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Resilient supplier selection and order allocation under operational and disruption risks

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ABSTRACT

This study proposes a bi-objective mixed possibilistic, two-stage stochastic programming model to address supplier selection and order allocation problem to build the resilient supply base under operational and disruption risks. The model accounts for epistemic uncertainty of critical data and applies several proactive strategies such as suppliers' business continuity plans, fortification of suppliers and contracting with backup suppliers to enhance the resilience level of the selected supply base. A five-step method is designed to solve the problem efficiently. The computational results demonstrate the significant impact of considering disruptive events on the selected supply base.

1. Introduction

Today's competitive global market is forcing companies to outsource some of their products and services. Outsourcing can help companies to reduce costs and enhance their competitive capabilities through focusing on their core competencies (Schoenherr et al., 2012). A group of suppliers from which a company purchases goods and services is called the "supply base". Selecting the best supply base is a challenging decision in outsourcing and it plays a critical role in the success of supply chains; especially global ones (Bhutta and Huq, 2002). The Supplier Selection and Order Allocation (SS&OA) problem is a complex decision problem involving multiple tangible and intangible criteria (Aissaoui et al., 2007; Ho et al., 2010). It aims to select the best portfolio of suppliers and to optimally allocate the buyer's total demand among selected suppliers to satisfy different purchasing criteria. Other considerations include meeting the required minimum order quantity and the limited capacity of each supplier. Traditionally, the SS&OA problem has accounted for cost, quality and delivery time (i.e. QCD measures). However, today's global supply chains are more prone to unexpected natural and man-made disasters such as floods, volcanic eruptions, earthquakes, tsunamis, fires, transport accidents and labor strikes. In the wake of Japan's earthquake in 2011, Apple suffered from shortage of key parts for its iPad 2 including its flash memory and super-thin battery which were exclusively manufactured by Apple Japan (BBC News, 18 Mar 2011). Japan's 2011 earthquake-triggered tsunami and the Icelandic Volcano in 2010 disrupted global supply chains including the automotive sector and retail supply chains in UK

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(Massey, 7 April 2011; Hall, 16 Apr 2010). Auto maker Nissan was hit the hardest in the aftermath of Japan's 2011 earthquake because of its dependence on a factory in the earthquake zone that would supply 12% of its engines (BBC News, 18 Mar 2011). This forced the Nissan's UK Sunderland plant to shut down for three days because of shortage of parts from Japan (Massey, 7 Apr 2011). More recently, hurricane Sandy caused massive disruptions in US supply chains (Burnson, 30 Oct 2012). These events demonstrate that supply chain disruptions are detrimental to businesses from the lost productivity and revenue standpoint. As such, with the growing reliance on global sourcing in recent years and consequently the increase in the likelihood of disruptive incidents, providing a reliable level of resilience to the supply base to protect the buyer from shortages and disruption in the supply flow is all the more critical.

Generally speaking, supply chain risks can be divided into two risk categories: Operational and Disruption (Tang, 2006). Operational risks refer to those inherent uncertainties that inevitably exist in supply chains. These include, but are not limited to, customer demand and cost rate uncertainty, and also supply uncertainty due to operational difficulties like equipment failure, power outage and key personnel absence. Accounting for inherent uncertainty in the critical input data such as demand, cost, and capacity parameters through uncertainty programming approaches (e.g. fuzzy/possibilistic/stochastic/robust programming) is one way to deal with operational risks that is common in the literature (Sawik, 2011). Disruption risks refer to the major disruptions caused by natural, man-made or technological threats such as earthquakes, floods, terrorist attacks or employee strikes. Notably, operational risks are caused by medium to high likelihood, low impact as-usual events which have only short term negative effects while disruptions are caused by low likelihood, high impact disruptive events which may have short or long term negative effects on the system.

This paper aims to develop a new decision model to build resilient supply bases for global supply chains in response to uncertainties arisen from major disruptions caused by natural and man-made disasters and operational risks. To this end, a bi-objective mixed possibilistic, two-stage stochastic programming model with a new resilience objective is proposed in which several proactive strategies such as fortifying suppliers at different discrete levels and suppliers' business continuity plans are taken into account. Noteworthy, documented collection of procedures and information that is developed, compiled and maintained in readiness for use in an incident to enable an organization to continue to deliver its critical activities at an acceptable pre-defined level are called business continuity plans (ISO 22301, 2012). Furthermore, business continuity management is a management process which identifies possible internal and external threats/risks and their impact to business processes and provides a framework for organizational resilience (ISO 22301, 2012). In this way, implementing a business continuity management system (BCMS) within an organization can protect the organization against various disruptive events by providing suitable business disaster recovery/continuity plans for identified critical business processes/functions proactively (Sahebjamnia et al., 2015; Torabi et al., 2014). To the best of our knowledge, this paper is the first one in the literature which accounts for business continuity related concepts/measures in a supply chain planning decision problem especially in a SS&OA problem.

The remainder of the paper is organized as follows. Section 2 provides a review of the related literature. The problem description and proposed model with developing a new resilience objective are respectively elaborated in Sections 3 and 4. The solution procedure is presented in Section 5. Section 6 presents some numerical examples along with their computational results. Finally, Section 7 draws some conclusions from this study.

2. Literature review

A review of the related literature is presented below in two distinct but related research streams: supply disruption/risk management and resilient supply chains.

2.1. Supply disruption/ risk management

Over the past few decades, especially after 11th September 2001, risk management has received increasing attention from both practitioners and academia so that around fifty tools and methodologies have been developed for risk management (Shi-Cho et al., 2008). Chopra and Sodhi (2004) categorised potential supply chain risks into nine categories: (a) Disruptions, (b) Delays, (c) Systems, (d) Forecast, (d) Intellectual property, (e) Procurement, (f) Receivables, (g) Inventory, and (h) Capacity. They identified events and conditions that drive these risks and the mitigation strategy against each kind of risk. In this section, we review the most relevant published works accounting for disruption risks and common mitigation strategies used in the supply side of a supply chain especially those addressing SS&OA problem under disruption.

Dual/multiple sourcing instead of single sourcing is a common approach to decreasing supply disruption risk in the literature. Although single sourcing is less expensive than multiple sourcing in normal conditions, supplier disruption in single sourcing case can result in greater loss than dual/multiple sourcing. Accordingly, some works address determining the optimal number of suppliers in the presence of disruption risks. For example, for the first time, Berger et al. (2004) assumed two types of catastrophes: "super-events" which affect many/all suppliers and "unique events" which disrupt a single supplier. They considered the financial loss caused by disasters and the operating cost of working with multiple suppliers and proposed a decision tree to decide on optimal number of suppliers by minimizing the expected cost function. Ruiz-Torres and Mahmoodi (2006) developed an extension to the Berger et al. (2004) and presented a decision model for optimizing the allocation of demand across a set of suppliers by considering three key cost factors: the expected losses due to supplier failure to deliver, the purchasing costs, and the cost of maintaining a set of suppliers. Yu et al. (2009) looked at debate between single sourcing and dual sourcing when demand is price-sensitive and the market scale increases when a supply disruption occurs. They concluded that either single or dual sourcing can be effective depending on the magnitude of the disruption probability. Meena and Sarmah (2013) developed a mixed integer non-linear programming model for order allocation by a manufacturer/buyer among multiple suppliers under supply disruption risks while considering different capacity, failure probability and quantity discounts for each supplier aiming to minimize the total cost.

Contracting with backup suppliers is another approach which aims to ameliorate supply disruption risk. Hou et al. (2010) considered a buyer who has two supply options: a cheaper but unreliable supplier (the main one) while the other one is perfectly reliable and responsive, but is more expensive (the backup supplier). They studied a buy-back contract between the buyer and the backup supplier when the main supplier experiences disruptions.

Fortification of suppliers against major disruptions is another proactive strategy which supply chain managers recently began employing to mitigate the impacts of disruption risks. For example, after Thailand's great flood in 2011, factory managers of the Nava Nakorn industrial zone, where over 220 factories of electronics and computer components suppliers are located, decided to construct a giant flood wall around the perimeter and sealable aluminum flood barriers across entrance points (The New York Times, 21 Jan 2012). In this respect, Sawik (2013) addressed the SS&OA problem under disruption risk by considering fortification of suppliers as an effective strategy to decrease disruption risks. One of the main assumptions in Sawik (2013) is that the capacity of a fortified supplier remains unchanged after any disruptive event. This may not be realistic. For example, fortifying a supplier against flood risk may not protect it against other disruptive events such as earthquakes. In an effort to be more realistic, in this paper, we give an extension to this assumption and assume that the fortification of a supplier will decrease the impact of disruption events on supplier's production capacity based on the level of protection and the type of disruption event.

2.2. Resilient supply chains

Resilience is a multidisciplinary concept, and an interesting subject of scientific research in different disciplines such as psychology, ecology, economy. Resilience can also be found in emerging interdisciplinary fields such as emergency management, sustainable development and supply chain risk management. Supply chain resilience is a relatively new concept that can be defined as "the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function" (Ponomarov and Holcomb, 2009). Also, Falasca et al. (2008) defined resilience as the ability of a supply chain system to reduce the probabilities of disruptions, to reduce the consequences of those disruptions and the time to recover disrupted operations to their normal performance. There are many practical advices in the literature in order to design a resilient supply chain (see for example: Rice and Caniato, 2003; Christopher and Peck, 2004; Sheffi, 2005). According to Sheffi (2005), the companies can develop the resilience in three general ways: (1) creating redundancies throughout the supply chain; for example with holding extra inventory, maintain low capacity utilization, and contracting with multiple suppliers, (2) increasing supply chain flexibility; for example with adoption of standardized processes, using concurrent instead of sequential processes, plan to postpone, align procurement strategy with supplier relationships, and (3) changing the corporate culture. Christopher and Peck (2004) highlighted a number of discernible general principles that underpin resilience in supply chains. They concluded that resilience implies flexibility and agility and its implications extend beyond process redesign to fundamental decisions on sourcing and the establishment of more collaborative supply chain relationships based on far greater transparency of information.

In spite of increasing publications about supply chain resilience in recent years, there are few quantitative models that either address supply chain resilience performance, or assess effect of different strategies for providing supply chain resilience. As mentioned by Spiegler et al. (2012), resilience implies not only minimizing deviations from a targeted state, but also re-achieving this target as fast as possible. Hence, some of papers tried to model supply chain performance with different resilience related performance measures. Datta et al. (2007) studied a multi-product, multi-country supply chain and for the first time, presented an agent-based computational framework with the aim of improving operational resilience. They judged supply chain resilience in terms of four performance measures: customer service level, production change-over time, average inventory and total average network inventory. Falasca et al. (2008) proposed a simulation-based framework with incorporating three determinants of supply chain resilience (density, complexity, and node criticality) into the process of supply chain design. They developed a quantitative approach for assessing supply chain resilience using the 'resilience triangle' introduced by Tierney and Bruneau (2007).

Colicchia et al. (2010) focused on inbound supply risk in a global sourcing context and assumed the variability of the supply lead-time as a proxy of the supply chain resilience. To assess the greenness and resilience of the automotive companies, Azevedo et al. (2011) presented a multi attribute model to create a composite index entitled GResilient with using Delphi technique. Carvalho et al. (2012) simulated a three-echelon supply chain concerned with a real case and evaluated six alternative supply chain scenarios (defined by additional stock and alternative transportation after the occurrence of a disruption) for improving supply chain resilience. Miller-Hooks et al. (2012) formulated the problem of measuring a freight transportation network's resilience level as a two-stage stochastic program to determine the optimal set of preparedness and recovery actions in transportation arcs needed to achieve resilience level. They defined network resilience level as the expected fraction of demand that can be satisfied at post-disaster. Schmitt and Singh (2012) developed a simulation model motivated by an actual supply chain and analyzed inventory placement and back-up strategies in a multi-echelon network and their effects on reducing supply chain risk and improving the system's resilience. They used the percentage of customers who are satisfied immediately from stock as a performance metric monitored by the simulation. In another interesting work, Spiegler et al. (2012) developed the integral of time multiplied by the absolute error (ITAE) as an appropriate control engineering measure of resilience in a one-echelon make-to-stock supply chain and argued that the minimum value of ITAE corresponds to the best response and recovery with the lowest deviation from the target, or readiness.

There are very few quantitative models addressing the resilient supplier selection problem in the literature. Haldar et al. (2012) developed a four tier process using multi-attribute decision making methods and quality function deployment to rate and choose the best supplier(s). They used five criteria of resilience for the supplier selection process including the: supply chain density, supply chain complexity, responsiveness, node criticality and re-engineering. More recently, Haldar et al. (2014) proposed an integrated fuzzy group decision making approach for strategic supplier selection of a manufacturer via incorporating the importance degrees of specific attributes as linguistic variables formulated by triangular and trapezoidal fuzzy numbers. Sawik (2013) addressed the SS&OA problem with disruption risks and developed some protection (i.e. resilience) strategies including the selection of a number of suppliers to be protected against disruptions and allocation of emergency inventories to be pre-positioned at the protected suppliers in order to decrease the disruption risks and increasing the resilience level of supply network. Through some computational experiments, the author concluded that the probability of supply disruption is the most important factor for the allocation of demand among the suppliers and that diversified supply base can mitigate impact of disruption risks.

To the best of our knowledge, this is the first time that a bi-objective mixed possibilistic, two-stage stochastic model is proposed to analyze the trade-off between cost and resilience level of supply base. The model accounts for epistemic uncertainty (i.e. lack of knowledge about the precise values) of critical data and includes a new resilience objective function to calculate the resilience level of the selected supply base. Furthermore, for the first time in the literature, the proposed model collectively considers different proactive strategies such as suppliers' business continuity plans, fortification of suppliers at various discrete levels and contracting with backup suppliers to enhance the resilience level of the selected supply base.

