendix A

VaR and *CVaR* are introduced elaborately here based on works of Uryasev (2000) and Rockafellar and Uryasev (2002). Let $\gamma \in (0, 1)$ be the confidence level for the loss distribution across all scenarios, and is assumed to be fixed by DM to control the risk of very high losses due to catastrophic events. The DM only accepts decisions for which the total probability of scenarios with losses greater than *VaR* is not greater than $(1 - \gamma)$. Let $g(x, \beta_s)$ be the representative of positive values of losses which β_s has a finite discrete distribution with S realisations and corresponding likelihood given as π^s for β_s $\left(\sum_{s=1}^{S} \pi^s = 1\right)$. The $\gamma - CVaR$ is presented as the following minimisation program.

$$\alpha - CVaR = Min\left\{VaR + \frac{1}{1-\gamma} E\left[\left(g\left(x, \beta_s\right) - VaR\right)^+\right]\right\} \tag{A1}$$

Where $(g(x, \beta_s) - VaR)^+$ is $Max\{g(x, \beta^s) - VaR, 0\}$, and $E[(g(x, \beta_s) - VaR)^+]$ is the expected value of $(g(x, \beta_s) - VaR)^+$ over all scenarios. It is obvious that the above program is non-linear. Let us define TC_s as:

$$TC_s = \left(g\left(x, \beta_s\right) - VaR\right)^+ \tag{A2}$$

In other words, TC_s is the amount of excess of loss, i.e., $g(x, \beta_s)$, from *VaR* in scenario *s*. There for, we have a linear programming model as:

$$\alpha - CVaR = \text{Min}\left\{ VaR + \frac{1}{1-\gamma} \sum_{s=1}^{S} \pi^s TC^s \right\} \tag{A3}$$

Subject to:

$$TC^s \geq g\left(x, \beta_s\right) - VaR; \quad \forall s \in S \tag{A4}$$

$$TC^s \geq 0; \quad \forall s \in S \tag{A5}$$

Consider that in this paper we have:

$$g\left(x, \beta_s\right) = DC + PC_s \tag{A6}$$

Appendix B

Linearisation process of the equation (7) and constraint (21) are reported here. In this regard, we define Q_{ils} as an auxiliary variable, where we have:

$$Q_{ils} = Re_{ils} \delta'_{is}; \quad \forall i \in J, l \in L, s \in S \tag{A7}$$

In addition, the following constraints are added to the original model.

$$Q_{ils} - \left(M \times \left(1 - Re_{ils}\right)\right) \leq \delta'_{is}; \quad \forall i \in J, l \in L, s \in S \tag{A8}$$

$$Q_{ils} + \left(M \times \left(1 - Re_{ils}\right)\right) \geq \delta'_{is}; \quad \forall i \in J, l \in L, s \in S \tag{A9}$$

$$Q_{ils} \leq Re_{ils}; \quad \forall i \in J, l \in L, s \in S \tag{A10}$$

$$Q_{ils} \geq 0; \quad \forall i \in J, l \in L, s \in S \tag{A11}$$

Therefore, the linear for of equation (7) and constraint (21) are obtained as reported in equation (A12) and constraint (A13), respectively:

$$RMRA = \sum_{i \in I} Ca_i y_i + \sum_{i \in J} \sum_{k \in K} EI_{ik} + \sum_{s \in S} \sum_{i \in J} \sum_{l \in L_{is}} p_s \left[\left(\left(Re_{ils} - Q_{ils}\right) \varepsilon_{ils} Ca_i\right)\right] \tag{A12}$$

$$\sum_{k \in K} (x'_{iks} + xb'_{iks}) \leq \delta'_{is} Ca_i + \sum_{l \in L_{is}} \left[\left(Re_{ils} - \delta'_{is}\right) \varepsilon_{ils} Ca_i\right] \tag{A13}$$

Appendix C

Linearisation process of the second phrase in equation (10) is presented here. We can introduce new variables $t_{ii'}$ and the following constraints:

$$t_{ii'} \geq v_i - v_{i'}; \quad \forall i, i' \in I \tag{A14}$$

$$t_{ii'} \geq -(v_i - v_{i'}); \quad \forall i, i' \in I \tag{A15}$$

Therefore, constraints (A14) and (A15) are added to the original model and the linearisation form of the third objective function (*PR*), i.e., equation (10), is accordingly presented as follows:

$$MinPR = \sum_{i\in I} \tilde{\Psi}_i \upsilon_i + \sum_{i\in I} \sum_{i \prec i' \in I} \tilde{\Psi}_{ii'} t_{ii'} \tag{A16}$$

Appendix D

This Appendix E explains details of required parameters of the presented experiments in Section 6. Table A1 shows uniform distributions that are used to generate the required crisp and centre of symmetric fuzzy parameters.

