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ORIGINAL RESEARCH

A hybrid approach for resilient sourcing and supply chain network design

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Abstract
In the face of increasing global uncertainties and the growing vulnerability of supply chains to disruptions, designing resilient supply chains has emerged as a critical challenge for modern businesses. We aim to present a novel two-phase hybrid approach for designing a supply chain resilient to major disruptions and operational interruptions. The first phase of the proposed approach focuses on evaluating the supplier performance using a unified data envelopment analysis model. Using the obtained scores, the second phase then determines outsourcing and network design decisions using a stochastic robust bi-objective optimization model. The optimization model minimizes the total supply chain cost and maximizes the overall supplier performance. To enhance the supply chain resilience, a number of reactive and proactive risk mitigation strategies are incorporated in the model. These strategies include multiple sourcing, facility fortification, the use of substitutable products, extra production capacities, and holding safety stock inventory. An accelerated Benders decomposition algorithm is developed to solve the proposed model. The application of the proposed model and approach is investigated using data from a real case study. The practical results and their implications are discussed. Our analyses focus on (1) exploring the relationship between supplier performance level and supply chain cost, (2) examining the impact of the unified data envelopment analysis model on sourcing decisions, (3) evaluating the effectiveness of resilience strategies, (4) analyzing the advantages of the proposed solution approach for solving problems of different sizes and (5) assessing the performance of the proposed stochastic programming approach.

Keywords Supplier evaluation and selection · Sourcing · Supply chain network design · Disruption risk · Data envelopment analysis · Benders decomposition

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1 Introduction

Supply chain network design (SCND) decisions are strategic in nature and include decisions such as determining the number, location and capacity of the facilities and the technologies to be adopted in these facilities to optimally match supply with demand (Sabouhi et al., 2020; Sadghiani et al., 2015). The rapid globalization and increasing interdependencies among supply chain (SC) entities make effective SCND decisions more critical than ever. Since such decisions are costly and often irreversible, SC networks are designed with a long-term perspective and should therefore be robust to potential disruptions and external uncertainties (Snyder et al., 2007). According to Tang (2006) and Esmaeilikia et al. (2016), there exist two types of risks facing a SC. The first type is frequent interruptions or operational risks related to intrinsic uncertainties such as variations in costs and demand. The second type is termed as disruption risks arising from unexpected natural and/or man-made disasters like strikes, floods, and earthquakes.

Disruption risks are rare events with devastating effects. Operational risks have less detrimental consequences, but may occur more frequently. As a result, in most situations, the impact of major disruptions is more pronounced than that of frequent interruptions. Today's SCs are more vulnerable to disruptions due to just-in-time outsourcing and distribution and lean practices (Cardoso et al., 2015). The floods in Iraq (2018), Philippines (2013) and Thailand (2011), the tsunami in Japan (2011), and the earthquakes in Iran (2018), Pakistan (2013) and Chili (2011 and 2015) are recent examples of such catastrophic disasters. The occurrence probability of such disasters is often unknown; hence, the best approach would be to minimize the adverse impacts by designing more resilient SCs (Jabbarzadeh et al., 2016).

A resilient SC refers to a SC that is capable of absorbing disruptions and maintaining operations at some level (Bhamra et al., 2011). A major challenge in designing a resilient SC is predicting the probability of a disaster occurrence due to the lack of historical data from preceding disasters (Jabbarzadeh et al., 2016). The interaction between disruption and operational risks can further add to this complexity. In this context, the ability of SCs to rapidly adapt to unforeseen circumstances and recover to optimal operational levels is considered one of the key success factors in complex and uncertain environments. These challenges reinforce the necessity to design SC networks that can operate sustainably under disruptions and frequent interruptions. The design and planning of such SCs is an emerging research topic in the SC literature (Fahimnia et al., 2015; Jabbarzadeh et al., 2018a).

Another trend in today's SCs is the shift toward more intense outsourcing to minimize supply costs. Outsourcing certain operations can contribute to a SC's competitive advantage by allowing a firm to focus on core competencies that distinguish the company from its competitors (Schoenherr et al., 2012). Selecting and managing the supply base is a challenging task (Mari et al., 2019). Supplier selection and order allocation (SS&OA) problem aims to choose the best suppliers and optimally distribute total orders among the selected suppliers so as to satisfy the given requirements (Ho et al., 2010). Supplier evaluation is a multi-criteria decision problem with conflicting factors that has significant impact on the SS&OA outcomes (Tavana et al., 2023). In academic literature, there are different models for evaluating suppliers (Aashi & Rajesh, 2023). Due to the increasing reliance on global suppliers, managing SS&OA under disruption risks is becoming paramount.

Research efforts on resilient SC design predominantly focus on managing facility disruptions disregarding SS&OA decisions and potential disruptions at the supplier side. However, outsourcing and supplier disruptions are common phenomena in global SCs (Torabi et al., 2015). Supplier disruptions in the aftermath of an earthquake in Japan (2011) incurred substantial losses for many electronics firms such as Apple Japan due to shortage of key manufacturing components (Fuller, 2012). Evaluating supplier performance is vital for designing resilient SCs under disruption risks, particularly in cases of facility or supplier failures. In uncertain environments, identifying reliable suppliers who can maintain performance under such risks ensures SC stability. Without a proper evaluation framework, SCs face risks like poor quality, delays, or even complete supplier disruptions. A comprehensive supplier performance assessment guides decision-making by identifying the most resilient and cost-efficient options. This is especially critical for SCs that rely heavily on outsourced components or services, as supplier performance directly influences overall resilience. Given the strategic significance of outsourcing decisions in today's SCs, it is essential to integrate SCND and SS&OA problems (which have been historically studied in isolation) to demonstrate the "real impact" of risk reduction strategies and the role of supplier performance evaluation on the overall resilience of the SC.

To tackle these challenges, we develop a hybrid methodology for designing a resilient SC network under facility and supplier disruption risks. A two-phase optimization approach is proposed. In Phase 1, a unified data envelopment analysis (DEA) model is utilized to assess the performance of the available suppliers under disruption risks. This evaluation enables decision-makers to effectively identify and rank suppliers according to input and output criteria, while excluding those with lower performance from the candidate list. Using the supplier evaluation results from Phase 1, a stochastic robust bi-objective optimization approach is utilized in Phase 2 to maximize the overall supplier performance under disruptions and minimize the total SC costs. The developed model is transformed into a single-objective model and the resulting model is solved using a combination of the ε-constraint method and the accelerated Benders decomposition algorithm (BDA). The implementation of our methodology is examined utilizing actual data from a degradable plastic bag industry.

The remainder of the study is presented as below. Section 2 reviews the relevant literature. Problem statement and mathematical models are provided in Sect. 3. The proposed solution approach is outlined in Sect. 4. The case problem and analysis of the numerical results are described in Sect. 5. Section 6 discusses the findings and their implications. In Sect. 7, final remarks and future directions in this field are presented.

2 Literature review

In spite of the increasing research on resilient SC design, only few studies have focused on developing and testing resilience strategies (RSs) to manage random disruptions. A summary of the RSs that have been predominantly used in the previous studies and their effect on SC performance under disruptions is presented in Table 1. For an extensive review of the literature in the area of resilience SC design, valuable sources include Xu et al., (2020), Hosseini et al., (2019a) and Bier et al., (2020).

Most of these studies address SS&OA problem and overlook the consequent impacts on SCND decisions. For example, Meena and Sarmah (2013) proposed a mathematical model to determine order allocation under supply disruptions that also accounts for price discounts. Kamalahmadi and Mellat-Parast (2016) presented a stochastic programming model that integrates supply base selection, transportation channel selection and order allocation in the face of regional and supplier disruptions. The authors presented contingency plans to minimize the expected total costs and reduce the adverse effects of disruptions. Lee (2017) formulated a multi-objective model to optimize the order allocation and emergency capacity for each

Table 1 Literature classification according to the RSs adopted

RS	Definition	Impact on SC performance	Related articles
Multiple sourcing	Using various suppliers to serve each facility	Reducing the dependence on a single sourcing and improving the SC redundancies	Sabouhi et al. (2018), Dehghani et al. (2018), Jabbarzadeh et al. (2018a), Hasani and Khosrojerdi (2016), Kamalahmadi and Mellat-Parast (2016), Namdar et al. (2018), Meena and Sarmah (2013), Sabouhi et al. (2021)
Facility fortification	Equipping facilities with protection systems	Minimizing facility vulnerability against disruptions	Sabouhi et al. (2018), Dehghani et al. (2018), Jabbarzadeh et al. (2016), Fattahi et al. (2017), Azad et al. (2013), Torabi et al. (2015), Sawik (2013b), Sawik (2013a), Hasani and Khosrojerdi (2016), Sabouhi et al. (2021), Alikhani et al. (2023), Taghavi et al. (2023a), Taghavi et al. (2023b), Shi and Ni (2024)
Using substitutable products/component	Using a comparable or similar product to fulfill the demands when the original product is not available	Addressing product supply shortage in the face of disruptions	Dehghani et al. (2018), Hasani and Khosrojerdi (2016), Sabouhi et al. (2021)
Adding extra production capacity	Expanding the existing production capacities	Addressing production capacity shortage in random disruptions	Vahidi et al. (2018), Jabbarzadeh et al. (2018a), Kamalahmadi and Mellat-Parast (2016), Nayeri et al. (2022), Aldrighetti et al. (2023), Hosseinitabar et al. (2024)
Holding safety stock inventory	Storing an extra quantity of products in facilities	Compensating product shortage in facility disruptions	Sawik (2013a), Sawik (2013b), Sabouhi et al. (2018), Lee (2017), Hasani and Khosrojerdi (2016), Torabi et al. (2015), Sabouhi et al. (2021), Alikhani et al. (2023), Fazel et al. (2023), Torshizi et al. (2024), Safari et al. (2024), Feng et al. (2023)

supplier considering multiple-breakpoint quantity discount and supply failure risks. Hosseini et al. (2019b) applied a probabilistic graphical model to calculate the probability of disruption scenarios for SS&OA problem. They proposed a stochastic bi-objective model to consider supplier reliability, extra supply capacities and backup sourcing. Utilizing conditional value at risk measure, Sawik (2013a), (2013b), Namdar et al., (2018) studied a resilient SS&OA problem to cope with supply disruptions. Taghavi et al., (2023b) also employed this measure to propose a two-stage stochastic programming model for green and resilient SS&OA, incorporating vehicle routing. The abovementioned studies focus on strategic aspects disregarding the operational risk considerations.

A bi-objective mixed possibilistic, stochastic optimization model was proposed by Torabi et al., (2015) for design of a SC that accounts for operational and disruption risks. The model incorporated resilient strategies such as safety buffer, multi-sourcing and supplier fortification. In a similar study, a bi-objective mixed possibilistic-stochastic programming model was presented by Vahidi et al., (2018) to design a sustainable and resilient supply base to respond to disruption and operational risks. Considering quantity discounts and efficiency of suppliers, Sabouhi et al., (2018) presented a hybrid methodology according to fuzzy DEA and mathematical programming techniques for designing a SC resilient to some of the major disruptions and operational interruptions. Jabbarzadeh et al., (2018a) presented a stochastic bi-objective programming model for determining outsourcing decisions in a multi-echelon SC accounting for resilient strategies to mitigate disruptions at factories and suppliers. The model aimed to minimize the effects of random disruptions on the sustainability performance of a SC. Using conditional value at risk measure, Taghavi et al., (2023a) introduced a two-stage fuzzy-stochastic programming model for a resilient supply portfolio selection, incorporating lead-time-sensitive manufacturers. A two-stage distributionally robust model was proposed by Feng et al., (2023) to address SS&OA problem under risk-averse criterion.