3. Problem description and formulation

In this paper, we consider a manufacturer who produces different types of products. After conducting a strategic decision process (Vining and Globerman, 1999), the manufacturer has decided to outsource some items required for the production to a pre-determined set of qualified suppliers. The pre-determined suppliers are divided into two groups. The first group of suppliers have acceptable performances in traditional criteria (QCD measures) but they do not have any clear plans for continuity and recovery purposes after disruptions. The second group includes those suppliers that have implemented a certain level of business continuity management system. This second group has pre-established business continuity and disaster recovery plans to deal with major disruptions. More specifically, we assume that the second group includes those suppliers which are better than the first group's suppliers in quality and delivery criteria but not as good as the first group in cost criterion.

For each supplier in the second group, a *disruption profile* including the main characteristics of the established business continuity management system (e.g. recovery times) is formed. In particular, each supplier's disruption profile consists of the following items:

- Different types of disruptive events that can disrupt each respective supplier.
- The likelihood of these disruptive events and their impact on the supplier's critical processes/operations and subsequently production capacity. These can be determined according to the results of so-called "business impact analysis" and "risk assessment" processes which are crucial steps in the development stage of respective business continuity management system. Interested readers are referred to Torabi et al. (2014) to see more details on business impact analysis.
- Estimated recovery times for different fortification levels based on developed business continuity or disaster recovery plans to deal with disruptions.

It is worth noting that all possible disruption scenarios are analyzed to account for suppliers' disruption risks. In each possible scenario, each supplier may be faced with a disruptive event and each disruptive event may impact different suppliers in multiple ways. If a disruptive event occurs, each disrupted supplier of the first group will be negatively impacted such that it can only meet part of its obligation. However, the second group suppliers will be able to conduct their business continuity or disaster recovery plans and still be able to meet their obligations.

In order to make the model more practical, it is assumed that suppliers may have some unused production capacity even after the disruptive events. In the real world, companies sometimes have redundant processing capacity at other locations to enable critical business functions (such as handling customer orders, overseeing production and deliveries, and managing the supply chain) to be continued or recovered quickly (Intel Business Continuity Practices, 2014). So, these suppliers can have some capacity to produce even after the disruptive events. Also, there are some disruptive events that may not destroy the supplier's production capacity completely. For example, events such as labor strike or power outages lasting for two weeks where the considered time horizon is one month may decrease only 50 percent of supplier's production capacity.

Table 1
Characteristics of scenarios for an example with three suppliers and one disruptive event in each supplier.

Scenario no.	Set of non-disrupted suppliers	Set of disrupted suppliers	Remained capacity of suppliers (in percentage)
1	{1, 2, 3}	{}	{100, 100, 100}
2	{1, 2}	{3}	{100, 100, 0}
3	{1, 3}	{2}	{100, 20, 100}
4	{2, 3}	{1}	{20, 100, 100}
5	{1}	{2, 3}	{100, 40, 80}
6	{2}	{1, 3}	{0, 100, 20}
7	{3}	{1, 2}	{25, 0, 100}
8	{}	{1, 2, 3}	{20, 0, 0}

Table 1 shows the scenarios and their characteristics for an example with three suppliers and one disruptive event in each supplier.

It is also assumed that the amount of items sent from a disrupted supplier (especially second group's suppliers after recovery) cannot be more than purchased amounts from the supplier in the normal situation. However, the main advantage of the second group's suppliers is that they are able to deliver their obligation even when they experience disruption. Thus, if a second group's supplier is not disrupted while some other suppliers are, the manufacturer can buy more items from this supplier with considering it as a backup supplier. Additionally, since the probability of several disruptive events affecting a supplier simultaneously is very low in practice, it is assumed that under each scenario, at most one event can happen at each supplier. In the real world, those suppliers who are in the same geographic zones can be jointly affected after a disruptive event such as earthquake. Nevertheless, in this paper, it is assumed that suppliers are spatially dispersed, such that a disruptive event would not affect all suppliers simultaneously.

The following strategies are employed in the model to enhance the supply side resilience level of the manufacturer:

i. Allowing multiple sourcing for each outsourced item.
ii. Protecting (fortifying) some of second group's suppliers against disruptions: these suppliers can be fortified in different levels each of which has its own cost and reduction level of the impact of disruptions on suppliers' production capacity. For example, Table 2 shows the positive effect of fortification, i.e. the higher the fortification level the higher the remaining capacity in the aftermath of each respective disruptive event. It is assumed that this supplier can be fortified at four levels: level 1 indicates buying enough spare power generators, level 2 is revamping supplier's building with budget A, level 3 is buying power generators and renovation of supplier's building with budget A, and level 4 is renovation of supplier's building with budget B ($A < B$).
iii. Maintaining extra pre-positioned inventories, which could be used after any disruption at the fortified suppliers, is allowed. However, the available space at each supplier for inventory pre-positioning is limited (it is assumed to be equal to respective production capacity in this paper).
iv. Possibility of contracting with some suppliers as backup suppliers which will be used in emergency situations (these suppliers may provide excess required items with higher unit costs and lead-times). However, disrupted suppliers under each scenario cannot be served as backup suppliers.
v. Considering suppliers' business continuity plans and different recovery levels in the second group of suppliers (with considering this strategy, suppliers can meet higher levels of their obligations).

Furthermore, the planning horizon is assumed to be a single mid-term period (for example, a horizon of six months or one year) and the manufacturer's total demand must be met at the end of the planning horizon under any circumstances. Nevertheless, the manufacturer only pays for those items which are delivered (not for the ordered items which may not be delivered because of disruptions). Also, it is assumed that the overall defective rate of each purchased item by manufacturer must be lower than a pre-defined target level and according to the lean supply principles; the total number of main suppliers in the normal situation should not be greater than a pre-specified number.

Lastly, inherent uncertainty in demand and supply data is one of the main challenges in supply chain planning related decision problems (e.g. SS&OA problem). Including such uncertainty within formulated decision models is of vital importance for accurately representing the impact of possible realizations of uncertain parameters on the underlying decision problem being modeled (Klibi et al., 2010).

Generally speaking, randomness and fuzziness are two main sources of uncertainty (Mousazadeh et al., 2014). Randomness stems from the random (chance) nature of data where the underlying action can be repeated many times. In other words, every frequency-based phenomenon could be formulated as random/stochastic data for which, discrete or continuous probability distributions are estimated based on available and sufficient historical data. Stochastic (or robust) programming approaches are usually used to cope with this kind of uncertainty in the presence (or absence) of distributional information about such random data.

However, there might be not enough historical/objective data to model uncertain parameters as random data. This is especially the case for scenario-dependent parameters due to special characteristics of any disruption and non-repetitiveness of related events. So, it is difficult or even impossible/meaningless to find probabilistic distributions for such

Table 2
The amount of improvement in remaining capacity of a supplier in presence of each disruptive event because of its fortification at different levels.

Fortification level	Amount of increase in remaining capacity of supplier in the presence of each disruptive event (in percentage)			
	Earthquake	Flood	Power outage	Fire
1	0	0	100	0
2	20	30	0	30
3	20	30	100	30
4	40	40	0	70

uncertain parameters. Consequently, in such situations, we will be faced with imprecise parameters tainted with epistemic uncertainty whose impreciseness arises from the lack of knowledge regarding their exact values. Practically, in order to provide reasonable estimations for such imprecise parameters, we often have to rely on judgmental data extracted from decision makers (i.e. field experts). Naturally, these judgmental data are mainly based upon the experts' experiences, their subjective while professional opinions and feelings where there might be some relevant but insufficient objective data as well. Accordingly, these parameters could be formulated through the possibility theory as a complement to probability theory. In this way, a suitable possibility distribution could be adopted for each possibilistic data typically in the form of triangular or trapezoidal fuzzy numbers. Possibilistic programming approaches are usually applied to solve those optimization problems facing with such imprecise data (Torabi and Hassini, 2008; Pishvaee and Torabi, 2010).

It is worth noting that there are considerable differences between stochastic and possibilistic programming approaches as their underlying data come from different uncertain environments. As the main difference, stochastic programming approaches originate from probability theory and the presence of sufficient objective/historical data while possibilistic programming approaches originate from possibility theory and rely on subjective data extracted from experts' judgments due to unavailability and/or non-attainability of required objective data. More details on these differences can be found in Mousazadeh et al. (2014).

As an example for an imprecise (i.e. possibilistic) data, assume that the experts estimate the remained capacity of a supplier after a disruptive event to be "about 70%" according to their subjective knowledge and professional experiences and feelings. Meanwhile, they do not expect this percentage to be lower than 50% and higher than 85%. Such imprecise data could be modeled as a triangular fuzzy number for which, the most pessimistic, the most likely and the most optimistic values are 50%, 70% and 85%, respectively and denoted by the triangular fuzzy number (0.5, 0.7, 0.85).

In our model, there is an epistemic uncertainty regarding exact values of some critical parameters (such as demands and unit fortification costs of suppliers) due to incompleteness and/or unavailability of required data. As such, these data have to be estimated mostly by relying on the subjective opinions/experiences of experts. Accordingly, these parameters are assumed to be imprecise (possibilistic) in nature. In this way, it is assumed that a suitable possibility distribution based upon both available objective data and subjective opinions of decision makers has been estimated for each imprecise parameter in the form of a triangular fuzzy number, same as $\tilde{n} = (n^p, n^m, n^o)$, where n^p, n^m and n^o are the most pessimistic value, the most possible value, and the most optimistic value of $\tilde{n}$ estimated by a decision maker (Torabi and Hassini, 2008).

4. The proposed SS&OA model

In our problem setting, a scenario-based modeling is used to include a number of discrete scenarios, which account for disruption risks. Each random scenario is associated with a given likelihood (see Eq. (25)) and consists of given undisrupted and disrupted suppliers in which, each disrupted supplier is faced with one specific disruptive event. We also deal with imprecise (i.e. possibilistic) parameters tainted with epistemic uncertainty in our formulation in response to operational risks according to the aforementioned explanation about imprecise parameters in Section 3. Accordingly, a bi-objective mixed possibilistic, two-stage stochastic program with recourse is proposed to formulate the SS&OA problem under operational and disruption risks whose deterministic counterpart is finally derived given the discrete probability distribution of the scenarios' occurrences.

It is worth noting that the two-stage stochastic programming is one of the most widely applied approaches to deal with two-stage decision problems. In a two-stage model, an initial decision is made in the first stage before knowing what random scenario will be realized and what values the scenario-dependent parameters will take at the second stage. Consequently, a recourse action is taken in the second stage in order to compensate for the decision made in the first stage (Falasca and Zobel, 2011).

In the decision problem under consideration, determining the backup suppliers and purchasing quantities from the main suppliers as well as the fortification level of second group's suppliers and the level of pre-positioned inventories at fortified suppliers at pre-event phase (stage 1) constitute the first-stage decisions, since they must be made before the realization of any random disruption. Furthermore, given the realized random scenario at the post-event phase, determining the required extra quantities which must be purchased from the main and backup suppliers, required amount of pre-positioned inventories to be used at post-event phase and the recovery level of second group's disrupted suppliers are the second-stage or recourse decisions.

Below, we first define the notations, and then present the equivalent model of our original two-stage stochastic program. The latter is actually a scenario-based possibilistic programming model due to existence of imprecise parameters in our formulation. In Section 5, we will discuss how to convert this scenario-based possibilistic model into an equivalent auxiliary crisp model (i.e. the defuzzified model). Notably, the crisp model is the final deterministic counterpart of the scenario-based possibilistic model whose coefficients are entirely deterministic and can be directly solved by commercial optimization packages like GAMS or a customized solution algorithm like a meta-heuristic.

4.1. Notations

The sets, indices, parameters, and variables used to formulate the problem mathematically are described below. Notably, each parameter associated with the tilde sign ($\sim$) denotes an imprecise parameter associated with a triangular fuzzy number.

Indices and sets:

V	set of suppliers
I	set of first group's suppliers ($I \subset V$)
J	set of second group's suppliers ($J \subset V$)
E	set of possible disruptive events that might be occurred at suppliers
E_i	set of possible disruptive events that might be occurred at supplier i ($E_i \subset E$)
K	set of outsourced items
S	set of disruption scenarios ($\lvert S \rvert$ shows the total number of scenarios)
$\overline{V}_s$	set of suppliers that are disrupted under scenario s ($s \in S$ and $\overline{V}_s \subset V$)
V_s	set of suppliers that are not disrupted under scenario s ($s \in S$ and $V_s \subset V$)
U	set of possible fortification levels at the second group's suppliers
L_{ie}	set of possible recovery levels of supplier i after disruptive event e ($i \in J$ and $e \in E_i$)
i	index of suppliers ($i \in V$)
k	index of outsourced items ($k \in K$)
s	index of disruption scenarios ($s \in S$)
u	index of possible fortification levels at the second group's suppliers ($u \in U$)
e	index of possible disruptive events that might be occurred at suppliers ($e \in E$)
e_{is}	index of the happened disruptive event at the supplier i under scenario s ($i \in \overline{V}_s; s \in S$ and $e_{is} \in E_i$)
l	index of recovery levels at the second group's suppliers ($i \in J; e \in E_i$ and $l \in L_{ie}$)

Parameters:

$\tilde{d}_k$	demand of item k over the decision horizon
$\widetilde{A}_i$	fixed cost of ordering from supplier i as a main supplier
$\tilde{f}_i$	fixed cost of contracting with supplier i as a backup supplier
$\tilde{p}_{ik}$	unit price of item k purchased and shipped from supplier i
$\tilde{p}'_{ik}$	unit price of item k purchased and shipped from backup supplier i
$\widetilde{FR}_{iu}$	fortification cost of supplier i at level u ($i \in J$)
$\tilde{h}_{ik}$	per unit cost of pre-positioned emergency inventory of item k at supplier i ($i \in J$)
Ca_i	production capacity of supplier i at normal condition
Sc_i	available storage space of supplier i ($i \in J$)
a_{ik}	per unit capacity consumption of supplier i for item k
$\tilde{\varphi}_{ik}$	expected defect rate of supplier i for item k
R_k	maximum acceptable defect rate of purchased item k (a pre-defined target level)
LT_i	lead time of supplier i
LT'_i	lead time of backup supplier i
π_{ie}	occurrence likelihood of disruptive event e at supplier i ($e \in E_i$)
P_s	occurrence likelihood of scenario s
θ_{ie}	remained capacity of supplier i after disruptive event e (as a percentage of respective normal capacity)
β_{ieu}	amount of increase in remaining capacity at supplier i ($i \in J$) after event e because of its fortification at level u
RT^l_{ie}	recovery time of supplier i ($i \in J$) after event e at recovery level l ($l \in L_{ie}$)
CL^l_{ie}	capacity of supplier i ($i \in J$) after disruptive event e and recovery at level l (as a percentage of respective normal capacity)
b_{ik}	per unit required storage space of item k at supplier i
n	maximum number of main suppliers allowed to be used in the normal situation to follow lean supply principles
M	an arbitrary large constant