Table A1 Uniform distributions for random generation of the required parameters

Parameter	*Random distribution*	*Parameter*	*Random distribution*
A_i	Uniform (5,000, 8,000)	$\tilde{FC}_{i0}$	Uniform (400, 700)
P_{ik}	Uniform (45, 57)	$\tilde{FC}_{i\theta}$	1.2 $\tilde{FC}_{i(\theta-1)}$
P'_{ik}	Uniform (58, 67)	$\tilde{HC}_{ik}$	Uniform (54, 90)
$\tilde{SC}_k$	Uniform (350, 500)	$\tilde{RC}_{ik}$	0.8 P_{ik}
$\tilde{D}_k$	Uniform (12,000, 14,000)	$\tilde{Ca}_i$	Uniform (10,000, 12,500)
$\tilde{\theta}_{ik}$	Uniform (0.02, 0.08)	$\tilde{CaP}_i$	0.25* $\tilde{Ca}_i$
Co_i	Uniform (4,200, 6,200)	γ	0.90

Table A2 Fraction of production capacity of suppliers that is remained after realisation of disruption scenarios

Disruption scenarios	*Supplier 1*	*Supplier 2*	*Supplier 3*	*Supplier 4*	*Supplier 5*	*Supplier 6*
1	0.15	1	1	1	1	1
2	1	0.12	1	1	1	1
3	1	1	0.08	1	1	1
4	1	1	1	0	1	1
5	1	1	1	1	0.15	1
6	1	1	1	1	1	0
7	0.55	0.35	1	1	1	1
8	0.79	1	0.62	1	1	1
9	0.46	1	1	0.41	1	1
10	0.39	1	1	1	0.58	1
11	0.56	1	1	1	1	0.66
12	1	0.50	0.35	1	1	1
13	1	0.63	1	0.69	1	1

Table A2 Fraction of production capacity of suppliers that is remained after realisation of disruption scenarios (continued)

Disruption scenarios	*Supplier 1*	*Supplier 2*	*Supplier 3*	*Supplier 4*	*Supplier 5*	*Supplier 6*
14	1	0.31	1	1	0.35	1
15	1	0.44	1	1	1	0.60
16	1	1	0.52	0.48	1	1
17	1	1	0.67	1	0.41	1
18	1	1	0.32	1	1	0.45
19	1	1	1	0.68	0.34	1
20	1	1	1	0.39	1	0.68
21	1	1	1	1	0.55	0.30

Amount of production capacity of suppliers that is remained available after realisation of disruption scenarios are announced in Table A2. Also, as mentioned in section 6.1., two suppliers, i.e., supplier 4, supplier 5, have implemented business continuity systems, and are able to recover their production capacity after disruptions. In this regard, it is assumed that both of them have developed three levels for recovery efforts (including 25%, 50% and 100% recovery of lost production capacity). In addition, these two suppliers are able to be fortified at two levels, including 15% and 35% increase in remaining production capacity of suppliers after disruption scenarios. Accordingly, ε_{ils} and η_{ies} are set zero for all suppliers except supplier 4 and supplier 5. Finally, consider that confidence level in calculating *CVaR*, i.e., equation (3), is 0.95.

Appendix E

This appendix provides a brief description the method which is used to handle the ambiguity of data in the model based on works of Jiménez et al. (2007) and Parra et al. (2005).

Consider, $\tilde{n} = (n^p, n^m, n^o)$, with a triangular possibility distribution in the form of a triangular fuzzy number. The membership functions of $\tilde{n}$ is:

$$\mu_{\tilde{n}}(x) = \begin{cases} f_n(x) = \dfrac{x - n^p}{n^m - n^p} & \text{if } n^p \le x \le n^m \\ 1 & \text{if } x = n^m \\ g_n(x) = \dfrac{n^0 - x}{n^o - n^m} & \text{if } n^p \le x \le n^m \\ 0 & \text{if } x \le n^p \text{ or } x \ge n^0 \end{cases} \tag{A17}$$

The expected interval (*EI*) and expected value (*EV*) of $\tilde{n}$ are:

$$EI(\tilde{n}) = \left[E_1^n, E_2^n\right] = \left[\int_0^1 f_c^{-1}(x)\mathrm{d}x, \int_0^1 g_c^{-1}(x)\mathrm{d}x\right] = \left[\frac{1}{2}\left(n^p + n^m\right), \frac{1}{2}\left(n^m + n^o\right)\right] \tag{A18}$$

$$EV(\tilde{n}) = \frac{E_1^n + E_2^n}{2} = \frac{n^p + 2n^m + n^o}{4} \tag{A19}$$