On the other hand, numerous studies concentrate on the design of resilient SC networks under facility disruptions. Examples include the works of Jabbarzadeh et al., (2016), Fattahi et al., (2017), Dehghani et al., (2018), Nayeri et al., (2022), Alikhani et al., (2023), Shi and Ni, (2024), and Fazel et al., (2023). However, none of these works take SS&OA decisions and supply disruptions into account. This limitation has led to the development of models that integrate SS&OA and SCND problems to enhance resilience at the SC level. For instance, an optimization model was proposed by Hasani and Khosrojerdi, (2016) to design robust global SC networks under strategic disruptions and operational interruptions. The study investigated a medical SC network to test a metaheuristic algorithm to solve the problem. Sabouhi et al., (2020) presented a stochastic optimization model for the design of a resilient SC operating under disruptions at DCs, factories, suppliers and transportation links. They developed a multi-cut L-shaped method for solving the model.

In a multi-echelon SC, Aldrighetti et al., (2023) presented a model to design an efficient resilience portfolio. Utilizing an actual-life case problem, they showed that their model enables enhancing resilience at minimal costs by identifying an optimal combination of recovery and preparedness investments. A multi-mode, multi-product, and multi-objective mathematical model was introduced by Torshizi et al., (2024) for designing a sustainable and resilient global COVID-19 vaccine SC, integrating forward and reverse chains for vaccine distribution and waste management. Safari et al., (2024) formulated a multi-objective robust model to design a multi-product resilient sustainable SC under supply disruptions. Despite these advancements, most studies overlook the critical role of supplier performance evaluation for resilient sourcing and SCND under disruption and operational risks.

This paper makes significant contributions to the existing literature. First, it presents a hybrid approach that integrates SS&OA and SCND decisions to build resilience at the broader SC level. Unlike the previous efforts, this approach enables decision makers to explicitly assess the performance of suppliers utilizing a novel DEA methodology. Second, a robust bi-objective optimization model is presented that is able to address both operational and disruption risks using different RSs. The developed model also is able to consider different types of disruptions (i.e., partial and complete) at different SC levels (i.e., suppliers, distribution centers (DCs), and factories). Third, an accelerated BDA is developed that is able to manage the computational complexity of the problem as the number of disruption scenarios increases. Finally, a real case study of degradable plastic bag industry is proposed to examine the real-world application of the developed hybrid approach. Table 2 better describes the positioning of this study in comparison to existing literature.

3 Methodology

The problem under investigation is discussed in this section. The raw materials are shipped from the suppliers to the factories. The manufactured items are then transported from the factories to the customer locations through a set of DCs. There are existing factories in different regions. New factories and DCs with different capacity levels (CLs) can be opened in potential locations. So as to replicate the reality, we assume that the suppliers, DCs and factories are subject to disruptions. A disruption at each facility may incur a capacity loss, resulting in either partial capacity loss or complete shutdown of that facility. As previously defined in Table 1, the following RSs can be undertaken to deal with disruption risks.

- Multiple sourcing: Multiple suppliers can be assigned to each factory.
- Facility fortification: Suppliers, factories and DCs can be Equipped with protection systems at different levels. It is assumed that fortification helps improve the effect of disruptions depending on the level of investment. A facility with higher fortification costs/investment is better protected against disruptions. We regard the fortification cost/investment is a linear function of the fortification degree.
- Extra production capacity: It is possible to expand the existing production capacities to offset the lost capacities during disruptions.
- Safety stock inventory: DCs can keep a pre-specified quantity of products as safety stock inventory to cope with demand fluctuations.
- Substitutable products: It is possible to use a substitutable product to meet the demands in situations when the original product is unavailable.

Furthermore, to account for operational risks, it is assumed that some of the key input parameters including customer demand, cost parameters, and the percentage of lost capacities in facilities during disruptions are uncertain.

In the proposed model, decisions to be made are (1) the suppliers to work with, (2) the number, the capacity and location of DCs and factories, (3) the required fortification level of each facility, (4) the inventory levels in the DCs, (4) the amount of capacity expansion in the existing factories, (5) the flow of products and raw materials between different facilities, and (6) the lost sales incurred in customer locations.

We propose a hybrid methodology according to mathematical programming techniques and unified DEA. Phase 1 evaluates the performance of suppliers according to a set of input and output criteria. Outputs are categorized into undesirable and desirable measures. After evaluating the performance of each supplier using these measures, this phase allocates a performance score to each supplier. According to the achieved scores, the weaker suppliers are identified and removed from the list of candidate suppliers. In Phase 2, a stochastic robust

Table 2 The published models and their key features: The resilient SC design literature

References	Problem Type		Type of risk		Disruption area			RSs	Type of model		Solution approach		Approach	Case study
	SS&OA	ND	Operational	Disruption	Suppliers	Factories	DCs		Multi-objective	Single objective	Heuristics\ Meta-heuristics	Exact		
Sawik (2013a) and Sawik (2013b)	✓			C	✓			H, F		✓				
Meena and Sarmah (2013)	✓			C	✓			M		✓	✓			
Torabi et al. (2015)	✓		PP, SP	P, C	✓			H, F, CO	✓		✓			
Kamalahmadi and Mellat-Parast (2016)	✓			C	✓			A, M		✓				
Hasani and Khosrojerdi (2016)	✓	✓	RO	P, C	✓	✓	✓	M, F, H, U		✓	✓			ME
Lee (2017)	✓			C	✓			H, CO	✓					
Namdar et al. (2018)	✓			P, C	✓			M		✓				

Table 2 (continued)

References	Problem Type		Type of risk		Disruption area			RSs	Type of model		Solution approach		Approach	Case study
	SS&OA	ND	Operational	Disruption	Suppliers	Factories	DCs		Multi-objective	Single objective	Heuristics\ Meta-heuristics	Exact		
Vahidi et al. (2018)	✓		PP	P, C	✓			A, CO	✓		✓		HY	AU
Jabbarzadeh et al. (2018a)	✓			P, C	✓	✓		A, M, CO	✓				HY	PL
Sabouhi et al. (2018)	✓		PP, SP	P, C	✓			H, F, M		✓			HY	PH
Hosseini et al. (2019b)	✓			P, C	✓			A, M, CO	✓					
Sabouhi et al. (2020)	✓	✓		P, C	✓	✓		A, M, CO		✓		✓		I
Nayeri et al. (2022)		✓	PP, SP RO	P, C	✓	✓	✓	A, M, CO		✓				ME
Alikhani et al. (2023)		✓	SP	P, C	✓		✓	H, F, D		✓				R
Aldrighetti et al. (2023)	✓	✓		C	✓	✓		A, F, CO		✓	✓			PC
Taghavi et al. (2023b)	✓			P, C	✓			M, F, H		✓				
Taghavi et al. (2023a)	✓		PP, SP	P, C	✓			M, F, H		✓				

Table 2 (continued)

References	Problem Type		Type of risk		Disruption area			RSs	Type of model		Solution approach		Approach	Case study
	SS&OA	ND	Operational	Disruption	Suppliers	Factories	DCs		Multi-objective	Single objective	Heuristics\ Meta-heuristics	Exact		
Feng et al. (2023)	✓		SP, RO	P, C	✓			M, CO, H		✓				E
Torshizi et al. (2024)	✓	✓	SP	P, C	✓	✓	✓	A, M, F, H	✓					V
Safari et al. (2024)	✓	✓	SP, RO	P, C	✓	✓	✓	M, CO, H	✓					
This paper	✓	✓	SP, RO	P, C	✓	✓	✓	A, H, M, U, F	✓			✓	HY	PB

A: Adding extra production/supply capacity, AU: Automotive, C: Complete disruption, CO: Backup suppliers/ facilities, D: Direct shipping, E: electronic devices, F: Facility fortification, H: Holding safety stock inventory, HY: Hybrid, I: Industrial paint, M: Multiple sourcing, ME: Medication, ND: Network design, P: Partial disruption, PB: Plastic bag, PC: Plastic components, PH: Pharmaceutical, PL: Plastic pipe, PO: Photovoltaic, PP: Possibilistic programming, R: Retail industry, RO: Robust optimization, SP: Stochastic programming, U: Using substitutable product/component, V: Vaccine bi-objective model is proposed in which performance scores of suppliers gained from Phase 1 are considered as input parameters. The proposed model has two objectives: (1) minimizing the total SC cost under random disruptions, and (2) maximizing the expected efficiency scores of all selected suppliers. The proposed bi-objective model is solved using a combination of the ε-constraint method and the accelerated BDA. The process of this hybrid methodology is represented in Fig. 1. The following sections will further elaborate on each step of this process.

3.1 Evaluating supplier performance using a unified DEA model

Phase 1 of the proposed methodology applies DEA to assess the performance of suppliers considering conflicting criteria. DEA is regarded as one of the most powerful tools for measuring efficiency of decision making units (DMUs) (Azadeh et al., 2011). The effectiveness of DEA for supplier evaluation has been broadly investigated (Liu et al., (2000), Wu, (2009), Ma et al., (2014), Kumar et al., (2014), Mahdiloo et al., (2015), Azadi et al., (2015), Sabouhi et al., (2018)). One advantage of DEA is that it can obviate the need to assign predetermined weights to evaluation criteria and to normalize their weights using different dimensions (Babazadeh et al., 2015).

Traditional DEA approaches mainly focus on maximizing the outputs of the DMUs (Chauhan et al., 2006). However, in many real-world cases, DMUs may contain both undesirable and desirable outputs (Färe et al., 2005). For example, total revenue can be considered as a desirable output and total carbon emissions can be regarded as an undesirable output. To enhance the performance of a DMU, one would aim to minimize the undesirable outputs and maximize the desirable outputs (Sueyoshi & Goto, 2012). To overcome the limitation of the traditional DEA approaches, we use the unified DEA introduced by Sueyoshi and Goto, (2011). In the unified DEA method, the outputs are classified into undesirable and desirable categories, and they are combined in a unified model. Phase 1 of the proposed methodology considers suppliers as DMUs with a set of desirable and undesirable measures. Utilizing the unified DEA method, the performance scores of the suppliers are obtained. Appendix A contains the details of the unified DEA model.

3.2 Modeling mathematical

Phase 2 of the hybrid methodology presents a stochastic robust bi-objective optimization model. In this model, supplier performance scores gained from the unified DEA model are regarded as input parameters. To develop the model, the notations are utilized as below.