First stage's variables:

x_{ik} quantity of item k purchased from supplier i ($i \in V$) at pre-disruption stage
z_i 1, if an order is placed with supplier i ($i \in V$) as the main supplier; 0, otherwise
z'_i 1, if a contract is arranged with supplier i ($i \in V$) as the backup supplier; 0, otherwise
y_{iu} 1, if supplier i ($i \in J$) is fortified at level u; 0, otherwise
w_{ik} quantity of pre-positioned inventory of item k at fortified supplier i ($i \in J$)

Scenario-based (i.e. second stage's) variables:

x'_{iks} quantity of item k that the manufacturer will receive from supplier i ($i \in V$) at post-disruption stage under scenario s
q_{iks} quantity of item k used from the pre-positioned inventory in supplier i ($i \in J$) at post-disruption stage under scenario s
q'_{iks} quantity of item k purchased from backup supplier i ($i \in V$) at post-disruption stage under scenario s
$RL^{l}_{ie_{is}}$ 1, if disrupted supplier i ($i \in J$) is recovered at level l after event e_{is} ($e_{is} \in E_i$) at post-disruption stage under scenario s; 0, otherwise

---

Fig. 1 depicts the two different stages and their related variables. It should be noted that as mentioned earlier, x'_{iks} is the amount of item k that the manufacturer will receive from supplier i under scenario s which is a portion of x_{ik} (see constraint (16)). Nevertheless, if supplier i is not disrupted under scenario s ($i \in V_s$), the manufacture will receive the quantities that are ordered in the normal situation (i.e. $x'_{iks} = x_{ik} \ \forall s \in S, \ k \in K, \ i \in V_s$). In this way, if supplier i is disrupted under scenario s, therefore, $x_{ik} - x'_{iks}$ represents the ordered but undelivered quantity of item k under this scenario. Accordingly, in the developed model, we use x_{ik} instead of x'_{iks} for undisrupted suppliers under scenario s ($i \in V_s$) to avoid excess variables. For example, see constraints (6).

4.2. Formulation

4.2.1. Objective functions

Total expected cost: The first objective function aims to minimize the total expected cost including the fixed ordering, purchasing and shipping costs from main suppliers, costs of contract with backup suppliers, fortification costs, holding costs of pre-positioned inventories, expected costs of purchasing and shipping items from backup suppliers and pre-positioned inventories at fortified suppliers subtracted by expected cost of ordered but undelivered items.

$$\begin{aligned}\text{Min } TC = &\sum_{i\in V}\tilde{A}_i z_i + \sum_{i\in V}\sum_{k\in K}\tilde{p}_{ik}x_{ik} + \sum_{i\in V}\tilde{f}_i z'_i + \sum_{i\in J}\sum_{u\in U}F\tilde{R}_{iu}y_{iu} + \sum_{i\in J}\sum_{k\in K}\tilde{h}_{ik}w_{ik} \\ &+ \sum_{s\in S}P_s\left[\sum_{i\in V_s}\sum_{k\in K}\tilde{p}'_{ik}q'_{iks} + \sum_{i\in J}\sum_{k\in K}\tilde{p}_{ik}q_{iks} - \sum_{i\in \overline{V}_s}\sum_{k\in K}\tilde{p}_{ik}(x_{ik} - x'_{iks})\right]\end{aligned} \tag{1}$$

Resilience level of supply bas: As an effort to quantify the resilience of a system, for the first time Bruneau et al. (2003) introduced the "*resilience triangle*" which depends on the operating level loss and recovery time (see Fig. 2). This triangle leads to a measure named "*loss of resilience*" in a system as follows:

$$R = \int_{t_0}^{t_1} [100 - Q(t)]dt \tag{2}$$

where $Q(t)$ represents the quality of the system's infrastructure (i.e. usable capacity of the system) at the given time t. As mentioned before, Eq. (2) merely represents the loss of resilience, not the resilience itself. Also, smaller triangles naturally correspond to smaller values for R. To fix this problem, Zobel (2010) introduced the "*predicted resilience*" as follows:

$$R(X,T) = \frac{T^* - \frac{XT}{2}}{T^*} = 1 - \frac{XT}{2T^*} \quad X \in [0,1], \ T \in [0,T^*] \tag{3}$$

where T^* (or $T^* \times 1$) is the larger area from which the area of resilience triangle for X and T is subtracted from it (see Fig. 3).

Noteworthy, T^* is an upper bound on the length of recovery process, which is determined by the decision maker to represent the maximum allowable time that the manufacturer would be willing to wait for the recovery process to be terminated. Any recovery process that takes longer than T^*, would simply be replaced by an alternative one or abandoned. In business continuity management system (BCMS) terminology, T^* corresponds to the maximum tolerable period of disruption (MTPD) which is one of the most important measures to keep the recovery process justifiable. Furthermore, the predicted resilience is calculated based on Eq. (3) whenever the area above the response curve is triangle (i.e. when the recovery process is linear over time). Otherwise, it must be calculated according to the shape of this area. Zobel (2014) has calculated the resilience level of a system when the recovery process is non-linear. The recovery process in our problem setting is shown in Fig. 4. In this figure, A, B, and C represent the amount of items provided by three different resilience strategies, and LT_A, LT_B, and LT_C denote the time of receiving items from the related resilience strategy. As can be seen, the area above the response curve

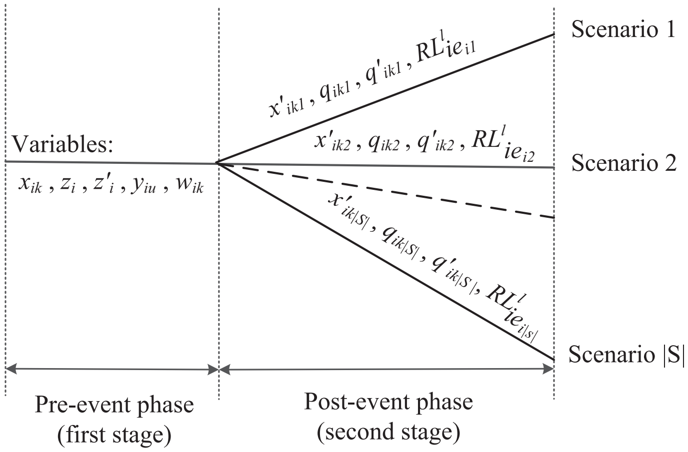

Fig. 1. Representation of two different stages and related variables.

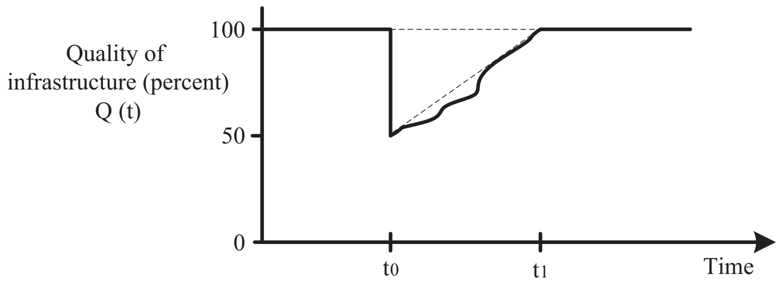

Fig. 2. Resilience triangle (adapted from Bruneau et al., 2003).

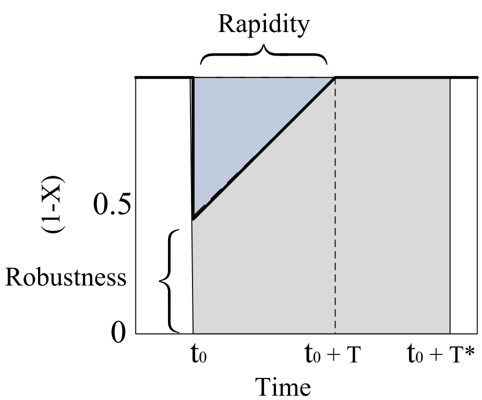

Fig. 3. Predicted resilience (adapted from Zobel, 2010).

(i.e. the shaded area which denotes the loss of resilience) is not triangle in our problem setting and it is calculated as $A * LT_A + B * LT_B + C * LT_C$.

Keeping above definitions in mind, in order to calculate the total resilience level of the selected supply base we calculated the amount of items that the buyer will not receive without considering the resilience strategies including the inventory pre-positioning (*A* strategy), contracting with backup suppliers (*B* strategy), and second group's suppliers' fortification and recovery according to their business continuity management system (*C* strategy) as a scale for calculating the robustness, and the needed time for receiving these items based on related strategies as a scale for calculating rapidity. In fact, the first part shows the impact of disruptions on the manufacturer (*deviation from a targeted state*) and the second part shows capability of the manufacturer to respond to the supply disruptions as fast as possible (*re-achieving the target after disruption as fast as possible*). Thus, a new quantitative measure to calculate the loss of resilience of the selected supply base is proposed as follows:

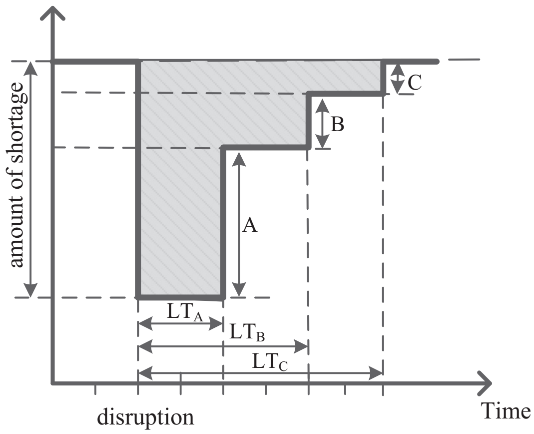

Fig. 4. The recovery process in the problem.

$$RE' = \sum_{s\in S} P_s \left[\sum_{i\in V_s}\sum_{k\in K} LT'_i q'_{iks} + \sum_{i\in J}\sum_{k\in K} LT_i q_{iks} + \sum_{i\in J\cap \overline{V}_s}\sum_{k\in K}\left(\left(x'_{iks} - \theta_{ie_{is}} x_{ik}\right)\left(LT_i + \sum_{l\in L_{ie}} RT^l_{ie_{is}} RL^l_{ie_{is}}\right)\right)\right] \tag{4}$$

The first two terms of Eq. (4) are the amount of items purchased from backup suppliers and the amount of items used from pre-positioned inventory multiplied by the time needed for receiving these items from backup and main suppliers, respectively. The third term approximates the excess amount of items that the second-type suppliers serve after disruption. This amount is calculated according to their recovery level multiplied by the sum of delivery and recovery times. Please note that the third term is non-linear. Obviously, a lower value of the calculated term (RE') results in higher resilience of the supply network. To fix this problem, the predicted resilience (i.e. Eq. (3)) is used with a modification to show the resilience level of the selected supply base. In the original predicted resilience, the vertical axis changes from 0 to 1. However, the vertical axis in our problem denotes the total amount of items that the manufacturer needs. To include this difference, the following formula is used:

$$RE = 1 - \frac{RE'}{Q \cdot T^*} \tag{5}$$

where Q denotes the total amount of items that the manufacturer needs. It should be mentioned that the manufacturer may also face with some inner disruptions such as major machine breakdowns or workers strike but the second objective function is calculating only the supply side's resilience of the manufacturer.