In this regard, without loss of generality consider fuzzy numbers $\tilde{a}$ and $\tilde{b}$, the degree in which $\tilde{a}$ is bigger than $\tilde{b}$ can be computed as:

$$\mu_M\left(\tilde{a}, \tilde{b}\right) = \begin{cases} 0 & \text{if } E_2^a - E_1^b < 0, \\ \dfrac{E_2^a - E_1^b}{E_2^a - E_1^b - \left(E_1^a - E_2^b\right)} & \text{if } 0 \in \left[E_1^a - E_2^b, E_2^a - E_1^b\right], \\ 1 & \text{if } E_1^a - E_2^b > 0 \end{cases} \tag{A20}$$

It is called $\tilde{a}$ is bigger than, or equal, to $\tilde{b}$ (i.e., $\tilde{a} \geq \tilde{b}$) at least in a degree *a*, when $\mu_M(\tilde{a}, \tilde{b}) \geq \alpha$. In the same way we can say that $\tilde{a}$ is indifferent to $\tilde{b}$ in a degree *a*, denoted by $\tilde{a} \approx \tilde{b}$, if the following constraints are hold simultaneously: $\tilde{a} \leq_{\alpha/2} \tilde{b}$ and $\tilde{a} \geq_{\alpha/2} \tilde{b}$.

In this regard, consider given a decision vector $x \in R^n$. This vector is called α-feasible (i.e., *x* is feasible in a degree of *a*, when we have:

$$\min\left\{\mu_M\left(\tilde{a}x, \tilde{b}\right)\right\} = \alpha \tag{A21}$$

Now, consider the following possibilistic linear programming model:

$$\min \quad z = \tilde{c}^t x \tag{A22}$$

s.t.

$$\tilde{a}_i x \geq_\alpha \tilde{b}_i; \quad i = 1, ..., l \tag{A23}$$

$$\tilde{a}_i x \approx_\alpha \tilde{b}_i; \quad i = l+1, ..., m \tag{A24}$$

$$x \geq 0 \tag{A25}$$

The equivalent crisp form of constraints (46) are:

$$\frac{E_2^{a_i x} - E_1^{b_i}}{E_2^{a_i x} - E_1^{a_i x} + E_2^{b_i} - E_1^{b_i}} \geq \alpha; \quad i = 1, ..., l \tag{A26}$$

Or:

$$\left[(1-\alpha)E \ + \alpha E \ \right] x \geq \alpha E \ + (1-\alpha)E \ ; \quad i = 1, ..., l \tag{A27}$$

As we know, each equality constraint (i.e., $\tilde{a}_i x =_\alpha \tilde{b}_i$) can be replaced by two inequality constraints (i.e., $\tilde{a}_i x \geq_{\alpha/2} \tilde{b}_i$ and $\tilde{a}_i x \leq_{\alpha/2} \tilde{b}_i$). Therefore, the equivalent crisp form of equality constraints (47) are:

$$\left.\begin{aligned}&\left[\left(1-\frac{\alpha}{2}\right)E_2^{a_i}+\frac{\alpha}{2}E_1^{a_i}\right]x \geq \frac{\alpha}{2}E_2^{b_i}+\left(1-\frac{\alpha}{2}\right)E_1^{b_i}\\&\left[\frac{\alpha}{2}E_2^{a_i}+\left(1-\frac{\alpha}{2}\right)E_1^{a_i}\right]x \leq \left(1-\frac{\alpha}{2}\right)E_2^{b_i}+\frac{\alpha}{2}E_1^{b_i}\end{aligned}\right\} ;\quad i=l+1,\ldots,m \tag{A28}$$

Accordingly, the equivalent crisp α-parametric counterpart of the original model, i.e., (45)–(48), can be represented as follows (consider the fuzzy parameter in the objective function is replaced by its respective expected value, i.e., *EV*):

$$\min \quad z = EV(\tilde{c})x \tag{A29}$$

s.t.

$$\left[(1-\alpha)E_2^{a_i}+\alpha E_1^{a_i}\right]x \geq \alpha E_2^{b_i}+(1-\alpha)E_1^{b_i};\quad i=1,\ldots,l \tag{A30}$$

$$\left[\left(1-\frac{\alpha}{2}\right)E_2^{a_i}+\frac{\alpha}{2}E_1^{a_i}\right]x \geq \frac{\alpha}{2}E_2^{b_i}+\left(1-\frac{\alpha}{2}\right)E_1^{b_i};\quad i=l+1,\ldots,m \tag{A31}$$

$$\left[\frac{\alpha}{2}E_2^{a_i}+\left(1-\frac{\alpha}{2}\right)E_1^{a_i}\right]x \leq \left(1-\frac{\alpha}{2}\right)E_2^{b_i}+\frac{\alpha}{2}E_1^{b_i};\quad i=l+1,\ldots,m \tag{A32}$$

$$x \geq 0 \qquad \text{(A32)}$$