3.3 Sets and indices:

N	Set of existing factories, indexed by n
N'	Set of potential locations for new factories, indexed by n'
O	Set of all factories ($N \cup N'$), indexed by o
M	Set of suppliers, indexed by m

F	Set of products, indexed by f, l
K	Set of raw material types, indexed by k
W	Set of potential locations for DCs, indexed by w
V	Set of CLs for DCs, indexed by v
S	Set of disruption scenarios, indexed by s
I	Set of customers, indexed by i
U	Set of fortification levels for suppliers, indexed by u
U'	Set of fortification levels for factories, indexed by u'
V'	Set of CLs for new factories, indexed by v'
W'	Set of fortification levels for DCs, indexed by w'

3.3.1 Parameters:

x_{mu}	Fixed cost of working with supplier m with fortification level u
τ_{km}	Capacity of supplier m for providing raw material k
ψ_{km}	Equal to 1 if supplier m can provide raw material k; 0, otherwise
α_m	Performance score of supplier m obtained from the unified DEA model
π_s	Occurrence probability of scenario s
σ_{mus}	Percentage of disrupted capacity for supplier m with fortification level u under scenario s
φ_n^{min}	Minimum production of existing factory n
φ_n	Capacity of existing factory n
φ_n^{max}	Maximum expandable capacity of existing factory n
e_n	Unit cost of expanding capacity in existing factory n
$c_{nu'}$	Fortification cost of existing factory n at level u'
$t_{v'n'u'}$	Fixed opening cost of a new factory with CL v' and fortification level u' at location n'
$\nu_{ou's}$	Percentage of disrupted capacity for factory o with fortification level u' under scenario s
$\theta_{v'n'}$	Capacity of a new factory with CL v' at location n'
μ_{kf}	Amount of raw material k needed to produce a unit of product f
p_{fos}	Unit production cost of product f in factory o under scenario s

β_{fl}	Equal to 1 if product f is substitutable with product l; 0, otherwise
q_{kmos}	Unit purchasing cost of raw material k from supplier m for factory o under scenario s
$z_{vww'}$	Fixed opening cost of a DC with CL v and fortification level w' at location w
δ_{vw}	Capacity of a DC with CL v at location w
h_{fw}	Unit holding cost of safety stock inventory for product f at DC w
λ_{w}	Maximum holding capacity for safety stock inventory at DC w
g_{fows}	Unit transportation cost of product f from factory o to DC w under scenario s
$\gamma_{ww's}$	Percentage of disrupted capacity for DC w with fortification level w' under scenario s
y_{fwis}	Unit transportation cost of product f from DC w to customer i under scenario s
b_{ifs}	Unit lost sales cost of product f at customer i under scenario s
d_{ifs}	Demand for product f in customer i under scenario s

3.3.2 Decision variables:

G_{fows}	Amount of product f transported from factory o to DC w under scenario s
P_{fos}	Amount of product f manufactured in factory o under scenario s
Q_{kmos}	Amount of raw material k transported from supplier m to factory o under scenario s
Y_{flwis}	Amount of product l as a substitute for product f shipped from DC w to customer i under scenario s
H_{fw}	Safety stock inventory of product f in DC w
R_{flwis}	Amount of safety stock inventory for product l as a substitute for product f shipped from DC w to customer i under scenario s
B_{ifs}	Lost sales of product f in customer i under scenario s
E_{n}	Amount of capacity expansion in existing factory n
X_{mu}	1 if supplier m with fortification level u is selected; 0, otherwise
$Z_{vww'}$	1 if a DC with CL v and fortification level w' is established at location w; 0, otherwise
$C_{nu'}$	1 if existing factory n is fortified at level u'; 0, otherwise
$T_{v'n'u'}$	1 if a new factory with CL v' and fortification level u' is opened at location n'; 0, otherwise

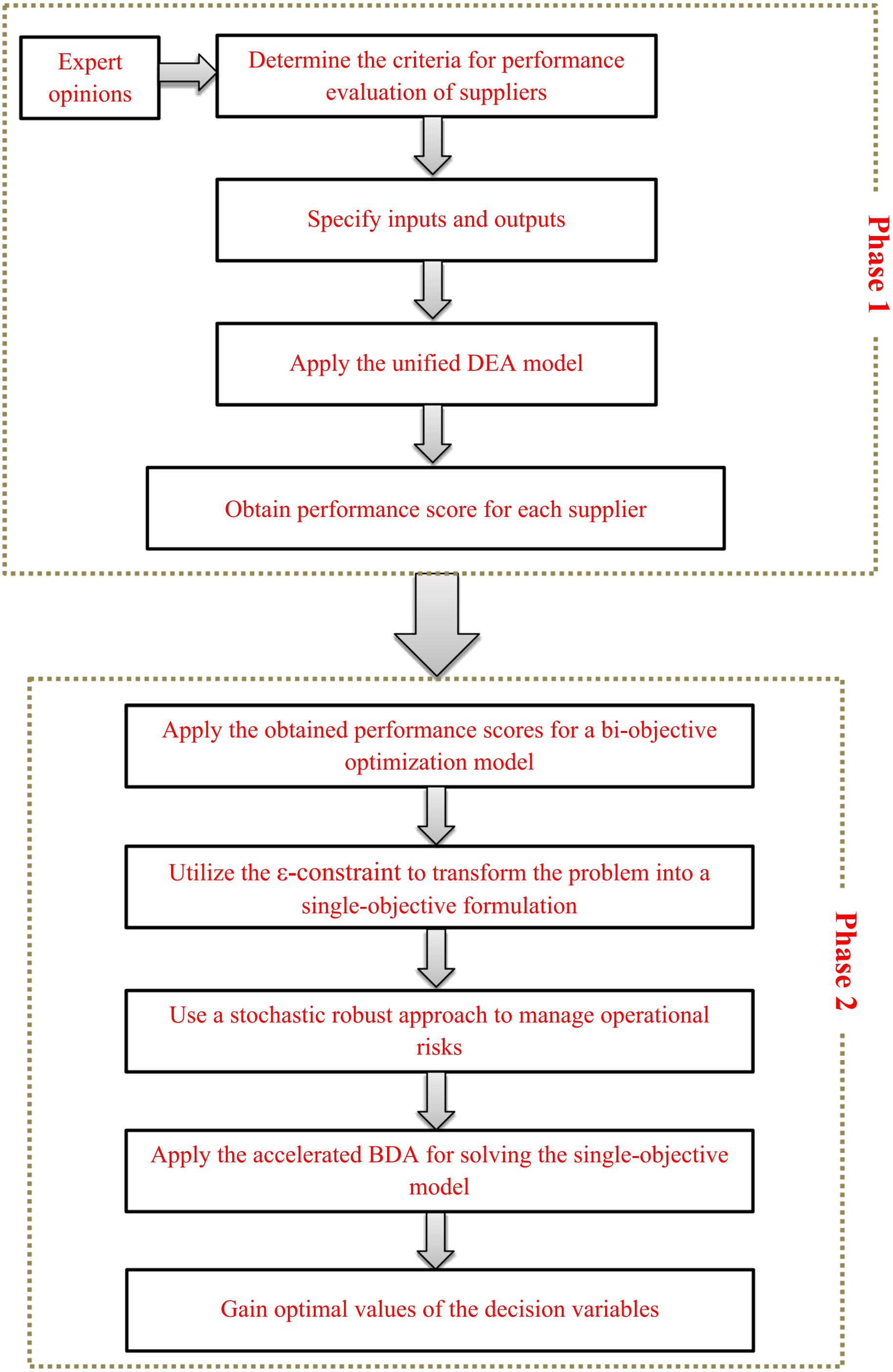

Fig. 1 The Structure of the proposed hybrid methodology

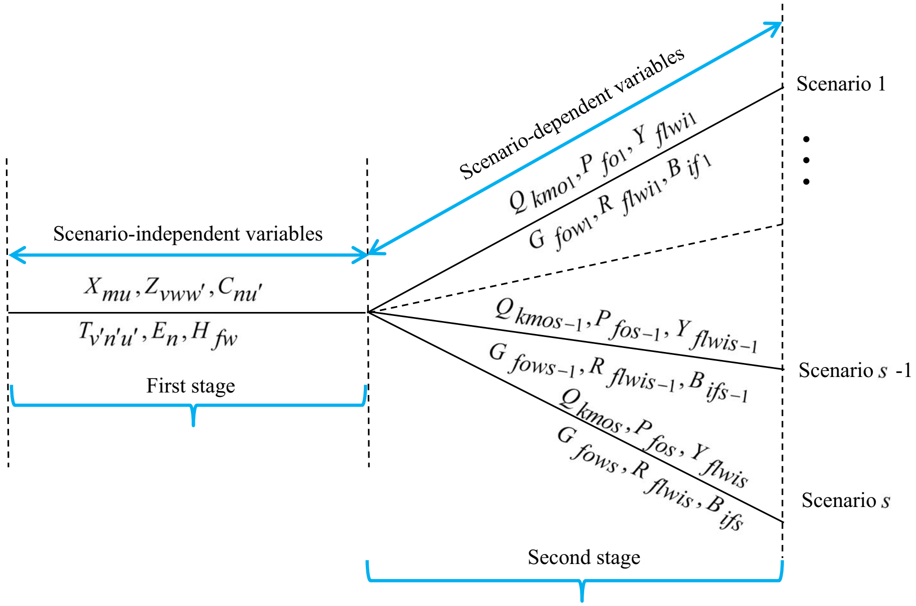

Fig. 2 The two stages of the proposed stochastic model and the associated decision variables

In a two-stage stochastic programming, decision variables can be divided into two types: scenario-independent and scenario-dependent variables (Birge & Louveaux, 2011). Decisions on scenario-independent variables, called first-stage decisions, are made before a disruption scenario is realized. In contrast, the values of scenario-dependent variables, known as second-stage decisions, are determined after the realization of a disruption scenario. The two stages of the presented stochastic model and the corresponding variables are illustrated in Fig. 2.

3.3.3 Objective functions

The model has two objectives. The first objective aims to minimize the expected total cost of the SC. The SC cost components consist of the supplier selection cost (SC), the fortification cost of factories (FC), the cost of establishing facilities (EC), the cost of expanding capacity (AC), holding cost (HC), the transportation cost (TC_s), the raw material cost (RC_s), the production cost (PC_s), and the cost of lost sales (LC_s). These components are formulated in Eqs. (1)-(9).

$$SC(\text{supplier selection cost}) = \sum_m \sum_u x_{mu} X_{mu} \tag{1}$$

$$FC(\text{fortification cost of factories}) = \sum_n \sum_{u'} c_{nu'} C_{nu'} \tag{2}$$

$$EC(\text{cost of establishing facilities}) = \sum_{u'} \sum_{n'} \sum_{v'} t_{v'n'u'} T_{v'n'u'} + \sum_v \sum_w \sum_{w'} z_{vww'} Z_{vww'} \tag{3}$$

$$AC(\text{cost ofexpanding capacity}) = \sum_n e_n E_n \tag{4}$$

$$HC(\text{holding cost}) = \sum_{f}\sum_{w} h_{fw}\, H_{fw} \tag{5}$$

$$\begin{aligned} &TC_s\,(transportation\ \cos t) \\ &= \sum_{f}\sum_{o}\sum_{w} g_{fows}\, G_{fows} + \sum_{f}\sum_{l}\sum_{w}\sum_{i} y_{lwis}\, Y_{flwis} + \sum_{f}\sum_{l}\sum_{w}\sum_{i} y_{lwis}\, R_{flwis} \end{aligned} \tag{6}$$

$$RC_s(\text{raw material cost}) = \sum_{k}\sum_{m}\sum_{o} q_{kmos}\, Q_{kmos} \tag{7}$$

$$PC_s(\text{production cost}) = \sum_{f}\sum_{o} p_{fos}\, P_{fos} \tag{8}$$

$$LC_s(\text{cost of lost sales}) = \sum_{i}\sum_{f} b_{ifs}\, B_{ifs} \tag{9}$$

Equation (1) formulates the supplier selection cost with different fortification levels. Equation (2) expresses the fortification cost of existing factories. Equation (3) shows the cost of establishing new factories and DCs with different capacity/fortification levels. Equation (4) represents the cost of expanding capacity in the existing factories. Equation (5) presents the holding cost of safety stock inventory at the DCs. Equation (6) calculates the total transportation costs related to the shipment of products from the factories to the DCs and from the DCs to the customers. Equation (7) illustrates the cost of supplying raw materials from the suppliers and their transportation to the factories. Equation (8) formulates the production costs in factories. The total lost sales cost is formulated in Eq. (9). Therefore, the first objective function (OF) is written as below:

$$Min\ Z_1 = \ SC\ + FC + EC + AC + HC + \sum_{s} \pi_s[RC_s + PC_s + LC_s + TC_s] \tag{10}$$