4.2.2. Constraints

$$\sum_{i\in V_s}\left(x_{ik} + q'_{iks}\right) + \sum_{i\in \overline{V}_s} x'_{iks} + \sum_{i\in J} q_{iks} \geqslant \tilde{d}_k \quad \forall s\in S,\ k\in K \tag{6}$$

$$\sum_{k\in K} a_{ik}\left(x_{ik} + q'_{iks}\right) \leqslant Ca_i \quad \forall s\in S,\ i\in V_s \tag{7}$$

$$\sum_{k\in K} a_{ik} x'_{iks} \leqslant \theta_{ie_{is}} Ca_i \quad \forall s\in S,\ i\in I\cap \overline{V}_s \tag{8}$$

$$\sum_{k\in K} a_{ik} x'_{iks} \leqslant \left[\left(\theta_{ie_{is}} + \sum_{u\in U} \beta_{ie_{is}u} y_{iu}\right)\left(1 - \sum_{l\in L_{ie}} RL^l_{ie_{is}}\right) + \sum_{l\in L_{ie}} CL^l_{ie_{is}} RL^l_{ie_{is}}\right] Ca_i \quad \forall s\in S,\ i\in J\cap \overline{V}_s \tag{9}$$

$$\theta_{ie_{is}} x_{ik} \leqslant x'_{iks} \quad \forall s\in S,\ i\in \overline{V}_s,\ k\in K \tag{10}$$

$$\sum_{k\in K} b_{ik} w_{ik} \leqslant Sc_i \sum_{u\in U} y_{iu} \quad \forall i\in J,\ s\in S \tag{11}$$

$$\sum_{i\in V_s} \tilde{\varphi}_{ik}\left(x_{ik} + q'_{iks}\right) + \sum_{i\in \overline{V}_s} \tilde{\varphi}_{ik} x'_{iks} + \sum_{i\in J} \tilde{\varphi}_{ik} q_{iks} \leqslant R_k \left[\sum_{i\in V_s}\left(x_{ik} + q'_{iks}\right) + \sum_{i\in \overline{V}_s} x'_{iks} + \sum_{i\in J} q_{iks}\right] \quad \forall s\in S,\ k\in K \tag{12}$$

$$\sum_{u \in U} y_{iu} \leqslant 1 \quad \forall i \in J \tag{13}$$

$$q_{iks} \leqslant w_{ik} \quad \forall s \in S,\ k \in K,\ i \in J \tag{14}$$

$$\sum_{k \in K} x_{ik} \leqslant M \cdot z_i \quad \forall i \in V \tag{15}$$

$$x'_{iks} \leqslant x_{ik} \quad \forall i \in \overline{V}_s,\ k \in K,\ s \in S \tag{16}$$

$$q'_{iks} \leqslant M \cdot z'_i \quad \forall i \in V,\ k \in K,\ s \in S \tag{17}$$

$$q'_{iks} = 0 \quad \forall s \in S,\ k \in K,\ i \in \overline{V}_s \tag{18}$$

$$\sum_{i \in V} z_i \leqslant n \tag{19}$$

$$\sum_{l \in L_{ie_{is}}} RL^l_{ie_{is}} \leqslant 1 \quad \forall s \in S,\ i \in J \cap \overline{V}_s \tag{20}$$

$$x_{ik}, x'_{iks}, w_{ik}, q_{iks}, q'_{iks} \geqslant 0 \quad \forall i \in V,\ k \in K,\ s \in S \tag{21}$$

$$y_{iu} \in \{0, 1\} \quad \forall i \in J,\ u \in U \tag{22}$$

$$z_i, z'_i \in \{0, 1\} \quad \forall i \in V \tag{23}$$

$$RL^l_{ie_{is}} \in \{0, 1\} \quad \forall i \in J,\ s \in S,\ l \in L_{ie_{is}} \tag{24}$$

Constraint (6) guarantees satisfying the manufacturer's demand for each item under each scenario. Constraint (7) ensures that the total ordered quantity to an undisrupted supplier as a main or backup supplier to be smaller than supplier's production capacity. Constraints (8) restrict purchasing quantity from the first group disrupted suppliers to suppliers' available production capacities after disruption. Constraint (9) limits purchasing amount from the second group's disrupted suppliers to suppliers' available production capacities after disruption while considering their fortification and recovery levels. It is noted that the first phrase in the right side of constraint (9) is non-linear. Constraint (10) guarantees that the quantity of items sent from a disrupted supplier under any scenario should be greater than or equal to the amount of items purchased from the supplier in the normal situation multiplied by the percentage of supplier's remained capacity after disruption. Constraint (11) represents that pre-positioned inventories are only stored in the fortified suppliers and the amount of pre-positioned inventories do not exceed the available storage space. Constraint (12) guarantees that the overall expected defective rate of each purchased item does not exceed the related maximum acceptable defective rate. Constraint (13) represents that a second group's supplier can be fortified at most at a specific level of fortification. Constraint (14) restricts amount of delivered items from the pre-positioned inventory to the amount provided at the pre-event phase. Constraint (15) guarantees that the amount of items purchased from a main supplier are equal to zero if an order is not placed with this supplier as a main supplier. Constraint (16) represents that the amount of each item sent from a disrupted supplier (especially the second group's suppliers after recovery) must be smaller than or equal to the purchased amount from the supplier in the normal situation (i.e. stage 1). Constraint (17) guarantees that the amount of each item purchased from a backup supplier is equal to zero if a contract is not arranged with the supplier as the backup supplier. Constraint (18) guarantees that the disrupted suppliers under each scenario cannot be used as backup suppliers under that scenario. Constraint (19) states that the total number of main suppliers in normal situation (i.e. pre-event phase) should be lower than the maximum number of main supplier in the normal situation according to the lean supply chain principles. Constraints (20) represent that each disrupted second group's supplier can be recovered at most at a specific recovery level under each scenario. Finally, constraints (21)–(24) show the type of decision variables. Also, with considering that disruptive events are occurred independently and at most one event occurs at each supplier under each scenario, likelihood of scenarios can be calculated as follows:

$$P_s = \left[\prod_{i \in V_s}\left(1 - \sum_{e \in E_i} \pi_{ie}\right)\right] \prod_{i \in \overline{V}_s} \pi_{ie_{is}} \tag{25}$$

As mentioned before, Eq. (5) and constraint (9) are non-linear. Since the non-linear terms are in the form of the products of two binary variables or the product of a binary variable and a continuous non-negative variable, they can be easily converted to linear forms based on methods used in You and Grossmann (2010). Noteworthy, although linearization introduces more constraints and variables, it significantly reduces the computational effort. The linear form of the proposed model is reported in Appendix A.

5. Solution procedure

The proposed possibilistic scenario-based model is very complicated in many different aspects: (1) there might be many scenarios in the model, even after implementing the scenario reduction procedure presented in Section 5.1, (2) the original scenario-based model is of possibilistic type and converting it to an equivalent parametric crisp model requires solving several crisp models, which obviously needs an efficient solution technique to keep the required computation time reasonable, (3) the resulting crisp models are bi-objective and an efficient multi-objective method must be used to find their compromise solutions, and (4) the resulting single-objective models in Section 5.3 are non-linear and solving them with exact methods is not an easy task (note that even linearization adds around twelve sets of new constraints to these non-linear model), Therefore, according to the high complexity of the proposed possibilistic scenario-based model, we use a five-step solution procedure to solve it efficiently. These steps are as follows:

Step 1	reduce the number of random disruption scenarios using the FCM clustering technique and construct the possibilistic scenario-based (i.e. the mixed possibilistic two-stage stochastic programming) model
Step 2	convert the resulting possibilistic scenario-based model into two equivalent auxiliary crisp (i.e. deterministic) bi-objective models
Step 3	convert the obtained crisp bi-objective models from Step 2 to their equivalent single objective models via well-known augmented ε-constraint method
Step 4	solve the equivalent single objective models to obtain the efficient (i.e. Pareto-optimal) solutions of bi-objective models resulting at Step 2 using a tailored Differential Evolution (DE) algorithm
Step 5	repeat Step 4 with a new ε vector to obtain a new efficient solution in the form of an interactive approach by interacting with decision makers to obtain finally the most preferred efficient solution

The details of the algorithms used in steps 1 to 4 are described in Sections 5.1 to 5.4, respectively.

5.1. Scenario reduction procedure

The number of random disruption scenarios in the designed model increases exponentially with increasing the number of qualified suppliers and disruptive events. For example, where the number of qualified suppliers and disruptive events in suppliers are respectively five and twenty, the total number of scenarios will be equal to $(20+1)^5$. Solving the problem with such huge number of scenarios is cumbersome or perhaps impossible; even with the help of meta-heuristic methods. In order to reduce the number of scenarios, the FCM algorithm is used to cluster possible disruptive events at suppliers to different clusters by which the centers of clusters are used as representatives of disruptive events. Two main characteristics of each disruptive event in scenarios including the occurrence likelihood of disruptive event e at supplier i (π_{ie}) and remained capacity of supplier i after disruptive event e (θ_{ie}) are used in the clustering procedure.

The FCM algorithm introduced by Bezdek (1974), is one of the most popular fuzzy clustering methods because it is efficient, straightforward, and easy to implement (Izakian and Abraham, 2011). FCM divides a set of E objects $X = \{x_1, x_2, \ldots, x_E\}$ in R^p space into C ($1 < C < E$) fuzzy clusters; where in our problem setting we can define E as the total number of possible events (i.e. disruptions) at each supplier, C as the reduced number of events at the supplier after applying FCM algorithm, and P as the main characteristics of disruptive events. Following five iterative steps show how the FCM algorithm can be applied to cluster possible events at supplier i in the problem (adopted from Bezdek, 1974).

Step 1. Produce a random membership matrix according to the following equation:

$$U = \begin{bmatrix} u_{11} & \cdots & u_{1E} \\ \vdots & u_{ce} & \vdots \\ u_{C1} & \cdots & u_{CE} \end{bmatrix} \quad 0 \leqslant u_{ce} \leqslant 1 \tag{26}$$

where u_{ce} is the membership degree of e^{th} event to cluster center c and E is the total number of possible events at the supplier i.

Step 2. Each cluster center is a virtual event with two main characteristics: the remained capacity of the supplier i after this virtual event c (θ_{ic}) and likelihood of the disruptive event c at this supplier (π_{ic}). Compute the cluster centers matrix (Ce) according to Eq. (27).

$$Ce = \begin{bmatrix} \frac{\sum_{e=1}^{E} u_{1e}^m \cdot \theta_{ie}}{\sum_{e=1}^{E} u_{1e}^m} & \frac{\sum_{e=1}^{E} u_{1e}^m \cdot \pi_{ie}}{\sum_{e=1}^{E} u_{1e}^m} \\ \vdots & \vdots \\ \frac{\sum_{e=1}^{E} u_{Ce}^m \cdot \theta_{ie}}{\sum_{e=1}^{E} u_{Ce}^m} & \frac{\sum_{e=1}^{E} u_{Ce}^m \cdot \pi_{ie}}{\sum_{e=1}^{E} u_{Ce}^m} \end{bmatrix} \quad 1 \leqslant m < \infty \tag{27}$$

Step 3. Compute the objective function of FCM algorithm according to Eq. (28).

$$J_{FCM}(U,C) = \sum_{e=1}^{E}\sum_{c=1}^{C} u_{ce}^{m} \cdot D(X_{ie}, Ce_c) \quad 1 < m \tag{28}$$

where m is a scalar termed the weighting exponent and $D(X_{ie}, Ce_c)$ is the Euclidean distance between event e with its two characteristics (π_{ie} and θ_{ie}) and c^{th} cluster center.

Step 4. Compute the new membership matrix according to Eq. (29).

$$U_{new} = \begin{bmatrix} \frac{D^{\frac{-2}{m-1}}(X_{i1}, Ce_1)}{\sum_{c=1}^{C} D^{\frac{-2}{m-1}}(X_{i1}, Ce_c)} & \cdots & \cdots & \frac{D^{\frac{-2}{m-1}}(X_{iE}, Ce_1)}{\sum_{c=1}^{C} D^{\frac{-2}{m-1}}(X_{iE}, Ce_c)} \\ \vdots & & & \vdots \\ \vdots & & & \vdots \\ \frac{D^{\frac{-2}{m-1}}(X_{i1}, Ce_C)}{\sum_{c=1}^{C} D^{\frac{-2}{m-1}}(X_{i1}, Ce_c)} & \cdots & \cdots & \frac{D^{\frac{-2}{m-1}}(X_{iE}, Ce_C)}{\sum_{c=1}^{C} D^{\frac{-2}{m-1}}(X_{iE}, Ce_c)} \end{bmatrix} \tag{29}$$

Step 5. Repeat step (2) to (4) until the following condition is satisfied:

$$|(J_{FCM})_J - (J_{FCM})_{J-1}| < \varepsilon \tag{30}$$

where ε is the error level.

It is noted that the obtained cluster centers are the new set of virtual events for supplier i. These five steps can be applied to reduce the number of disruptive events at each supplier. With reducing the number of events at each supplier, the total number of disruption scenarios will be reduced accordingly.

5.2. The equivalent crisp model

Several methods have been developed in the literature to transform a possibilistic model to an equivalent crisp one. Literature review approves that the credibility-based possibilistic programming approaches including the expected value, the chance-constrained programming and the dependent chance-constrained programming models (see for example, Ghodratnama et al., 2012; Pishvaee et al., 2012) are the most applied approaches to account for epistemic uncertainty in input data. Among them, the possibilistic chance constrained programming approach is the most applied one in which the decision maker can set a minimum confidence level as an appropriate safety margin for satisfaction of each possibilistic constraint (see for example, Pishvaee et al., 2012). Recently, Xu and Zhou (2013) extended the possibilistic chance constrained programming approach by proposing the new fuzzy measure *Me* which is an extension to credibility measure. *Me* unifies two standard fuzzy measures, i.e. the possibility (*Pos*) and necessity (*Nec*) measures. The advantage of these two measures is to specify the degree of which a fuzzy (possibilistic) variable takes values in an interval with varying optimistic–pessimistic attitudes. Noteworthy, the possibility measure indicates the possibility level of occurring an uncertain event that involves possibilistic parameters, while the necessity measure shows the minimum possibility level of occurring an uncertain event. Meanwhile, the credibility measure represents the certainty degree of occurring an uncertain event. In practice, decision makers have different optimistic–pessimistic attitudes, and these optimistic–pessimistic parameters are determined based on their own experiences and judgments. The possibility (*Pos*) and necessity (*Nec*) are two measures that demonstrate those attitudes which are extremely optimistic and pessimistic. However, the measure *Me* is more flexible to avoid extreme attitudes (i.e. something between optimistic and pessimistic views).

In this paper, the *Me*-based possibilistic programming method proposed by Xu and Zhou (2013) is adopted to solve the possibilistic scenario-based model. With considering (Θ, $P(\Theta)$, Pos) as a possibility space, Xu and Zhou (2013) defined the fuzzy measure *Me* as follows:

$$Me\{A\} = Nec\{A\} + \lambda(Pos\{A\} - Nec\{A\}) \tag{31}$$

where A is a set in $P(\Theta)$ and $\lambda(0 \leqslant \lambda \leqslant 1)$ is an optimistic–pessimistic parameter to determine the combined attitude of decision maker where $(Pos\{A\} - Nec\{A\})$ is the range within which the value of the measure changes from pessimistic to optimistic one.

For better understanding, consider the following general multi-objective possibilistic model:

$$\begin{cases} \max[f_1(x,\xi), f_2(x,\xi), \ldots, f_m(x,\xi)] \\ \text{s.t.} \begin{cases} g_r(x,\xi) \leqslant 0, \quad r = 1,2,\ldots,p \\ x \in \mathrm{X} \end{cases} \end{cases} \tag{32}$$

where ξ is the vector of fuzzy/possibilistic variables (i.e. imprecise coefficients of objective functions and constraints). Now, by using the expected value and chance constrained operators, we can rewrite the model (32) as follows:

$$ECM:\begin{cases}\max[E[f_1(x,\xi)],E[f_2(x,\xi)],\ldots,E[f_m(x,\xi)]]\\ \text{s.t.}\\ Ch\{g_r(x,\xi)\leqslant 0\}\geqslant \delta_r, \quad r=1,2,\ldots,p\\ x\in X\end{cases} \tag{33}$$

where E and Ch denote the expected value and chance constrained operators, respectively. There are several kinds of definitions for the expected value of a fuzzy variable. Xu and Zhou (2013) showed that the expected value of the triangular fuzzy variable $\xi = (r_1, r_2, r_3)$ when $r_1 \geqslant 0$ can be calculated from Eq. (34).

$$E[\xi]=\frac{(1-\lambda)}{2}r_1+\frac{1}{2}r_2+\frac{\lambda}{2}r_3 \tag{34}$$

where λ is the optimistic–pessimistic parameter which is set by decision maker.

Also, in order to measure the chance of a fuzzy event, Xu and Zhou (2013) used the general fuzzy measure Me:

$$Ch\{g_r(x,\xi)\leqslant 0\}\geqslant \delta_r \iff Me\{g_r(x,\xi)\leqslant 0\}\geqslant \delta_r \tag{35}$$

where δ_r ($r = 1,2,\ldots,p$) denotes the decision maker's minimum confidence level for satisfaction of r-th possibilistic constraint. Accordingly, by applying Eq. (35), model (33) is changed to:

$$ECM:\begin{cases}\max[E[f_1(x,\xi)],E[f_2(x,\xi)],\ldots,E[f_m(x,\xi)]]\\ \text{s.t.}\\ Me\{g_r(x,\xi)\leqslant 0\}\geqslant \delta_r, \quad r=1,2,\ldots,p\\ x\in X\end{cases} \tag{36}$$

Xu and Zhou (2013) proved that for any $x_0 \in X$ the following relations are true:

$$Pos\{g_j(x_0,\xi)\leqslant 0\}\geqslant Me\{g_j(x_0,\xi)\leqslant 0\}\geqslant Nec\{g_j(x_0,\xi)\leqslant 0\}\geqslant \delta_j \tag{37}$$

Finally, with using Eq. (37), they transformed model (36) into two approximated crisp models, i.e. the lower approximation model (LAM) and the upper approximation model (UAM) as follow:

$$LAM:\begin{cases}\max[E[f_1(x,\xi)],E[f_2(x,\xi)],\ldots,E[f_m(x,\xi)]]\\ \text{s.t.}\\ Nec\{g_r(x,\xi)\leqslant 0\}\geqslant \delta_r \quad r=1,2,\ldots,p\\ x\in X\end{cases} \tag{38-1}$$

$$UAM:\begin{cases}\max[E[f_1(x,\xi)],E[f_2(x,\xi)],\ldots,E[f_m(x,\xi)]]\\ \text{s.t.}\\ Pos\{g_r(x,\xi)\leqslant 0\}\geqslant \delta_r \quad r=1,2,\ldots,p\\ x\in X\end{cases} \tag{38-2}$$

Now, suppose that the objective functions are linear (i.e. $f_j(x,\xi)=\sum_{i=1}^{n}\tilde{c}_{ij}\cdot x_i;\ j=1,\ldots,m$), and the fuzzy parameter $\tilde{c}_{ij}$ is considered as the triangular fuzzy number $\tilde{c}_{ij}=(c_{ij},\alpha_{ij}^c,\beta_{ij}^c)$; where c_{ij}, α_{ij}^c and β_{ij}^c are the mean value, left and right spreads of $\tilde{c}_{ij}$ respectively. Accordingly, the equivalent models representing the LAM and UAM are as follows:

$$LAM:\begin{cases}\max\sum_{i=1}^{n}\left(\frac{(1-\lambda)}{2}\cdot c_{ij}+\frac{c_{ij}}{2}+\frac{\lambda}{2}\cdot c_{ij}\right)\cdot x_i, \quad j=1,2,\ldots,m\\ \text{s.t.}\\ b_r-\delta_r\alpha_r^b\geqslant a_r^Tx+(1-\delta_r)\beta_r^{aT}x \quad r=1,2,\ldots,p\\ x_i\geqslant 0, \quad i=1,2,\ldots,n\end{cases} \tag{39-1}$$

$$UAM:\begin{cases}\max\sum_{i=1}^{n}\left(\frac{(1-\lambda)}{2}\cdot c_{ij}+\frac{c_{ij}}{2}+\frac{\lambda}{2}\cdot c_{ij}\right)\cdot x_i, \quad j=1,2,\ldots,m\\ \text{s.t.}\\ b_r+(1-\delta_r)\beta_r^b\geqslant a_r^Tx-(1-\delta_r)\alpha_r^{aT}x \quad r=1,2,\ldots,p\\ x_i\geqslant 0, \quad i=1,2,\ldots,n\end{cases} \tag{39-2}$$

In practice, people's attitudes are usually different and may fluctuate between extremely optimistic attitude (*Pos*) and extremely pessimistic attitude (*Nec*). The most important advantage of Xu and Zhou's method is that the two approximation models (LAM and UAM) appropriately fit the changing optimistic–pessimistic attitudes of different decision makers. Noteworthy, since the UAM uses an optimistic attitude in constraints, the feasible region of the UAM is larger than that of the LAM. As a result, the UAM will give better optimal solution, theoretically. When both of the LAM and the UAM are solved simultaneously, we will have an interval as a solution where the lower and upper bounds are the outputs of UAM and LAM, respectively. By employing these two models, the decision maker will have the upper bound and the lower bound of the optimal decision. In this way, more information is provided to the decision maker which will be helpful when selecting the final solution among the suggested ones (Xu and Zhou, 2013). The two crisp models of our proposed model using the *Me* measure are reported in Appendix B.

5.3. The augmented ε-constraint method

Both of the LAM and UAM (developed in the previous section) are bi-objective models. Several methods have been developed in the literature to solve the multi-objective programming models (e.g. weighted sum method, goal programming, ε-constraint method, Tchebycheff-based methods and fuzzy programming approaches). In this paper, we apply an improved version of the ε-constraint method by which the bi-objective models related to LAM and UAM are converted to their single-objective counterpart. In the ε-constraint method, the most important objective function (the first objective in this paper) is optimized while the other objectives (here the second objective function) are added to the constraints as follows:

$$\begin{aligned} \max \quad & TC(x) \\ \text{s.t.} \quad & RE(x) \geqslant \varepsilon_2 \\ & x \in S \end{aligned} \tag{40}$$

In this way, the efficient (i.e. Pareto-optimal) solutions of our bi-objective LAM and UAM are obtained by parametrical variation in the right hand side (ε_2) of constrained objective function (Mavrotas, 2009). The range of ε_2 can be calculated by optimizing the constrained objective *RE* separately subject to the feasible set *S* and establishing the pay-off table. Then, via dividing the range of constrained objective *RE* (r) to q equal intervals, different values for ε_2 can be calculated as follows:

$$r = RE^{\max} - RE^{\min}; \quad \varepsilon_2^l = RE^{\max} - \frac{r}{q} \times l \quad l = 0, \ldots, q-1 \tag{41}$$

Nevertheless, the general form of ε-constraint method has some disadvantages. For example, this method does not guarantee efficiency of the obtained solutions (i.e. reaching to weakly efficient solutions). Mavrotas (2009) addressed some of these disadvantages and proposed an improved version of the ε-constraint method, called augmented ε-constraint method. The formulation of the augmented ε-constraint method for our problem is shown below.

$$\begin{aligned} \max \quad & TC(x) + (\varphi \times s_2) \\ \text{s.t.} \quad & RE(x) - s_2 = \varepsilon_2 \\ & x \in S, \ s_2 \in R^+ \end{aligned} \tag{42}$$

where φ is an adequately small number (usually between 10^{-3} and 10^{-6}) and augmented term $\varphi \times s_2$ assures yielding just efficient solution for each epsilon vector. This method is then used to solve the bi-objective LAM and UAM and finding efficient solutions for our problem.

5.4. Differential evolution Algorithm

The proposed possibilistic scenario-based model is very complicated in many different aspects: (1) there are many scenarios in the model, even after implementing the scenario reduction procedure, (2) the original decision model is non-linear and solving it with exact methods is not an easy task (note that even linearization adds around twelve sets of new constraints to the original mathematical model), and (3) the original model is of possibilistic type and converting it to an equivalent parametric crisp model requires solving more mathematical models, which obviously increases the required computation time. Therefore, according to the high complexity of the model, we use a meta-heuristic solution procedure to solve the UAM and LAM more efficiently. Meta-heuristic algorithms are approximate methods used to solve large-scale optimization problems in a reasonable time (Taillard et al., 2012). DE proposed by Storn and Price (1995) is a population based Meta-heuristic algorithm which has attracted great attention in recent years due to its robustness and flexibility for solving numerical optimization problems (Mallipeddi et al., 2011). Similar to other evolutionary algorithms such as Genetic algorithm (GA), DE uses crossover, mutation and selection operators. In order to guide search process, DE uses information of current population direction and distance between two individuals which is an important advantage of DE in comparison with other evolutionary algorithms. The main steps of DE algorithm are generation of an initial population, evaluation, mutation, crossover and selection. Like GAs, the operators are repeated until a predefined stopping criterion such as maximum generation number is satisfied. The devised operators for our particular problem are briefly explained in the following.

z_1=rand (0,1)	z'_1=rand (0,1)	y_1=randi(0,u)
z_2=rand(0,1)	z'_2=rand(0,1)	y_2=randi(0,u)
⋮	⋮	⋮
z_L=rand(0,1)	z'_L=rand(0,1)	y_L=randi(0,u)

Fig. 5. The first matrix of solution representation.

5.4.1. Initial population

Devising a suitable representation scheme showing the solution characteristics is one of the most important steps in designing an evolutionary algorithm for a particular problem. The proposed model in section (4) has 4 scenario-based variables, 5 decision variables and 19 constraints. We devised different structures to find the most suitable structure to deal with this number of variables and constraints. The selected structure consists of five different matrices and each matrix specifies amount of specific variables. For example, the first matrix, as is shown in Fig. 5, specifies the amount of z_i, z'_i and y_{iu} in which *rand* (0, 1) is a random number generator within the range [0, 1] and *randi* (0, u) is a random integer number generator within the range [0, u].

Of note is that, the devised structure deals with most of constraints. However, some constraints may not be satisfied in the initial structure. To deal with these unsatisfied constraints, following methods are applied to ensure reaching to feasible solutions:

- applying feasibility checks;
- using penalty functions in the fitness function.

5.4.2. Mutation

For each vector $x_{i,G}, i = 1, 2, \ldots, NP$, a mutant vector can be generated as follows:

$$v_{i,G+1} = x_{r_1,G} + F \cdot (x_{r_2,G} - x_{r_3,G}) \tag{43}$$

where r_1, r_2 and r_3 are randomly chosen integers so that $r_1 \neq r_2 \neq r_3 \neq i$ and $r_1, r_2, r_3 \in \{1, 2, \ldots, NP\}$. Also, F is a real and constant factor between 0 and 2 which controls the amplification of the differential variation.

5.4.3. Crossover

In a DE algorithm, crossover operator mixes the parent vectors with the mutated vector in order to produce a new trial vector. The trial vector $y_{i,G+1} = (y_{1i,G+1}, y_{2i,G}, \ldots, y_{Di,G+1})$ can be defined as follow:

$$y_{ji,G+1} = \begin{cases} v_{ji,G+1} & \text{if } a_j \leqslant CR \text{ or } j = b_i \\ x_{ji,G} & \text{if } a_j > CR \text{ and } j \neq b_i \end{cases}, \quad j = 1, 2, \ldots, D \tag{44}$$

where $a_j \in [0, 1]$ is a random generated number for the jth element, $CR \in [0, 1]$ is the crossover constant which is set by the decision maker and b_i is randomly chosen index $\in \{1, 2, \ldots, D\}$. Note that elements of the trial matrices may not be within the range [0, 1]. Therefore, a feasibility check is designed so that each unfeasible element will be exchanged with a random number within the range [0, 1].

5.4.4. Selection

Using the selection operator, each produced trial vector $y_{i,G+1}$ is compared to its target vector $x_{i,G}$. If $y_{i,G+1}$ yields a better function value than $x_{i,G}$, then $y_{i,G+1}$ becomes a member of $G+1$ generation instead of $x_{i,G}$; otherwise, the old value $x_{i,G}$ is retained in the next generation.

In order to validate the proposed DE algorithm, we have compared its performance with the results obtained by the well-known MIP solver (i.e. CPLEX solver) in Appendix C. The results show that the proposed DE can solve both the bi-objective models of UAM and LAM using the augmented ε-constraint method (presented in Section 5.3) with an acceptable performance.

6. Computational experiments

6.1. Numerical example

In this section, a numerical example and its computational results are presented to show the applicability and usefulness of the proposed model for real applications. To this end, we consider a manufacturer who wants to buy three different items from four available pre-qualified suppliers (S_1, S_2, S_3 and S_4). Twenty different disruptive events are considered for each supplier. It is supposed that only supplier S_4 has implemented a business continuity management plan and have suitable business continuity plans to deal with disruptive events with two levels of fortification and two levels of recovery. Uniform distributions are used to generate the required imprecise and crisp parameters which have been reported in Appendix D. Each imprecise parameter used in this example has been modeled by an appropriate possibility distribution in the form of a symmetric triangular fuzzy number with symmetrical spreads being equivalent to twenty percent of the central values.

The number of possible scenarios in the numerical example is equal to $(20+1)^4$. According to step 1 of the proposed solution method, *fcm* function in MATLAB R2012a is used to reduce the number of disruptive events in each supplier from twenty to three. Related data to considered disruptive events in suppliers and calculated suppliers' cluster centers as representatives of disruptive events are respectively shown in Tables 3 and 4.