The second OF maximizes the expected performance scores of all suppliers. Recall that the supplier performance scores are gained by using the unified DEA, as described in Sect. 3.2.1. Equation (11) formulated the second OF.

$$Max\ Z_2 = \sum_{s} \pi_s \left[\sum_{k}\sum_{m}\sum_{o} \alpha_m\, Q_{kmos} \right] \tag{11}$$

3.3.4 Model constraints

The two OFs in Eqs. (10) and (11) are subject to the following constraints.

$$\sum_{o} Q_{kmos} \le \sum_{u} (1 - \sigma_{mus})\tau_{km}\, X_{mu} \qquad \forall\ k,\ m,\ s \tag{12}$$

$$\sum_{f} P_{fns} \le \sum_{u'} (1 - \nu_{nu's})(\varphi_n + E_n)C_{nu'} \qquad \forall\ s,\ n \tag{13}$$

$$\sum_{f} P_{fn's} \le \sum_{v'}\sum_{u'} (1 - \nu_{n'u's})\theta_{v'n'}\, T_{v'n'u'} \qquad \forall\ n',\ s \tag{14}$$

$$\sum_{f}\sum_{o} G_{fows} \le \sum_{w'}\sum_{v} \delta_{vw} Z_{vww'}(1 - \gamma_{ww's}) \qquad \forall\ w,\ s \tag{15}$$

$$\sum_{f} P_{fns} \geq \varphi_n^{\min} \sum_{u'} (1 - \nu_{nu's}) C_{nu'} \qquad \forall\, s,\ n \tag{16}$$

$$E_n \leq \varphi_n^{\max} \qquad \forall\, n \tag{17}$$

$$\sum_{m} \psi_{km}\, Q_{kmos} = \sum_{f} \mu_{kf} P_{fos} \qquad \forall\, o,\ k,\ s \tag{18}$$

$$P_{fos} = \sum_{w} G_{fows} \qquad \forall\, f,\ o,\ s \tag{19}$$

$$\sum_{o} G_{lows} = \sum_{f} \sum_{i} \beta_{fl} Y_{flwis} \qquad \forall\, w,\ l,\ s \tag{20}$$

$$\sum_{l} \sum_{w} \beta_{fl} (Y_{flwis} + R_{flwis}) + B_{ifs} = d_{ifs} \qquad \forall\, i,\ f,\ s \tag{21}$$

$$\sum_{u'} C_{nu'} = 1 \qquad \forall\, n \tag{22}$$

$$\sum_{u} X_{mu} \leq 1 \qquad \forall\, m \tag{23}$$

$$\sum_{u'} \sum_{v'} T_{v'n'u'} \leq 1 \qquad \forall\, n' \tag{24}$$

$$\sum_{v} \sum_{w'} Z_{vww'} \leq 1 \qquad \forall\, w \tag{25}$$

$$\sum_{f} H_{fw} \leq \sum_{v} \sum_{w'} \lambda_w Z_{vww'} \qquad \forall\, w \tag{26}$$

$$\sum_{f} \sum_{i} \beta_{fl} R_{flwis} \leq H_{lw} \qquad \forall\, w,\ l,\ s \tag{27}$$

$$X_{mu},\ C_{nu'},\ T_{v'n'u'},\ Z_{vww'} \in \{0,\ 1\} \qquad \forall\, v,\ m,\ u,\ u',\ n,\ v',\ w',\ w,\ n' \tag{28}$$

$$E_n \geq 0 \qquad \forall\, n \tag{29}$$

$$H_{fw} \geq 0 \qquad \forall\, f,\ w \tag{30}$$

$$Q_{kmos},\ P_{fos},\ Y_{flwis},\ G_{fows},\ R_{flwis},\ B_{ifs} \geq 0 \qquad \forall\, w,\ o,\ s,\ k,\ f,\ m,\ i,\ l \tag{31}$$

For different disruption scenarios, constraints (12)-(15) impose the capacity limitation of suppliers, factories (both new and existing factories) and DCs, respectively. Constraint (16) demonstrates the minimum production in existing factories. Constraint (17) enforces upper limits to excess production capacity in existing factories. Constraint (18) warrants the supply of the required raw material in factories. Constraints (19)-(21) declare the flow balance constraints at factories, DCs and customers, respectively. Constraint (22) enforces that each of the existing factories is fortified at a specific level. Constraint (23) indicates that a supplier can be equipped at most at a one level which specifies the type of fortification. Constraints (24) and (25) warrant that at most one facility can be opened in potential locations for the factories and DCs, respectively. Constraint (26) guarantees that safety stock inventories are only stored in the established DCs. This constraint also imposes upper limits to the holding capacity of safety stock inventory in DCs. Constraint (27) indicates the maximum amount of safety stock inventory transported from DCs to customers. The type of decision variables is shown by constraints (28)-(31).

3.3.5 Linearization

The model formulation (1–31) is nonlinear by the term $\sum_{u'}(1-\nu_{nu's})(\varphi_n + E_n)\,C_{nu'}$ in Constraint (13). This formulation is linearized utilizing a new auxiliary variable named $\Gamma_{nu'}$ and new constraints (32)-(36) as follows:

$$\sum_f P_{fns} \leq \sum_{u'}(1-\nu_{nu's})(\varphi_n C_{nu'} + \Gamma_{nu'}) \qquad \forall\ s,\ n \tag{32}$$

$$\Gamma_{nu'} \leq E_n \qquad \forall\ u',\ n \tag{33}$$

$$\Gamma_{nu'} \leq C_{nu'} M_{big} \qquad \forall\, u',\ n \tag{34}$$

$$E_n - M_{big}(1 - C_{nu'}) \leq \Gamma_{nu'} \qquad \forall\, u',\ n \tag{35}$$

$$\Gamma_{nu'} \geq 0 \qquad \forall\, u',\ n \tag{36}$$

where M_{big} is a big number. One possible value for M_{big} is φ_n^{max}, as the quantity of capacity expansion cannot exceed the maximum expandable capacity of existing factories. Also, the auxiliary $\Gamma_{nu'}$ is expressed as below:

$$\Gamma_{nu'} = C_{nu'} E_n \qquad \forall\, u',\ n \tag{37}$$

3.3.6 Converting into a single-objective formulation

To transform the problem into a single-objective model, we employ the ε-constraint method. Unlike typical multi-objective techniques (e.g., weighted methods), the ε-constraint method does not necessitate allocating weights to objectives (Jabbarzadeh et al., 2018a). Instead, one of the OFs is used as the primary function to optimize the problem, and the other OFs are transformed into constraints. For each of the newly added constraints, an upper bound is considered. A set of efficient solutions are obtained by solving the resulting single-objective model for different upper bounds of the new constraints. To further elaborate this, we presume a multi-objective model with ρ OFs as below.

$$Min_{k\in\upsilon}\,\{T(k) = (T_1(k),\ T_2(k),\ \ldots T_\rho(k))\}, \tag{38}$$

where k shows the vector of decision variables and υ indicates the space of feasible solutions. Also, $T(k)$ is the vector of ρ OFs. Using the ε-constraint method, Eq. (38) is transformed into a single-objective as below.

$$Min_{k\in\upsilon}\, T_\rho(k) \tag{39}$$

$$T_i(k) \leq \varepsilon_i\ \forall i \in \{1,\ 2,\ \ldots,\ P\}/\{p\} \tag{40}$$

where $T_p(k)$ is minimized as the primary OF and the remaining OFs are expressed as constraints (For a more detailed understanding of the ε-constraint method, we may consult Mavrotas (2009)). Using this approach, we now transform the OF in Eq. (11) into a constraint with upper bound ε, hereafter named *performance level*. The resulting single-objective model is as below.

$$\text{Min } Z_1 \tag{41}$$

Subject to:

$$Z_2 \geq \varepsilon \tag{42}$$

Constraints (12) and (14)-(36).

A sensitivity analysis on the values of ε is conducted to generate a set of good solutions. Specifically, OF (41) under constraints (12), (14)-(36), and (42) is solved multiple times with different values of ε. The method described by Mavrotas (2009) is used to determine the values of ε. This method helps identify the range of OF Z_2. The maximum value of Z_2 is gained by maximizing OF (11) under constraints (12) and (14)-(36). To obtain the minimum value of Z_2, we first minimize OF (10) subject to under the same constraints. Subsequently, the value of OF (11) is calculated by substituting the optimal values of the decision variables. The resulting value provides the minimum value of Z_2. Let Z_2^{min} and Z_2^{max} represent the minimum and maximum values of Z_2. The values of ε are then chosen within this range.

3.3.7 A stochastic robust optimization model

To better manage operational and disruption risks, the presented model in Sect. 3.2.4 is extended using a robust optimization (RO) approach. RO and its wide range of applications have been proven to be effective when dealing with data uncertainty (Ben-Tal and Nemirovski, 2000). The scenario-based RO, introduced by Mulvey et al. (1995), has been one of the most effective methods to model the dependency between uncertain parameters (Jabbarzadeh et al., 2018b). Aghezzaf et al. (2010) extended this approach by incorporating the maximum regret to the OF as a variability measure. The method can be presented as follows.

$$\text{Min}\ \eta \sum_s \pi_s \phi_s + (1-\eta)\ \underset{s}{Max}(\phi_s - \phi_s^*) \tag{43}$$

Subject to:

$$k \in \upsilon \tag{44}$$

where π_s is the occurrence probability of scenario s and $k \in \upsilon$ indicates the feasible space for the problem. Furthermore, ϕ_s is a deterministic minimization problem for each scenario s and ϕ_s^* is the optimal value for ϕ_s. Equation (43) entails two terms. The first term shows the expected value of the problem ϕ_s and the second term indicates the maximum regret for the all scenarios of problem ϕ_s. The regret for each scenario can be defined as the value difference between a made decision and the optimal decision. Parameter η lies in interval [0, 1] and its value is determined by the decision-maker to show the trade-off between the maximum regret and expected value. Due to the simultaneous presence of the Min and Max operators, Eq. (43) is nonlinear. We can however easily convert the model into a linear equivalent by introducing a new decision variable (Q') and including an additional Eq. (47) as follows (for more details about the approach please refer to Aghezzaf et al. (2010)).

$$\text{Min}\eta \sum_s \pi_s \phi_s + (1-\eta)Q' \tag{45}$$

Subject to:

$$k \in \upsilon \tag{46}$$

$$Q' \geq (\phi_s - \phi_s^*) \qquad \forall s \tag{47}$$

Based on the above, the total SC cost under each scenario can be obtained from Eq. (48).

$$\phi_s = SC + FC + EC + AC + HC + RC_s + PC_s + LC_s + TC_s \qquad \forall s \tag{48}$$

Substituting ϕ_s from Eq. (48) into Eqs. (45) and (47), the robust counterpart of the proposed model is written as below.

$$\begin{aligned} Min\, Z_1 = \eta\ (SC\ + FC + EC + AC + HC + \\ \sum_s \pi_s [RC_s + PC_s + LC_s + TC_s]) + (1 - \eta)\, Q' \end{aligned} \tag{49}$$

Subject to:

$$Q'\ \geq SC\ + FC + EC + AC + HC + RC_s + PC_s + LC_s + TC_s - \phi_s^* \qquad \forall s \tag{50}$$

Constraints (12), (14)-(36) and (42).