The first objective is considered as the most important objective and the second objective as a constraint in the augmented ε-constraint method. Considering clustering centers and $\varepsilon_2 = 240,000$, Table 5 provides the corresponding results to LAM and UAM models according to the different decision maker's confidence levels ($\delta; \delta_i = \delta \forall i$) in which the optimistic–pessimistic parameter (λ) and φ are set respectively to 0.5 and 10^{-4}. The DE algorithm was coded in MATLAB R2009a in a PC with Intel Core i5 CPU, 2.53 GHz and 6 GB of RAM. Also, it was run 10 times for each δ, and the best solution was reported.

Table 3
Characteristics of the considered disruptive events.

Disruptive event	S_1		S_2		S_3		S_4	
	θ_{ie}	π_{ie}	θ_{ie}	π_{ie}	θ_{ie}	π_{ie}	θ_{ie}	π_{ie}
1	0.384	0.041	0.452	0.042	0.297	0.025	0.563	0.041
2	0.480	0.023	0.254	0.039	0.535	0.012	0.163	0.038
3	0.322	0.004	0.593	0.016	0.157	0.004	0.567	0.023
4	0.053	0.027	0.151	0.032	0.489	0.003	0.405	0.017
5	0.343	0.046	0.119	0.040	0.517	0.017	0.322	0.046
6	0.377	0.009	0.396	0.027	0.492	0.047	0.057	0.040
7	0.321	0.035	0.600	0.003	0.419	0.041	0.088	0.048
8	0.576	0.040	0.361	0.046	0.254	0.037	0.202	0.020
9	0.532	0.008	0.517	0.013	0.369	0.036	0.547	0.004
10	0.496	0.010	0.547	0.014	0.206	0.044	0.093	0.019
11	0.339	0.019	0.439	0.030	0.251	0.025	0.535	0.039
12	0.090	0.047	0.250	0.022	0.263	0.007	0.370	0.041
13	0.229	0.023	0.238	0.014	0.373	0.046	0.147	0.020
14	0.514	0.040	0.148	0.041	0.178	0.016	0.388	0.008
15	0.522	0.032	0.274	0.009	0.184	0.004	0.496	0.025
16	0.030	0.036	0.578	0.033	0.144	0.037	0.293	0.000
17	0.228	0.020	0.568	0.040	0.085	0.005	0.454	0.009
18	0.290	0.030	0.515	0.039	0.386	0.033	0.175	0.043
19	0.061	0.048	0.491	0.034	0.238	0.022	0.352	0.007
20	0.3	0.038	0.040	0.021	0.202	0.038	0.168	0.046

Table 4
Characteristics of suppliers' cluster centers as representatives of disruptive events.

Cluster centers	S_1		S_2		S_3		S_4	
	θ_{ie}	π_{ie}	θ_{ie}	π_{ie}	θ_{ie}	π_{ie}	θ_{ie}	π_{ie}
1	0.062	0.170	0.164	0.191	0.365	0.184	0.537	0.140
2	0.518	0.164	0.395	0.171	0.506	0.094	0.136	0.263
3	0.317	0.243	0.555	0.193	0.19	0.221	0.360	0.129

Table 5
Summary of results for LAM and UAM models according to different decision maker's confidence levels.

	$\delta = 0.8$		$\delta = 0.9$		$\delta = 1.0$	
	TC	*RE*	*TC*	*RE*	*TC*	*RE*
LAM	472,695	0.789	418,110	0.791	344,127	0.899
UAM	276,741	0.919	310,504	0.914	344,370	0.902

Table 6
Results of sensitivity analysis on LAM parameters.

λ	$\delta_i = 0.7$ [TC, RE]	$\delta_i = 0.8$ [TC, RE]	$\delta_i = 0.9$ [TC, RE]	$\delta_i = 1$ [TC, RE]
0	[459,674, 0.780]	[417,056, 0.800]	[355,785, 0.863]	[311,714, 0.882]
0.2	[484,288, 0.780]	[435,924, 0.789]	[363,617, 0.876]	[326,935, 0.891]
0.4	[487,512, 0.780]	[457,190, 0.796]	[392,522, 0.868]	[338,764, 0.905]
0.6	[512,282, 0.786]	[485,791, 0.805]	[427,582, 0.860]	[352,349, 0.899]
0.8	[546,896, 0.789]	[491,381, 0.805]	[430,405, 0.874]	[370,635, 0.893]
1.0	[584,958, 0.782]	[513,708, 0.790]	[441,578, 0.869]	[402,517, 0.866]

As shown in Table 5, optimistic and pessimistic attitudes have significant impacts on results. In a fuzzy environment, providing a crisp (certain) solution to the decision makers is somehow unrealistic. Nevertheless, the important advantage of using two proposed approximation models in the applied defuzzifying procedure is providing an interval for objective functions according to the selected confidence levels (δ). In this way, the decision makers can know the upper and lower bounds of the optimal decision according to their favorite attitudes and confidence levels and thus more information is provided to the decision maker (Xu and Zhou, 2013).

Different solutions can be found by changing the value of optimistic–pessimistic attitude and confidence levels. Table 6 shows the different optimal values for the objectives of LAM model with different λ and δ while considering $\varepsilon_2 = 240,000$.

As can be seen in Table 6, because of using the LAM, the value of first objective (which is considered as the objective function of augmented ε-constraint method) is improved by increasing the confidence levels while it is increased by increasing the optimistic–pessimistic parameter.

As mentioned before, different solutions can be obtained by changing ε_2. The best and worst values of the second objective in LAM model with considering $\lambda = 0.5$, $\varphi = 10^{-4}$ and $\delta = 1.0$ are 65,701 and 109,731. Table 7 shows values of the objective functions of LAM efficient solutions for different l with considering $\lambda = 0.5$, $\varphi = 10^{-4}$ and $\delta = 1.0$. Also, the estimated Pareto frontier obtained from Table 7 is shown in Fig. 6.

6.2. Managerial insights

Considering different likelihoods for disruptive events in suppliers may lead to different supply bases. To better understand the impact of likelihoods on the fraction of total demand purchased from each supplier, we considered the numerical example which is given in Section 6.2 and following five cases:

1. Without considering disruptive events.
2. Likelihoods of disruptive events are equal to 1/4 of the initial considered likelihoods (considered likelihoods in the numerical example).
3. Likelihoods of disruptive events are equal to 1/2 of the initial considered likelihoods.
4. Likelihoods of disruptive events are equal to the initial considered likelihoods.
5. Likelihoods of disruptive events are equal to 1.2 of the initial considered likelihoods.

To this end, the fraction of total demand purchased from suppliers can be calculated from the following equation:

$$U_i = \frac{\sum_{k\in K}\sum_{s\in S_1} P_s(x_{ik} + q'_{iks}) + \sum_{k\in K}\sum_{s\in S_2} P_s x'_{iks} + \sum_{k\in K}\sum_{s\in S} P_s q_{iks}}{\sum_{i\in V}\left[\sum_{k\in K}\sum_{s\in S_1} P_s(x_{ik} + q'_{iks}) + \sum_{k\in K}\sum_{s\in S_2} P_s x'_{iks} + \sum_{k\in K}\sum_{s\in S} P_s q_{iks}\right]} \quad \forall i \in V \tag{45}$$

where U_i is the fraction of total demand purchased from supplier i (i.e. purchasing share) and S_1 and S_2 denote the set of those scenarios within which the supplier i respectively is not disrupted and disrupted.

Table 7
Efficient solutions of the LAM for different l.

l	TC	RE
0	344,127	0.899
1	352,974	0.903
2	369,917	0.907
3	378,022	0.911
4	387,893	0.915
5	394,110	0.919
6	401,671	0.923
7	433,887	0.928
8	441,703	0.932
9	457,531	0.936
10	478,145	0.940

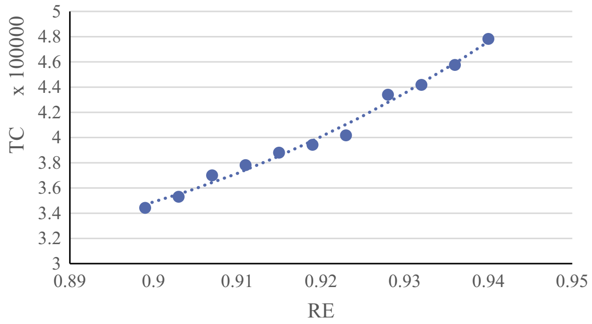

Fig. 6. The estimated Pareto frontier from LAM model.

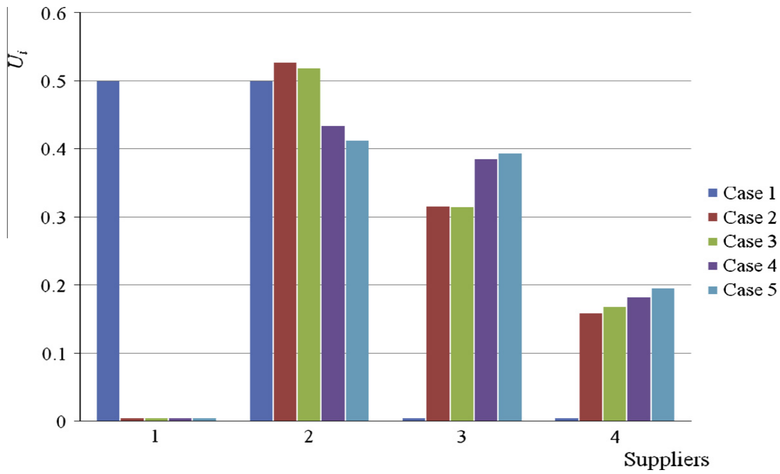

Fig. 7. The purchasing shares of suppliers in the LAM model in considered cases.

Table 8
Amount of objective functions for the LAM in considered disruption cases.

Case	*TC*	*RE*
1	261,800	1.000
2	312,722	0.970
3	326,785	0.944
4	344,446	0.898
5	369,602	0.880

Fig. 7 shows the purchasing shares of suppliers for the LAM with considering $\lambda = 0.5$, $\varphi = 10^{-4}$, $\delta = 1.0$ and $\varepsilon_2 = 160,000$. Also, amount of objective functions in each case are shown in Table 8.

Three main points can be extracted from Fig. 7 and Table 8:

1. Accounting for disruptive events can have a significant impact on the selected supply base. For example, as it is shown in Fig. 7, supplier 1 has a great share in the first case (without considering disruptive events), but it does not have any contribution among purchased items in other cases.
2. The purchasing shares of those suppliers with an implemented business continuity managements system are gradually increased with increasing of likelihoods of disruptive events (there is a direct relation between the likelihood of disruptive events and the fraction of total demand purchased from suppliers with an implemented business continuity managements system). For example, as it is shown in Fig. 7, the share of supplier 4 increases from case one to five as the likelihoods of disruptive events increase.
3. The likelihoods of disruptive events have a significant impact on the selected supply base. For example, the purchasing shares of suppliers (U_1, U_2, U_3, U_4) in the second case are (0, 0.53, 0.32, 0.16). However, in the fourth case these shares are (0, 0.43, 0.39, 0.18).

7. Conclusions and future work

In this paper, a novel scenario-based bi-objective possibilistic mixed integer linear model is developed to build resilient supply bases for global supply chains in response to uncertainties and disruptions caused by operational and disruption risks. The contributions of this paper to the literature are introducing a new supply side resilience objective function to calculate the resilience level of the selected supply base and considering several strategies such as suppliers' business continuity plans, fortification of suppliers and contract with backup suppliers to enhance the resilience level of the supply network. A five-step method is designed to solve the proposed model and computational experiments are provided to show the applicability and usefulness of the proposed model for real applications. The computational experiments indicate that accounting for disruptive events can have significant impact on selected supply bases. For example, a supplier may have a great share in supply base without considering disruptive events and no share in the case of considering disruptive events. Also, we find that likelihoods of disruptive events are key determinants in the selection of supply portfolio and there is a direct relation between the likelihood of disruptive events and the fraction of total demand purchased from suppliers with an implemented business continuity managements system. In this way, considering supply chain operational and disruption risks simultaneously and demonstrating the significant impact of considering disruptive events as well as their likelihoods on the selected supply base are other contributions of this paper.

In this paper, we assumed that disruptions occur independently and calculated the likelihood of scenarios accordingly. However, in the real world, suppliers in close proximity to each other may be simultaneously affected after a disruptive event like an earthquake. Also, geography is not the only factor that causes interdependence between disruptions. Multiple suppliers may be related in some other ways; for example, they may share a common tier-II supplier. Therefore, considering dependent disruptive events is an important possible direction for further research (e.g. see Li et al., 2013). Accounting for multiple concurrent disruptions at suppliers under each scenario (Zobel and Khansa, 2014) and developing new resilience functions for such situations is another research avenue. Extending the proposed model to multi-period horizon case and defining a new resilience objective for this case, is another interesting possible direction for further research. In this direction, since in some cases the disruption could last for multiple inventory cycles, a full recovery of disrupted suppliers could be considered. Lastly, developing an efficient exact method to solve the model especially in large-size instances can be a good direction for further research.

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Appendix A

Linearization process – As mentioned before, the third term of RE' function is non-linear. With expanding this term we would have:

$$\sum_{i\in J\cap\overline{V}_s}\sum_{k\in K}\left(\left(x'_{iks}-\theta_{ie_{is}}x_{ik}\right)\left(LT_i+\sum_{l\in L_{ie}}RT^l_{ie_{is}}RL^l_{ie_{is}}\right)\right)=\sum_{i\in J\cap\overline{V}_s}\sum_{k\in K}LT_i x'_{iks}+\sum_{i\in J\cap\overline{V}_s}\sum_{k\in K}\sum_{l\in L_{ie}}RT^l_{ie_{is}}x'_{iks}RL^l_{ie_{is}}-\sum_{i\in J\cap\overline{V}_s}\sum_{k\in K}LT_i\theta_{ie_{is}}x_{ik}$$
$$-\sum_{i\in J\cap\overline{V}_s}\sum_{k\in K}\sum_{l\in L_{ie}}RT^l_{ie_{is}}\theta_{ie_{is}}x_{ik}RL^l_{ie_{is}} \tag{A-1}$$

As it is obvious, $x'_{iks}RL^l_{ie_{is}}$ and $x_{ik}RL^l_{ie_{is}}$ in the above term are non-linear. To linearize $x'_{iks}RL^l_{ie_{is}}$ we can introduce two new continuous non-negative variables $XPRL_{ikls}$ and $XPRL1_{ikls}$, and the following constraints:

$$XPRL_{ikls}+XPRL1_{ikls}=x'_{iks}\quad \forall i\in J\cap\overline{V}_s,\ k\in K,\ l\in L_{ie_{is}},\ s\in S \tag{A-2}$$

$$XPRL_{ikls}\leqslant M\cdot RL^l_{ie_{is}}\quad \forall i\in J\cap\overline{V}_s,\ k\in K,\ s\in S \tag{A-3}$$

$$XPRL1_{ikls}\leqslant M(1-RL^l_{ie_{is}})\quad \forall i\in J\cap\overline{V}_s,\ k\in K,\ l\in L_{ie_{is}},\ s\in S \tag{A-4}$$

$$XPRL_{ikls}\geqslant 0,\ XPRL1_{ikls}\geqslant 0\quad \forall i\in J\cap\overline{V}_s,\ k\in K,\ l\in L_{ie_{is}},\ s\in S \tag{A-5}$$

Similarly, to linearize $x_{ik}RL^l_{ie_{is}}$ we can introduce two new continuous non-negative variables XRL_{ikls} and $XRL1_{ikls}$, and the following constraints:

$$XRL_{ikls}+XRL1_{ikls}=x_{ik}\quad \forall i\in J\cap\overline{V}_s,\ k\in K,\ l\in L_{ie_{is}},\ s\in S \tag{A-6}$$

$$XRL_{ikls}\leqslant M\cdot RL^l_{ie_{is}}\quad \forall i\in J\cap\overline{V}_s,\ k\in K,\ l\in L_{ie_{is}},\ s\in S \tag{A-7}$$

$$XRL1_{ikls} \leqslant M(1 - RL^{l}_{ie_{is}}) \quad \forall i \in J \cap \overline{V}_s,\ k \in K,\ l \in L_{ie_{is}},\ s \in S \tag{A-8}$$

$$XRL_{ikls} \geqslant 0,\ XRL1_{ikls} \geqslant 0 \quad \forall i \in J \cap \overline{V}_s,\ k \in K,\ l \in L_{ie_{is}},\ s \in S \tag{A-9}$$

Therefore, constraints (A-2)–(A-9) are added to the model and the linearization form of second objection function (RE) is accordingly stated as follows:

$$RE = 1 - \left[\begin{array}{l} \sum_{s\in S} P_s \Big(\sum_{i\in V_s} \sum_{k\in K} LT'_i q'_{iks} + \sum_{i\in J} \sum_{k\in K} LT_i q_{iks} \\ \quad + \sum_{i\in J\cap \overline{V}_s} \sum_{k\in K} LT_i x'_{iks} + \sum_{i\in J\cap \overline{V}_s} \sum_{k\in K} \sum_{l\in L_{ie}} RT^{l}_{ie_{is}} XPRL_{ikls} \\ \quad - \sum_{i\in J\cap \overline{V}_s} \sum_{k\in K} LT_i \theta_{ie_{is}} x_{ik} - \sum_{i\in J\cap \overline{V}_s} \sum_{k\in K} \sum_{l\in L_{ie}} RT^{l}_{ie_{is}} \theta_{ie_{is}} XRL_{ikls} \Big) \end{array}\right] \Big/ QT^{*} \tag{A-10}$$

Also, the right side of constraint (9) is non-linear. We can expand this term as below:

$$\left(\theta_{ie_{is}} + \sum_{u\in U} \beta_{ie_{is}u} y_{iu}\right)\left(1 - \sum_{l\in L_{ie}} RL^{l}_{ie_{is}}\right) = \theta_{ie_{is}} - \sum_{l\in L_{ie}} \theta_{ie_{is}} RL^{l}_{ie_{is}} + \sum_{u\in U} \beta_{ie_{is}u} y_{iu} - \left(\sum_{u\in U} \beta_{ie_{is}u} y_{iu}\right)\left(\sum_{l\in L_{ie}} RL^{l}_{ie_{is}}\right) \tag{A-11}$$

Obviously, $\left(\sum_{u\in U} \beta_{ie_{is}u} y_{iu}\right)\left(\sum_{l\in L_{ie}} RL^{l}_{ie_{is}}\right)$ in above term is also non-linear. Same as before, to linearize it we introduce two new continuous non-negative variables $YRL_{ie_{is}}$ and $YRL1_{ie_{is}}$, and the following constraints:

$$YRL_{ie_{is}} + YRL1_{ie_{is}} = \sum_{u\in U} \beta_{ie_{is}u} y_{iu} \quad \forall s \in S,\ i \in J \cap \overline{V} \tag{A-12}$$

$$YRL_{ie_{is}} \leqslant M \cdot \sum_{l\in L_{ie}} RL^{l}_{ie_{is}} \quad \forall s \in S,\ i \in J \cap \overline{V} \tag{A-13}$$

$$YRL1_{ie_{is}} \leqslant M\left(1 - \sum_{l\in L_{ie}} RL^{l}_{ie_{is}}\right) \quad \forall s \in S,\ i \in J \cap \overline{V} \tag{A-14}$$

$$YRL_{ie_{is}} \geqslant 0,\ YRL1_{ie_{is}} \geqslant 0 \quad \forall s \in S,\ i \in J \cap \overline{V} \tag{A-15}$$

Therefore, constraints (A-12)–(A-15) are added to the model and the linearization form of constraint (9) is stated as follows:

$$\sum_{k\in K} a_{ik} x'_{iks} \leqslant \left[\tilde{\theta}_{ie_{is}}\left(1 - \sum_{l\in L_{ie}} RL^{l}_{ie_{is}}\right) + \sum_{u\in U} \beta_{ie_{is}u} y_{iu} - YRL_{ie_{is}} + \sum_{l\in L_{ie}} CL^{l}_{ie_{is}} RL^{l}_{ie_{is}}\right] Ca_i \quad \forall s \in S,\ i \in J \cap \overline{V}_s \tag{A-16}$$

Appendix B

The two crisp models of our proposed model using the Me measure can be rewritten as follows:

LAM model:

$$\begin{aligned} \text{Min } TC = & \sum_{i\in V} \left(\tfrac{(1-\lambda)}{2} (A_i - \alpha^{A}_i) + \tfrac{A_i}{2} + \tfrac{\lambda}{2} \left(A_i + \beta^{A}_i\right) \right) z_i \\ & + \sum_{i\in V} \sum_{k\in K} \left(\tfrac{(1-\lambda)}{2} (p_{ik} - \alpha^{p}_{ik}) + \tfrac{p_{ik}}{2} + \tfrac{\lambda}{2} (p_{ik} + \beta^{p}_{ik}) \right) x_{ik} \\ & + \sum_{i\in V} \left(\tfrac{(1-\lambda)}{2} (f_i - \alpha^{f}_i) + \tfrac{f_i}{2} + \tfrac{\lambda}{2} (f_i + \beta^{f}_i) \right) z'_i \\ & + \sum_{i\in J} \sum_{u\in U} \left(\tfrac{(1-\lambda)}{2} (FR_{iu} - \alpha^{FR}_{iu}) + \tfrac{FR_{iu}}{2} + \tfrac{\lambda}{2} (FR_{iu} + \beta^{FR}_{iu}) \right) y_{iu} \\ & + \sum_{i\in J} \sum_{k\in K} \left(\tfrac{(1-\lambda)}{2} (h_{ik} - \alpha^{h}_{ik}) + \tfrac{h_{ik}}{2} + \tfrac{\lambda}{2} (h_{ik} + \beta^{h}_{ik}) \right) w_{ik} \\ & + \sum_{s\in S} P_s \Bigg[- \sum_{i\in \overline{V}_s} \sum_{k\in K} \left(\tfrac{(1-\lambda)}{2} (p_{ik} - \alpha^{p}_{ik}) + \tfrac{p_{ik}}{2} + \tfrac{\lambda}{2} (p_{ik} + \beta^{p}_{ik}) \right) (x_{ik} - x'_{iks}) \\ & \qquad + \sum_{i\in V_s} \sum_{k\in K} \left(\tfrac{(1-\lambda)}{2} (p'_{ik} - \alpha^{p'}_{ik}) + \tfrac{p'_{ik}}{2} + \tfrac{\lambda}{2} (p'_{ik} + \beta^{p'}_{ik}) \right) q'_{iks} \\ & \qquad + \sum_{i\in J} \sum_{k\in K} \left(\tfrac{(1-\lambda)}{2} (p_{ik} - \alpha^{p}_{ik}) + \tfrac{p_{ik}}{2} + \tfrac{\lambda}{2} (p_{ik} + \beta^{p}_{ik}) \right) q_{iks} \Bigg] \end{aligned}$$

$$\text{Max } RE = 1 - \left[\sum_{s\in S} P_s \left(\sum_{i\in V_s}\sum_{k\in K} LT'_i q'_{iks} + \sum_{i\in J}\sum_{k\in K} LT_i q_{iks} + \sum_{i\in J\cap\overline{V}_s}\sum_{k\in K} LT_i x'_{iks} + \sum_{i\in J\cap\overline{V}_s}\sum_{k\in K}\sum_{l\in L_{ie}} RT^l_{ie_{is}} XPRL_{ikls} - \sum_{i\in J\cap\overline{V}_s}\sum_{k\in K} LT_i \theta_{ie_{is}} x_{ik} - \sum_{i\in J\cap\overline{V}_s}\sum_{k\in K}\sum_{l\in L_{ie}} RT^l_{ie_{is}} \theta_{ie_{is}} XRL_{ikls}\right)\right] \Big/ QT^*$$

s.t.

$$\sum_{i\in V_s}(x_{ik} + q'_{iks}) + \sum_{i\in\overline{V}_s} x'_{iks} + \sum_{i\in J} q_{iks} \geqslant d_k + (1-\delta_1)\beta^d_k \quad \forall s\in S,\ k\in K$$

$$\sum_{i\in V_s}\left(\varphi_{ik} + (1-\delta_5)\beta^{\rho}_{ik}\right)(x_{ik} + q'_{iks}) + \sum_{i\in\overline{V}_s}(\varphi_{ik} + (1-\delta_5)\beta^{\rho}_{ik})x'_{iks} + \sum_{i\in J}(\varphi_{ik} + (1-\delta_5)\beta^{\rho}_{ik})q_{iks}$$
$$\leqslant R_k\left[\sum_{i\in V_s}(x_{ik} + q'_{iks}) + \sum_{i\in\overline{V}_s} x'_{iks} + \sum_{i\in J} q_{iks}\right] \quad \forall s\in S,\ k\in K$$

+ other crisp constraints.

UAM model:

$$\begin{aligned}
\text{Min } TC = & \sum_{i\in V}\left(\tfrac{(1-\lambda)}{2}(A_i - \alpha^A_i) + \tfrac{A_i}{2} + \tfrac{\lambda}{2}(A_i + \beta^A_i)\right) z_i \\
& + \sum_{i\in V}\sum_{k\in K}\left(\tfrac{(1-\lambda)}{2}(p_{ik} - \alpha^p_{ik}) + \tfrac{p_{ik}}{2} + \tfrac{\lambda}{2}(p_{ik} + \beta^p_{ik})\right) x_{ik} \\
& + \sum_{i\in V}\left(\tfrac{(1-\lambda)}{2}(f_i - \alpha^f_i) + \tfrac{f_i}{2} + \tfrac{\lambda}{2}(f_i + \beta^f_i)\right) z'_i \\
& + \sum_{i\in J}\sum_{u\in U}\left(\tfrac{(1-\lambda)}{2}(FR_{iu} - \alpha^{FR}_{iu}) + \tfrac{FR_{iu}}{2} + \tfrac{\lambda}{2}(FR_{iu} + \beta^{FR}_{iu})\right) y_{iu} \\
& + \sum_{i\in J}\sum_{k\in K}\left(\tfrac{(1-\lambda)}{2}(h_{ik} - \alpha^h_{ik}) + \tfrac{h_{ik}}{2} + \tfrac{\lambda}{2}(h_{ik} + \beta^h_{ik})\right) w_{ik} \\
& + \sum_{s\in S} P_s \Bigg[-\sum_{i\in\overline{V}_s}\sum_{k\in K}\left(\tfrac{(1-\lambda)}{2}(p_{ik} - \alpha^p_{ik}) + \tfrac{p_{ik}}{2} + \tfrac{\lambda}{2}(p_{ik} + \beta^p_{ik})\right)(x_{ik} - x'_{iks}) \\
& \qquad + \sum_{i\in V_s}\sum_{k\in K}\left(\tfrac{(1-\lambda)}{2}(p'_{ik} - \alpha^{p'}_{ik}) + \tfrac{p'_{ik}}{2} + \tfrac{\lambda}{2}(p'_{ik} + \beta^{p'}_{ik})\right) q'_{iks} \\
& \qquad + \sum_{i\in J}\sum_{k\in K}\left(\tfrac{(1-\lambda)}{2}(p_{ik} - \alpha^p_{ik}) + \tfrac{p_{ik}}{2} + \tfrac{\lambda}{2}(p_{ik} + \beta^p_{ik})\right) q_{iks}\Bigg]
\end{aligned}$$

$$\text{Max } RE = 1 - \left[\sum_{s\in S} P_s \left(\sum_{i\in V_s}\sum_{k\in K} LT'_i q'_{iks} + \sum_{i\in J}\sum_{k\in K} LT_i q_{iks} + \sum_{i\in J\cap\overline{V}_s}\sum_{k\in K} LT_i x'_{iks} + \sum_{i\in J\cap\overline{V}_s}\sum_{k\in K}\sum_{l\in L_{ie}} RT^l_{ie_{is}} XPRL_{ikls} - \sum_{i\in J\cap\overline{V}_s}\sum_{k\in K} LT_i \theta_{ie_{is}} x_{ik} - \sum_{i\in J\cap\overline{V}_s}\sum_{k\in K}\sum_{l\in L_{ie}} RT^l_{ie_{is}} \theta_{ie_{is}} XRL_{ikls}\right)\right] \Big/ QT^*$$

s.t.

$$\sum_{i\in V_s}(x_{ik} + q'_{iks}) + \sum_{i\in\overline{V}_s} x'_{iks} + \sum_{i\in J} q_{iks} \geqslant d_k - (1-\delta_6)\alpha^d_k \quad \forall s\in S,\ k\in K$$

$$\sum_{i\in V_s}\left(\varphi_{ik} - (1-\delta_{10})\alpha^{\rho}_{ik}\right)(x_{ik} + q'_{iks}) + \sum_{i\in\overline{V}_s}(\varphi_{ik} - (1-\delta_{10})\alpha^{\rho}_{ik})x'_{iks} + \sum_{i\in J}(\varphi_{ik} - (1-\delta_{10})\alpha^{\rho}_{ik})q_{iks}$$
$$\leqslant R_k\left[\sum_{i\in V_s}(x_{ik} + q'_{iks}) + \sum_{i\in\overline{V}_s} x'_{iks} + \sum_{i\in J} q_{iks}\right] \quad \forall s\in S,\ k\in K$$

+ other crisp constraints.