4 Solution approach

The single-objective model presented in Sect. 3 is a large scenario-based mixed-integer programming (MIP) problem. In such problems, the computational complexity grows proportionally with the problem's size (Khatami et al., 2015). Solving the developed model with MIP solvers such as CPLEX may therefore require significant computational time as the problem size increases. BDA, pioneered by Benders (1962), is a powerful algorithm with proven effectiveness to solve large-scale MIP problems such as SCND (see for instance, Pishvaee et al. (2014), Rekabi et al. (2023)). For comprehensive information on BDA and its applications in SCND, one can refer to Garcia-Herreros et al. (2014).

The main problem is decomposed into a master problem (MP) and a sub-problem (SP) by BDA. The SP covers the second-stage decisions, whereas the MP consists of first-stage decisions (Attari et al., 2018). Therefore, to solve the model, we propose a BDA enhanced with an acceleration method known as Pareto optimal cuts. This method has been utilized in previous studies, including Jeihoonian et al. (2017), Jeihoonian et al. (2016), Alshamsi and Diabat (2018), Nur et al. (2020) and Alizadeh et al. (2024). The accelerated BDA improves the convergence speed compared to the ordinary BDA, reducing computational time and enhancing overall efficiency. The accelerated BDA includes three main steps that are discussed in the following subsections.

4.1 Developing the SP

The SP consists of the second-stage decisions, while assuming that the value of the first-stage decisions is known. To develop the SP, therefore, we assume that the first-stage decision values are available as follows.

$$\begin{aligned} X_{mu} = \overline{X}_{mu},\ \ C_{nu'} = \overline{C}_{nu'}\ ,\ \ Z_{vww'} = \overline{Z}_{vww'},\ \ T_{v'n'u'} \\ = \overline{T}_{v'n'u'},\ \ E_n = \overline{E}_n,\ \ H_{lw} = \overline{H}_{lw} \text{and } \Gamma_{nu'} = \overline{\Gamma}_{nu'}. \end{aligned}$$

With these inputs, the SP is formulated as follows.

$$Min\ SP = \eta \sum_s \pi_s [RC_s + PC_s + LC_s + TC_s]) + (1 - \eta)\, Q' \tag{51}$$

$$SC + FC + EC + AC + HC - \phi_s^* \qquad \forall s \tag{52}$$

$$\sum_{o} Q_{kmos} \leq \sum_{u} (1-\sigma_{mus})\tau_{km}\bar{X}_{mu} \qquad \forall m, k, s \tag{53}$$

$$\sum_{f} P_{fns} \leq \sum_{u'} (1-\nu_{nu's})(\varphi_n \bar{C}_{nu'} + \bar{\Gamma}_{nu'}) \qquad \forall s, n \tag{54}$$

$$\sum_{f} P_{fn's} \leq \sum_{v'}\sum_{u'} (1-\nu_{n'u's})\theta_{v'n'}\bar{T}_{v'n'u'} \qquad \forall n', s \tag{55}$$

$$\varphi_n^{\min} \sum_{u'} (1-\nu_{nu's})\bar{C}_{nu'} \leq \sum_{f} P_{fns} \qquad \forall s, n \tag{56}$$

$$\sum_{f}\sum_{o} G_{fows} \leq \sum_{w'}\sum_{v} \delta_{vw}\bar{Z}_{vww'}(1-\gamma_{ww's}) \qquad \forall w, s \tag{57}$$

$$\sum_{f}\sum_{i} \beta_{fl} R_{flwis} \leq \bar{H}_{lw} \qquad \forall l, s, w \tag{58}$$

Constraints (18)-(21), (31) and (42).

4.2 Obtaining an upper bound

To obtain an upper bound (UB) for the main problem, we develop the dual sub-problem (DSP). The optimal value of DSP can provide an UB for the OF of the main problem (Jeihoonian et al., 2016). Defining a^1, ..., a^{12} as the dual variables for the SP's constraints, the DSP is formulated in Appendix B.

4.3 Calculating a Lower bound

The optimal value of the MP can provide a Lower bound (LB) for the OF of the main problem (Jeihoonian et al., 2016). As discussed above, the MP consists of first-stage decisions (scenario-independent variables). Therefore, MP is formulated in Appendix C.

Equation (83) in Appendix C is the OF (49) without the second-stage decisions. Equation (84) in Appendix C shows the optimality cut, where $\widehat{a}^1$, ..., $\widehat{a}^{12}$ are optimal values of dual variables a^1, ..., a^{12} in DSP.

To accelerate BDA, we develop Pareto optimal cuts and add them to MP. Pareto optimal cuts, developed by Magnanti and Wong (1981), can help enhance the converge of the algorithm and reduce the number of iterations (Garcia-Herreros et al., 2014). The following auxiliary dual problem is solved to gain Pareto-optimal cut in each iteration.

$$\begin{aligned}
&Max \sum_{s} (SC + FC + EC + AC + HC - \phi_s^*)\, a_s^1 + \varepsilon\, a^2 \\
&- \sum_{k}\sum_{m}\sum_{s}\sum_{u} (1-\sigma_{mus})\,\tau_{km}\, X_{mu}^0 a_{kms}^3 - \sum_{n}\sum_{s}\sum_{u'} (1-\nu_{nu's})\,(\varphi_n\, C_{nu'}^0 + \Gamma_{nu'}^0)\, a_{ns}^4 \\
&- \sum_{n'}\sum_{s}\sum_{v'}\sum_{u'} (1-\nu_{n'u's})\,\theta_{v'n'}\, T_{v'n'u'}^0 a_{n's}^5 + \sum_{n}\sum_{s} \varphi_n^{min} \sum_{u'} (1-\nu_{nu's})\, C_{nu'}^0 a_{ns}^6 \\
&- \sum_{v}\sum_{s}\sum_{w}\sum_{w'} \delta_{vw} Z_{vww'}^0 (1-\gamma_{ww's})\, a_{ws}^7 + \sum_{i}\sum_{f}\sum_{s} d_{ifs}\, a_{ifs}^{11} - \sum_{l}\sum_{w}\sum_{s} H_{lw}^0\, a_{lws}^{12}
\end{aligned} \tag{59}$$

Subject to:

$$DSP^* = \sum_s (SC + FC + EC + AC + HC - \phi_s^*)\, a_s^1 + \varepsilon\, a^2$$

$$- \sum_k \sum_m \sum_s \sum_u (1 - \sigma_{mus})\, \tau_{km}\, \overline{X}_{mu} a_{kms}^3 - \sum_n \sum_s \sum_{u'} (1 - \nu_{nu's})\, (\varphi_n\, \overline{C}_{nu'} + \overline{\Gamma}_{nu'})\, a_{ns}^4$$

$$- \sum_{n'} \sum_s \sum_{v'} \sum_{u'} (1 - \nu_{n'u's})\, \theta_{v'n'}\, \overline{T}_{v'n'u'} a_{n's}^5 + \sum_n \sum_s \varphi_n^{min} \sum_{u'} (1 - \nu_{nu's})\, \overline{C}_{nu'} a_{ns}^6$$

$$- \sum_v \sum_s \sum_w \sum_{w'} \delta_{vw} \overline{Z}_{vww'}\, (1 - \gamma_{ww's})\, a_{ws}^7 + \sum_i \sum_f \sum_s d_{ifs}\, a_{ifs}^{11} - \sum_l \sum_w \sum_s \overline{H}_{lw}\, a_{lws}^{12} \tag{60}$$

Constraints (B2)-(B10).

Where DSP^* is the optimal value for DSP and $(X_{mu}^0,\ C_{nu'}^0,\ \Gamma_{nu'}^0,\ Z_{vww'}^0,\ E_n^0,\ H_{lw}^0,\ T_{v'n'u'}^0)$

$$\in \left\{ \begin{array}{l} (X_{mu},\ C_{nu'},\ \Gamma_{nu'},\ Z_{vww'},\ E_n,\ H_{fw},\ T_{v'n'u'}) : \\ \\ 0 < X_{mu} < 1,\ 0 < C_{nu'} < 1,\ 0 < Z_{vww'} < 1,\ 0 < T_{v'n'u'} < 1, \\ \\ 0 < \Gamma_{nu'} < \varphi_n^{max},\ 0 < E_n < \varphi_n^{max},\ 0 < H_{lw} < \lambda_w \end{array} \right\}.$$

Figure 3 depicts the steps of the accelerated BDA in the form of a flowchart.

5 Model implementation

5.1 The case problem

Plastic bags have been an integral part of our daily lives. They are widely used in virtually every industry. Plastic bags can be detrimental to environment if they are made from non-degradable materials. Each year, at least 6 million tons of plastic bags escape into the ocean, only 14% of which is recyclable (Eagle et al., 2016; Sharma et al., 2014). It is no wonder that plastic pollution has become one of the most critical environmental issues. An effective strategy to tackle these environmental concerns is the production and use of degradable plastic bags (Müller et al., 2012; Yurtsever & Yurtsever, 2018). Degradable plastic bags are made by blending a pro-degradant additive into the ordinary plastic during the production process allowing the bag to break down when exposed to heat or sunlight. The degradation time changes based on the amount of exposure to heat/sunlight. Degradable plastic bags have the following advantages over the ordinary ones: (1) they are recyclable, (2) their degradation process does not release methane, and (3) there is no difference in quality, texture, or strength between degradable and ordinary plastic bags.