Appendix C

In order to validate the proposed DE algorithm, it is compared with CPLEX solver. To this end, twenty test problems in different sizes were generated randomly. Table B1 shows the basic characteristics of the test problems. In this table, each problem is specified by four components. The first component denotes the number of items, the second and third ones refer to the number of suppliers and number of first group suppliers and the fourth component indicates the number of disruptive events in each supplier. For example, $3 \times 2 \times 1 \times 2$ denotes a problem with 3 items, 2 suppliers, 1 first group supplier, and 2

Table B1
Basic characteristics of the test problems.

No. of test problem	Problem specifications	No. of scenarios	No. of constraints	No. of continuous variables	No. of binary variables
1	$2 \times 3 \times 2 \times 2$	27	1379	704	44
2	$2 \times 3 \times 2 \times 3$	64	3699	1780	104
3	$3 \times 4 \times 1 \times 2$	81	6737	3402	118
4	$3 \times 4 \times 1 \times 3$	256	24,085	11,547	394
5	$4 \times 4 \times 1 \times 3$	256	30,916	15,136	394
6	$4 \times 5 \times 2 \times 2$	243	39,734	21,752	662
7	$6 \times 4 \times 1 \times 3$	256	45,090	22,314	394
8	$6 \times 4 \times 2 \times 4$	625	181,473	86,550	2,012
9	$8 \times 4 \times 2 \times 3$	256	86,913	44,606	780
10	$8 \times 6 \times 3 \times 2$	729	310,783	175,052	2934
11	$10 \times 4 \times 2 \times 4$	625	296,449	141,574	2012
12	$10 \times 7 \times 4 \times 2$	2187	1,444,341	832,652	11,686
13	$12 \times 5 \times 3 \times 3$	1024	717,991	374,898	4624
14	$12 \times 6 \times 4 \times 2$	729	549,397	317,014	3908
15	$15 \times 5 \times 2 \times 3$	1024	689,357	355,705	3086
16	$15 \times 10 \times 5 \times 1$	1024	968,707	624,897	5150
17	$18 \times 4 \times 2 \times 4$	625	526,401	251,622	2012
18	$18 \times 10 \times 5 \times 1$	1024	1,159,168	747,822	5150
19	$20 \times 6 \times 3 \times 2$	729	753,247	428,852	2934
20	$20 \times 10 \times 5 \times 1$	1024	1,286,142	829,772	5150

Table B2
Range of uniform distributions used to generate test problems' parameters.

Parameter	Range of uniform distribution	Parameter	Range of uniform distribution
d_k	[100, 400]	LT'_i	$[5, 15] + LT_i$
A_i	[400, 1000]	π_{ie}	[0.1, 0.4]
$p_{ik};\ i \in I$	[5, 20]	θ_{ie}	[0.2, 0.6]
$p_{ik};\ i \in J$	$[1, 3] + p_{ik};\ i \in I$	β_{ie1}	[0.05, 0.1]
f_i	[700, 1200]	β_{ie2}	$0.05 + \beta_{ie1}$
$FR_{i1};\ i \in J$	[200, 1000]	$RT^1_{ie_{is}}$	[30, 40]
$FR_{i2};\ i \in J$	$[300, 500] + FR_{i1}$	$RT^2_{ie_{is}}$	$10 + RT^1_{ie_{is}}$
$h_{ik};\ i \in J$	[1, 3]	CL^1_{ie}	0.6
Ca_i	[400, 1000]	CL^2_{ie}	0.8
φ_{ik}	[0.05, 0.15]	a_{ik}	[1, 2]
R_k	[0.1, 0.2]	b_{ik}	[2, 3]
LT_i	[30, 50]	n	2

Table B3
Comparative results for the first objective between CPLEX and the proposed DE algorithm.

No. of test problem	CPLEX			DE algorithm			RD%
	Result	Best possible	CPU time (s)	Average	Best result	CPU time (s)	
1	7200	7180	16	7591	7576	18	5.22
2	33,432	30,256	406	35,878	35,047	289	4.83
3	48,222	42,653	1019	52,128	51,025	434	5.81
4	22,545	20,647	6837	21,952	21,573	892	−2.63
5	47,016	42,048	5822	48,058	47,016	972	0
6	33,563	30,778	7483	36,489	34,199	1201	1.89
7	52,145	48,949	4237	57,449	54,874	1653	5.23
8	64,712	57,155	15,309	67,371	66,376	1732	2.57
9	60,388	56,869	9750	63,834	62,275	2084	3.12
10	99,340	96,943	12,931	105,709	101,613	2407	2.29
11	110,902	102,146	14,796	123,512	116,332	1967	4.90
12	NA[a]	NA	36,000	137,020	128,682	3833	_
13	184,948	166,406	21,362	177,191	169,973	2571	2.14
14	124,985	117,324	36,000	133,168	131,662	3008	5.34
15	270,926	250,476	17,240	277,672	275,084	3479	1.53
16	195,301	101,756	36,000	209,884	201,713	4962	−3.29
17	188,940	175,807	12,043	202,987	197,191	3201	4.37
18	201,865	129,565	36,000	191,873	186,679	5099	−0.75
19	152,769	136,523	27,183	161,694	157,387	4147	3.02
20	169,507	95,146	36,000	159,456	152,381	5317	−1.01

[a] Solution is not achieved in 10 h.

disruptive events in each supplier. Also, number of scenarios, constraints, continuous and binary variables for each test problem is shown in Table B1. Other test problems parameters are generated randomly based on uniform distributions which are reported in Table B2. Notably, all parameters of the test problems in the validation phase were considered as crisp (i.e. deterministic) data. Also, the T^{*} in each test problem is considered bigger than the biggest lead time plus the biggest recovery time. The DE algorithm was coded in MATLAB R2009a and CPLEX 10.0 solver in General Algebraic Modeling System (GAMS) was used to solve the test problems in a PC with Intel Core i5 CPU, 2.53 GHz and 6 GB of RAM. Furthermore, linearization process and transforming the original possibilistic model to its crisp counterpart were discussed in the paper. CPLEX solver was used to solve the linearized model and crisp counterpart to optimality while the designed meta-heuristic solves the non-linear crisp counterpart directly.

For a better comparison, the proposed DE algorithm was initially run with the aim of minimizing the first and second objectives and then it was run with the aim of minimizing augmented ε-constraint method's objective for the fifth, tenth, fifteenth and twentieth test problems. Tables B2–B5 show the comparative results between CPLEX and the proposed DE

Table B4
Comparative results for the second objective between CPLEX and the proposed DE algorithm.

No. of test problem	CPLEX			DE algorithm			RD%
	Result	Best possible	CPU time (s)	Average	Best result	CPU time (s)	
1	0.734	0.797	132	0.734	0.734	16	0.00
2	0.383	0.467	853	0.350	0.357	342	6.79
3	0.667	0.697	1482	0.646	0.654	381	1.95
4	0.373	0.406	5439	0.366	0.383	853	−2.68
5	0.380	0.465	4651	0.363	0.380	1143	0.00
6	0.743	0.773	9564	0.728	0.733	1591	1.35
7	0.654	0.669	5204	0.632	0.647	1949	1.07
8	0.639	0.687	13,365	0.604	0.618	2074	3.29
9	0.730	0.757	12,994	0.701	0.713	2504	2.33
10	0.871	0.896	14,594	0.857	0.863	2662	0.92
11	0.466	0.595	13,869	0.361	0.431	2094	7.51
12	0.714	0.893	36,000	0.845	0.847	4256	−18.63
13	0.921	0.935	19,840	0.837	0.857	2608	6.95
14	0.887	0.907	28,122	0.877	0.883	3734	0.45
15	0.611	0.681	20,294	0.577	0.611	3629	0.00
16	0.944	0.966	36,000	0.944	0.949	4438	−0.53
17	0.535	0.914	36,000	0.806	0.839	4182	−56.82
18	0.710	0.842	36,000	0.805	0.806	5724	−13.52
19	NA[a]	NA	36,000	0.772	0.776	4810	–
20	0.777	0.899	36,000	0.799	0.804	5471	−3.47

[a] Solution is not achieved in 10 h.

Table B5
Comparative results for the augmented ε-constraint method's objective between CPLEX and the proposed method.

No. of test problem	l	CPLEX			DE algorithm			RD%
		Result	Best possible	CPU time (s)	Average	Best result	CPU time (s)	
5	0	47,016	42,048	6158	48,053	47,016	1037	0
	1	54,752	50,636	7721	56,361	55,281	1151	0.97
	2	62,347	55,290	9336	65,026	64,952	1294	4.18
	3	67,134	61,810	10,974	79,966	68,104	1614	1.44
	4	71,076	65,787	17,096	75,903	74,603	2577	4.96
10	0	99,339	96,941	12,995	105,712	101,613	2653	2.29
	1	107,187	99,447	15,761	109,258	111,063	2712	3.62
	2	112,139	103,109	15,258	114,852	116,936	3651	4.28
	3	118,113	101,696	17,158	122,039	123,260	4775	4.36
	4	121,501	114,402	21,963	126,393	128,102	4818	5.43
15	0	270,926	261,903	19,361	277,643	275,084	3640	1.53
	1	273,338	265,985	20,281	287,693	286,511	3872	4.82
	2	281,966	271,086	22,988	295,959	293,523	4962	4.10
	3	289,897	273,890	27,948	317,590	308,305	5614	6.35
	4	387,639	191,935	36,000	327,438	324,598	6879	−1.62
20	0	173,139	95,146	36,000	160,995	157,935	6440	−8.78
	1	190,757	875,426	36,000	169,704	161,571	6753	−15.30
	2	NA[a]	NA	36,000	173,392	171,249	6524	_
	3	NA	NA	36,000	185,224	179,746	6702	_
	4	NA	NA	36,000	194,980	190,575	6336	_

[a] Solution is not achieved in 10 h.

algorithm for the first, second and ε-constraint model's objectives, respectively. The DE algorithm has been run ten times for each test problem, and the best and the average of the obtained solutions have been reported. In the augmented ε-constraint method, we consider the first objective as the most important objective and the second objective is added to constraints.

The comparison was performed by defining the relative deviation (RD) of the proposed DE's solution from the CPLEX solution. In Tables B3 and B5, the RD is defined as:

$$\mathrm{RD} = \frac{\text{proposed DE's best result} - \text{CPLEX result}}{\text{CPLEX result}}$$

To calculate RD in Table B4, the above formula is multiplied to a minus.

In Tables B3 and B5, the solutions and CPU times for each problem are compared for proposed DE algorithm and the CPLEX which is operated in GAMS. The results show that the relative deviation of the results of the proposed DE from the CPLEX solution is less than 0.08 in all test problems. In some cases, the DE algorithm gets the CPLEX solution or even produces better solution. Also, in the most cases, CPU time of the DE algorithm is less than that of the CPLEX and the proposed DE algorithm is much faster than CPLEX.

Appendix D

This appendix shows uniform distributions used to generate the required imprecise and crisp parameters in Section 6.2.

The uniform distributions used to generate the center of symmetric fuzzy parameters

Parameter	Respective uniform distribution
$\tilde{d}_k$	$5000 \times Ui[1,5]$
$\widetilde{A}_i$	$100 \times Ui[5,10]$
$\tilde{p}_{ik};\ i \in I$	$Ui[5,10]$
$\tilde{p}_{ik};\ i \in J$	$Ui[11,15]$
$\tilde{p}'_{ik}$	$\widetilde{p_{ik}} + 10$
$\tilde{f}_i$	$1000 \times Ui[5,10]$
$\widetilde{FR}_{i1}$	$2000 \times Ui[5,10]$
$\widetilde{FR}_{i2}$	$FR^m_{i1} + 5000$
$\tilde{h}_{ik}$	$Ui[1,3]$

The uniform distributions used to generate crisp parameters

Parameter	Respective uniform distribution
$LT_i;\ i \in I$	$10 \times Ui[6,7]$
$LT_i;\ i \in J$	$10 \times Ui[4,5]$
LT'_i	$LT_i + 10$
π_{ie}	$U[0.01,0.05]$
θ_{ie}	$U[0,0.6]$
a_{ik}	$Ui[1,3]$
Ca_i	$\lceil \sum_{k\in K} a_{ik}(1.7d^m_k) \times U[0.7,1.3] \rceil$
Sc_i	Ca_i
b_{ik}	$Ui[1,3]$
β_{ie1}	$U[0.05,0.1]$
β_{ie2}	$\beta_{ie1} + 0.05$
$RT^1_{ie_{is}}$	$10 \times Ui[2,3]$
$RT^2_{ie_{is}}$	$RT^1_{ie_{is}} + 10$
T^*	120
CL^1_{ie}	0.8
CL^2_{ie}	1
n	3

where $Ui[a, b]$ is a random integer number generator within the range $[a, b]$ and $U[a, b]$ is a operator that chooses a random number within the range $[a, b]$.

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