Moreover, the growing demand for eco-friendly products in global markets has encouraged governments and organizations to implement stricter regulations on plastic usage and waste management. This trend creates an urgent need for manufacturers to innovate and adopt sustainable practices, such as producing degradable plastic bags. By meeting these regulatory

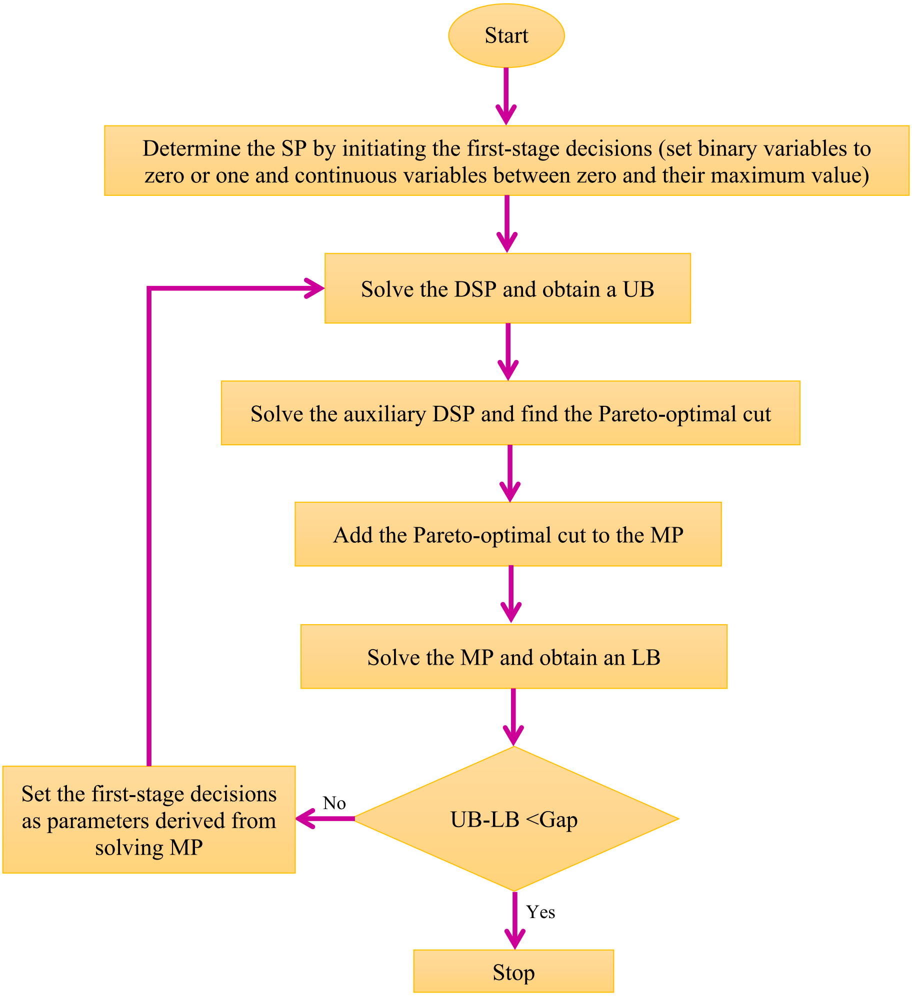

Fig. 3 Flowchart of the accelerated BDA

requirements, companies not only contribute to environmental conservation but also enhance their competitiveness and market share in regions with high consumer awareness. Consequently, incorporating such considerations in industries like plastic production has become a strategic imperative that aligns with long-term business goals and societal expectations.

5.2 Data collection

Iran Plastic Industry (IPI) is amongst the leading producers of degradable plastic bags in the Middle East. IPI produces four types of degradable plastic bags–nylon, nylex, garbage, and freezer bags—in six factories. Nylon and nylex plastic bags can be substituted with each other. In order to enter new markets, IPI needs to establish new production and distribution facilities. External SC experts have identified four potential locations to establish new

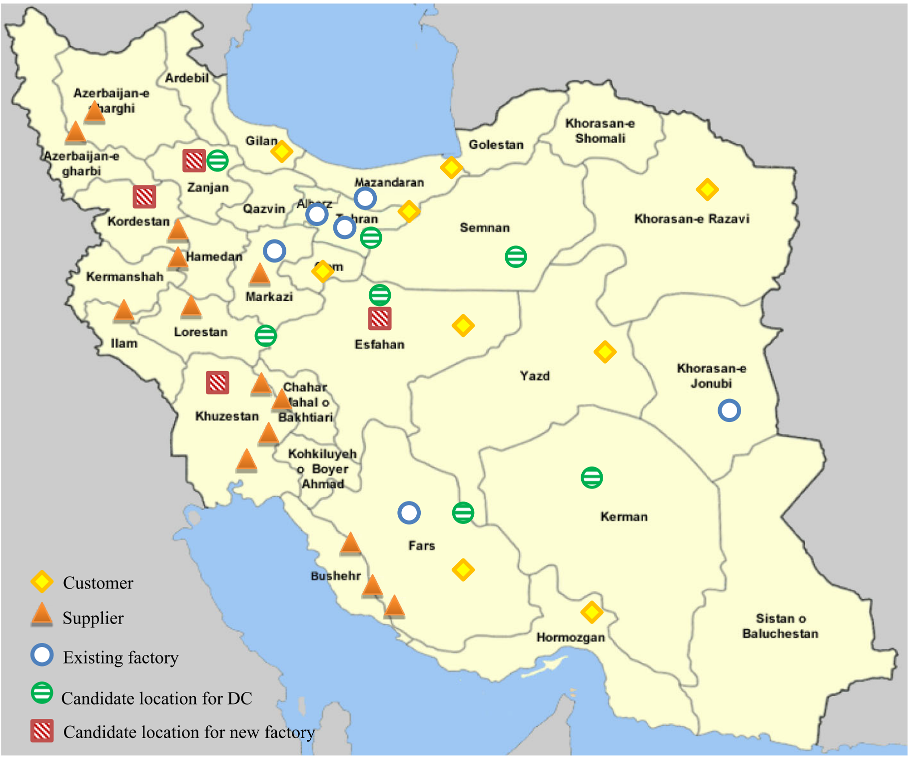

Fig. 4 IPI's SC configuration

factories and seven candidate locations for new DCs. Figure 4 illustrates the locations of markets/customers, existing factories, and potential sites for establishing new facilities.

The new factories and DCs can be established in medium or large sizes. For each facility, three fortification options are available (i.e., full fortification, moderate, and low). The facilities with full fortification degree are the most robust to disruptions. However, they are very expensive to establish and run. Facilities with low fortification degree are less costly to build, but also less robust to disruptions. Facilities with a moderate level of fortification stand between the two in terms of costs and robustness degree.

The raw materials have been sourced from 14 suppliers (petrochemical companies). The raw materials include low-density polyethylene, pro-degradant additive (used in all products), and high-density polyethylene (only used in nylex, garbage, and freezer bags). Table 3 illustrates the contract costs with suppliers. The suppliers are assessed according to a set of criteria determined by the experts of the National Petrochemical Company. The main assessment criteria are as follows.

- *Total investment:* This measure is considered as an input for the unified DEA model.
- *Greenhouse gas emissions:* IPI aims to improve the sustainability of its SC through the selection of suppliers that produce lower greenhouse emissions. This performance indicator is therefore considered as an undesirable output.

Table 3 Contract costs with suppliers (*104 $)

Suppliers	Fortification levels		
	1	2	3
1	11.25	13.75	15
2	11.88	13.75	14.38
3	12.50	13.75	16.25
4	11.25	13.75	15.63
5	10.63	14.38	15
6	11.88	13.75	16.25
7	11.25	13.75	15.00
8	13.13	13.75	18.13
9	13.13	13.75	15.63
10	11.88	13.75	15.63
11	12.5	13.75	16.25
12	12.5	13.75	16.25
13	11.88	13.75	15.63
14	11.25	13.75	14.38

- *Customer satisfaction:* This measure is related to product quality, on-time delivery, modern marketing, and customer relationship management. It is therefore considered as a desirable output.
- *Total sales:* A supplier's total sales equals sales volume multiplied by the unit price. A supplier with greater sales is often preferred as an indication of product/service popularity and supplier reputation. This measure is considered as a desirable output.

A panel of experts, comprising professionals with extensive experience in SC management, risk assessment, and resilience planning in the petrochemical and manufacturing sectors, was appointed. These experts conducted site visits to evaluate each supplier against these criteria. During the visits, data were collected through structured interviews and direct observations. The experts provided real-time insights into potential disruptions, such as fire risks at petrochemical sites, factories, and DCs. The disruption scenarios were classified into large-scale, medium-scale, and small-scale. The experts' insights, derived from a combination of interviews and observations, were documented to assess the potential impacts of these disruptions and propose strategies for their effective management. The following RSs were considered to cope with disruptions: (1) substitutable production, (2) facility fortification, (3) multiple sourcing, (4) extra production capacity in existing factories, and (5) safety stock inventory at DCs. We utilized our proposed model and methodology to complete a resilience analysis for IPI.

5.3 Initial computational results

5.3.1 Unified DEA model results

Table 4 provides the results of the unified DEA model according to the criteria introduced in Sect. 5.2. The gained performance scores can be used to rank the suppliers and evaluate

Table 4 The output of the proposed unified DEA model

Suppliers	Performance score
1	0.45
2	0.46
3	0.83
4	0.51
5	0.83
6	0.83
7	0.58
8	0.60
9	0.81
10	0.25
11	0.67
12	0.62
13	1.00
14	0.27

their performance. As can be seen, suppliers 10 and 13 are recognized as the suppliers with the lowest and highest performances, respectively.

5.3.2 SCND model results

Now, we implement the proposed stochastic robust model for the case problem and discuss the related numerical findings. Tables 5, 6 and Figs. 5, 6, 7 summarize the results. Table 5 shows optimal sourcing decisions at different service levels. From Table 5, we observe that suppliers 3 and 13 are selected in all instances, while supplier 8 is not chosen under any situation. This observation is justified in light of the fact that supplier 13 has the highest performance score. While the performance score of supplier 8 is acceptable, its high price makes it an unattractive supplier for IPI. Table 5 also shows that the selection of the suppliers 4, 6 and 7 is a function of the performance level. In comparison with suppliers 4 and 7, Supplier 6 demonstrates a better performance score despite being a more costly supplier. As the performance level increases, there is a tendency to contract with supplier 6. Another

Table 5 Sourcing results under different performance levels

Performance level	Total cost (M $)	Suppliers									
		3	4	5	6	7	8	9	11	12	13
$\varepsilon = 0.5$	4.15	FO*	FO			FO				FO	LF
$\varepsilon = 0.6$	4.28	FO	FO		FO	FO				FO	LF
$\varepsilon = 0.7$	4.99	FO	FO		FO	FO		MF		FO	FO
$\varepsilon = 0.8$	7.14	FO	MF	LF	FO	FO		FO		FO	FO
$\varepsilon = 0.9$	9.64	FO		FO	FO			FO	LF		FO

*Fortification levels FO: Full fortification, MF: Moderate fortification, LF: Low fortification

Table 6 Optimal decisions in factories and DCs under different performance levels

Performance level	Total cost (M $)	Factories										DCs						
		Existing						New										
		1	2	3	4	5	6	1	2	3	4	1	2	3	4	5	6	7
$\varepsilon = 0.5$	4.15	LF*	LF	LF	LF	LF	LF					M, LF		L, FO	M, LF	M, LF	M, LF	
$\varepsilon = 0.6$	4.28	LF	LF	LF	LF	LF	LF				L, FO	M, LF	M, LF	L, FO	M, LF	M, LF	M, LF	
$\varepsilon = 0.7$	4.99	LF	LF	LF	LF	LF	MF	L**, LF	L, FO	L, LF	L, FO	L, LF	M, LF	L, FO	M, LF	L, LF	L, FO	
$\varepsilon = 0.8$	7.14	LF	LF	LF	LF	LF	MF	L, FO	L, FO	L, FO	L, FO	L, MF	M, LF	L, FO	L, LF	L, FO	L, FO	M, LF
$\varepsilon = 0.9$	9.64	LF	LF	LF	LF	LF	MF	L, FO	L, FO	L, FO	L, FO	L, FO	L, LF	L, FO	L, LF	L, FO	L, FO	

*Fortification levels LF: Low fortification, MF: Moderate fortification, FO: Full fortification
**Facility sizes L: Large, M: Medium

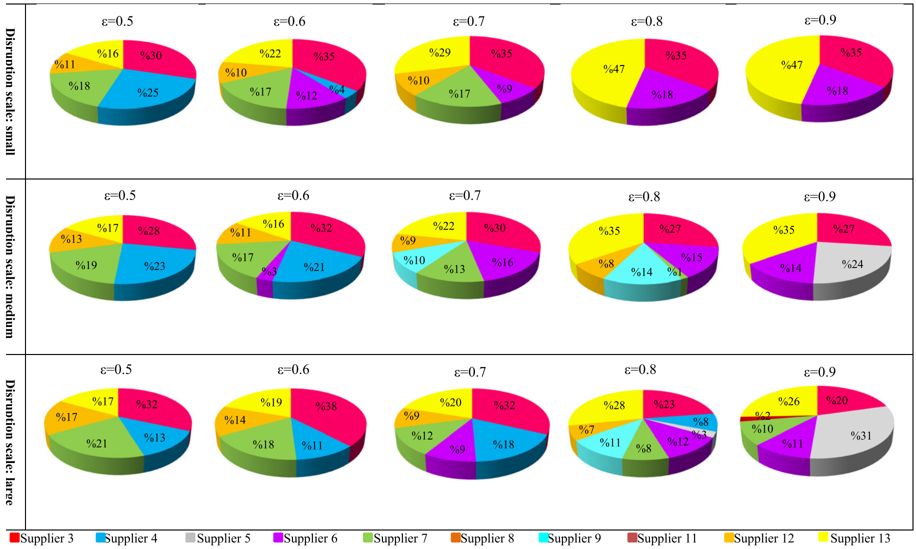

Fig. 5 Percentage raw material provided from each supplier for different performance levels and disruption scales

observation from Table 5 is that in the majority of cases, the selected suppliers exhibit full fortification. That is, the full fortification strategy seems a more economically viable to hedge against disruptions, compared to the other options.

For each disruption scale, Fig. 5 shows the involvement level of suppliers at different performance levels. This figure implies that the involvement level of each supplier depends on the performance level. As the performance level increases, IPI tends to purchase from suppliers with higher performance scores (i.e., supplier 13 and 5). Furthermore, Fig. 5 shows that the raw material purchase of supplier 12 increases as the scale of disruptions rises. We may conclude that supplier 12 contributes to building resilience in large-scale disruptions.

Table 6 indicates the optimal decisions for locating factories and DCs at different performance levels. Additionally, Figs. 6 and 7 depict the optimal network design decisions at $\varepsilon = 0.5$ and $\varepsilon = 0.8$, respectively. These figures and Table 6 show that the optimal solutions tend to establish fully fortified factories in dispersed locations as the performance level increases. In other words, more facilities are involved to meet the customers' demand with the rise in the performance level of the SC. This occurs because, when performance levels increase, more raw materials are purchased from suppliers with higher performance scores, resulting in more production and distribution of products along the SC. Interestingly, the optimal solutions do not include opening a medium-sized factory. Unlike new facilities, existing factories are fortified at low and moderate levels. We also observe that some DCs are opened in all instances (i.e., DCs 3, 4, 5, and 6). DCs opened in more vulnerable areas (such as DCs 3 and 6) have higher fortification levels. For example, in Fig. 6 at $\varepsilon = 0.5$, no new factories are established, whereas in Fig. 7 at $\varepsilon = 0.8$, all new factories are opened. Additionally, in Fig. 6, the number of allocations and the utilization of the entire SC facility are greater than in Fig. 7.

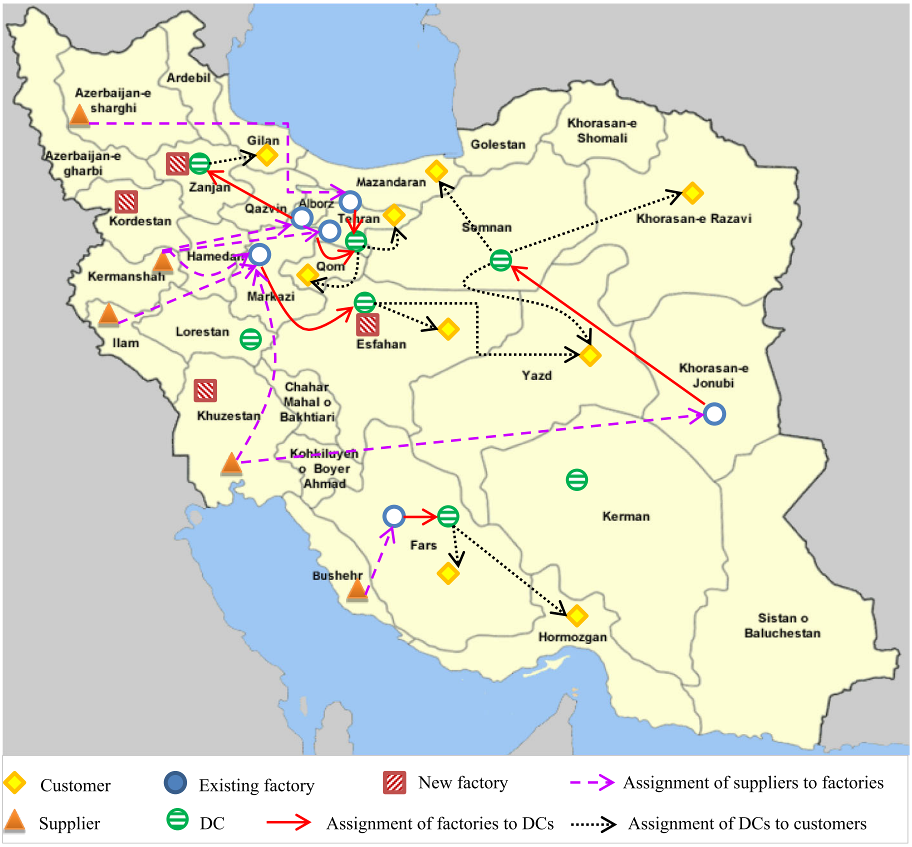

Fig. 6 Optimal design for the concerned SC at $\varepsilon = 0.5$

5.4 Analysis on phase 1: impact of unified DEA on sourcing decisions

In this section, utilizing the data of the case problem, we examine how Phase 1 of the proposed methodology can influence the sourcing decisions. For this purpose, we obtain and compare the sourcing decisions when the two following approaches are used:

1. *The classic SC design approach:* This approach determines sourcing decisions without applying the unified DEA method. Following this methodology, OF (48) is optimized under constraints of (12)-(35) and (49).
2. *The proposed hybrid approach:* This approach applies the unified DEA method to account for performance of suppliers, as described in Phase 1 of the proposed approach.

Figure 8 shows the involvement level of each supplier under both approaches. This figure reveals that suppliers 1, 2, 3, 7, 13 and 14 serve SC under the classic approach. However, suppliers 1, 2 and 14 are not selected under the proposed hybrid approach. The rationale behind this observation is as below. The classic approach overlooks the performance of suppliers by focusing only on SC costs. As a result, applying the classic approach leads to working with more cost-effective suppliers such as suppliers 1, 2 and 14 which have unsatisfactory performance scores. Unlike the classic approach, the hybrid approach ensures

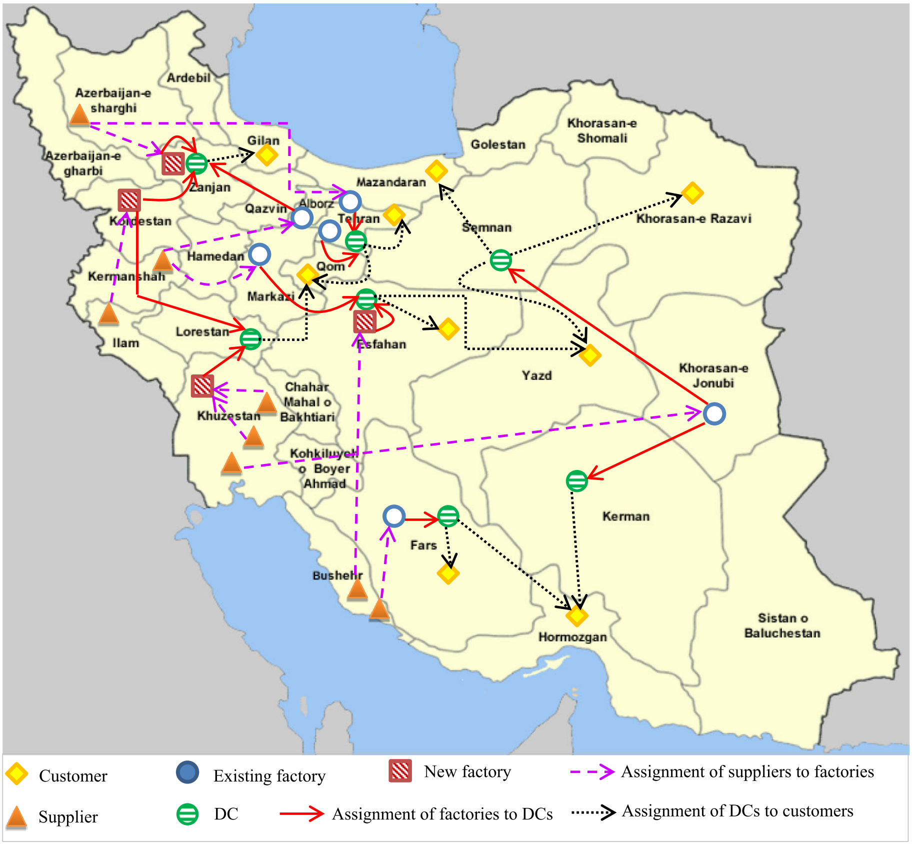

Fig. 7 Optimal design for the concerned SC at $\varepsilon = 0.8$

that the desired performance level is achieved. Accordingly, the proposed hybrid approach is able to simultaneously reduce the total SC costs and enhance the overall performance of suppliers.

5.5 Analysis on phase 2: impact of RSs on lost sales

This section examines how the RSs developed in Phase 2 of the proposed methodology can mitigate lost sales. The RSs include using multiple sourcing, fortifying facilities, holding safety stock inventory, adding extra production capacities, and using substitutable products.

To evaluate the benefit of each RS, we compare the total lost sales for the two following cases: a) when the RS is adopted and b) when the RS is not utilized. Figure 9 illustrates the results for each RS at different performance levels. The important finding from this figure is that all RSs lead to reductions in the percentage lost sales, independent of performance levels. This implies that IPI can benefit from applying each of the RSs in the face of disruptions.

According to Fig. 9, the two strategies of using multiple sourcing and holding safety stock inventory can significantly reduce the percentage lost sales. We also see that the strategies of adding extra production capacities and using substitutable products are less effective

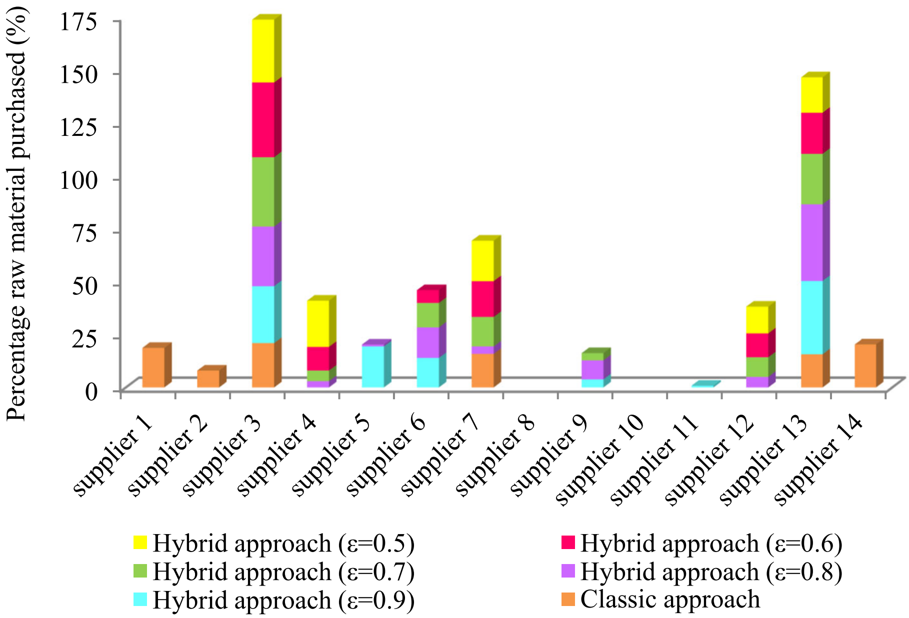

Fig. 8 Percentage raw material purchased from suppliers using the classic and proposed approaches

compared to the other strategies. Another observation is that the reduction behaviors in the percentage lost sales are almost similar at different performance levels. Therefore, it might be concluded that the RSs are consistently effective, regardless of the SC performance level.

5.6 Analysis on the proposed solution approach: accelerated BDA vs. CPLEX

To analyze the performance of the proposed accelerated BDA, we considered 14 test problems. The parameters of these test problems were generated randomly. For each test problem, Table 7 compares the performance of the accelerated BDA and CPLEX. From Table 7, what is evident is the superiority of the accelerated BDA over CPLEX, especially for larger problems. While BDA achieves optimal solutions within a reasonable timeframe for all instances, CPLEX is unable to reach feasible solutions for problems 9–15 in 36,000 s.

5.7 Advantage of stochastic RO model

This section aims to compare the effectiveness of the solutions obtained from the stochastic robust and deterministic models. In the deterministic model, the values of uncertain parameters are set equal to their expected values, forming a single-scenario model. The stochastic robust and deterministic models are solved independently to determine strategic decisions (i.e., first-stage decisions). Similarly, a number of simulations are generated for each uncertain parameter. Then, the first-stage variables obtained from the deterministic and robust

Fig. 9 The impacts of RSs on the percentage lost sales

Table 7 Performance of accelerated BDA versus CPLEX

Problem	The size of the problem	Accelerated BDA		CPLEX
	$\|N\| * \|O\| * \|F\| * \|K\| * \|W\| * \|I'\| * \|J\| * \|V\| * \|V'\| * \|U\| * \|U'\| * \|W'\| * \|S\|$	Solution Time (s)	Iterations	Solution Time (s)
16.6	5*6*2*2*5*1*4*2*2*2*2*2*10	7	47.2	1
122.9	5*7*3*3*6*1*7*2*2*3*3*3*15	7	167.9	2
137.5	7*8*3*3*6*1*7*2*2*3*3*3*20	9	287.1	3
226.4	8*9*4*3*7*2*8*2*2*3*3*3*25	10	332.4	4
914.4	10*10*4*3*7*2*9*2*2*3*3*3*30	10	347.3	5
2270	10*11*4*4*7*2*10*2*2*3*4*3*35	14	420	6
3790	12*12*5*5*8*2*10*3*2*3*4*3*40	15	498	7
5526	12*12*5*5*8*3*11*3*3*3*4*4*45	16	655	8
> 36,000	13*13*5*6*9*3*12*3*3*4*4*4*50	20	1220	9
> 36,000	14*13*6*6*9*3*12*3*3*4*4*4*55	22	2080	10
> 36,000	15*14*6*7*10*3*13*3*4*4*4*4*60	24	3440	11
> 36,000	15*15*7*7*10*3*13*4*4*4*4*4*65	24	5060	12
> 36,000	16*15*7*8*11*4*14*4*4*4*4*4*70	30	6401	13
> 36,000	16*16*8*8*11*4*15*4*4*4*4*4*75	32	7220	14
> 36,000	18*17*8*8*12*4*15*4*4*4*4*4*80	35	7080	15

models are substituted into each simulation model in the following compact form:

$$\begin{aligned} MinZ_1 &= Cx^* + Fy^* + G_{real}w + \sigma^a R^a + \sigma^b R^b + \sigma^c R^c, \\ Aw - R^a &\le E_{real}x^*, \\ Bw + R^b &\ge P_{real}x^*, \\ Nw &= 0, \\ Kw + R^c &= D_{real}x^*, \\ Qw &\le Hy^*, \\ w,\ R^a,\ R^b,\ R^c &\ge 0. \end{aligned} \tag{61}$$

In the compact model above, y^* and x^* represent the optimal values of the continuous and binary decision variables, respectively, which are the first-stage decisions. Additionally, w denotes a vector of second-stage decisions. The vectors C and F indicate the coefficients of the OF, and Q, K, N, B, A and H represent the constraint coefficient matrices. P_{real}, E_{real}, G_{real} and D_{real} are associated with the simulation values for uncertain parameters. Furthermore, R^b, R^a and R^c are positive decision variables that measure constraint violations, and σ^b, σ^a and σ^c, called penalty levels, represent the penalty costs associated with them, respectively. Here, we assume that the penalty levels for constraint violations are same. Finally, to compare both models, the standard deviation (Std Dev) and mean of the OF values are calculated under ten simulations and five penalty levels.

Figure 10 compares the Std Dev and mean of the OF values for the robust and deterministic models. As shown in the generated simulations, both the Std Dev and mean increase with higher penalty levels. The stochastic robust model demonstrates superiority over the deterministic model by maintaining lower Std Dev and mean values across different penalty levels. Notably, the lower Std Dev of the robust model highlights its ability to provide solutions that

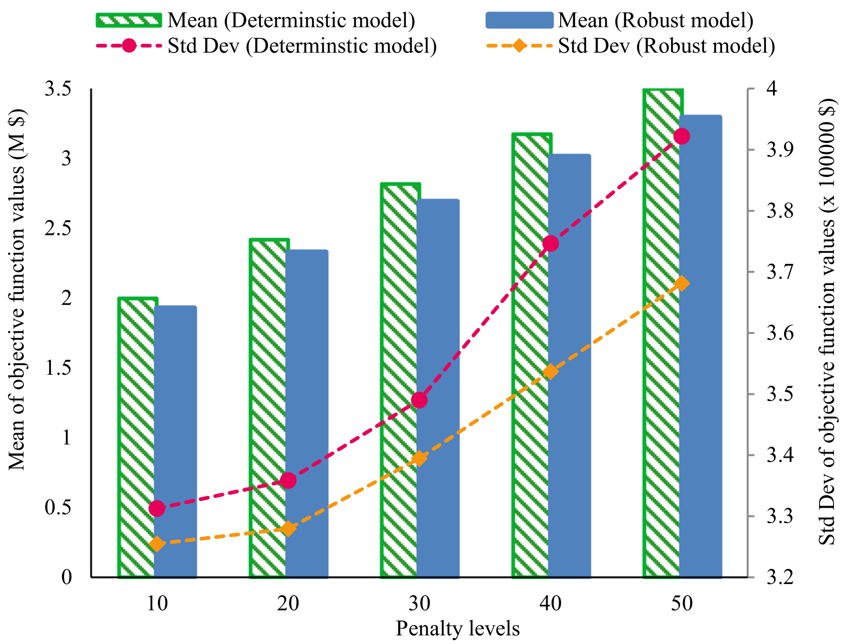

Fig. 10 Performance of stochastic robust and deterministic models under penalty levels

are highly resilient to variations in uncertain parameters. Specifically, the stochastic robust model ensures a stable design for the SC of the plastics industry, which is highly valuable in SC management.

6 Discussion

The literature review indicates that the simultaneous consideration of efficiency and resilience has rarely been explored in SC design literature. Most existing studies do not incorporate network design and outsourcing decisions to build resilient SCs. Only a few studies address operational and disruption risks across various SC levels, considering different RSs to manage these risks. Moreover, effective solution methods for handling the computational complexity of stochastic models have been infrequently applied in resilient SC design.

The results of this study provide a significant contribution to the literature on resilient SC design, particularly in managing disruptions and operational risks. While previous studies in the field have often focused on either cost minimization or resilience separately, this research simultaneously addresses both efficiency and resilience, introducing a novel two-phase approach. The proposed model integrates a unified DEA and stochastic robust optimization, offering a practical approach for evaluating supplier performance and incorporating network design and outsourcing decisions. This approach ensures that SC networks are more resilient to disruptions while optimizing both costs and supplier performance.

Below, we summarize some important managerial insights derived from the numerical findings:

- When the performance level increases, the SC tends to involve suppliers with higher performance scores which makes it more expensive. Additionally, more facilities are involved to meet the customers' demand as the SC's performance level improves. Interestingly, there is the nearly linear pattern of increase in the total cost with the rise in the SC's performance level. This finding allows managers to estimate the expected total cost in the face of disruptions when aiming to enhance the overall performance of suppliers.
- The numerical results show that the RSs are efficient in reducing the total lost sales in disruptions. Specifically, comparing the total lost sales of the case problem demonstrates that applying the strategies of "multiple sourcing" and "holding safety stock inventory" can significantly reduce the percentage lost sales. The reduction patterns in the total lost sales are almost analogous for different performance levels indicating that the RSs can be consistently effective regardless of the SC performance level.
- To solve large-scale stochastic models, the accelerated BDA exhibits superior performance in terms of number of iterations and runtime compared to CPLEX.
- The proposed stochastic RO model outperforms the deterministic model in terms of mean and Std Dev at different penalty levels.

Research aimed at demonstrating the applicability of the proposed approach using case study data often faces numerous limitations and challenges, and this research is no exception. These limitations in data collection stem from a lack of transparency in certain statistics and information, as well as difficulties in obtaining, organizing, and validating documentation. Furthermore, limited access to experts and time constraints during interviews add further complications to the data collection process.

7 Conclusions

This study proposed a two-phase optimization approach for designing a resilient SC network to random disruptions at suppliers, factories, and DCs. Our approach includes two phases. In Phase 1, the performance of suppliers is assessed using a unified DEA technique. In Phase 2, a stochastic RO model is proposed for determining RSs and network design decisions that can hedge SC against operational and disruption risks. A combination of the ε-constraint method and accelerated BDA was used to transform the problem into a single-objective formulation and solve the model. Our hybrid approach was applied to an actual case problem from degradable plastic bag industry. The results revealed that the unified DEA could improve sourcing decisions. It was also shown that the proposed methodology could reduce lost sales by incorporating RS to SC planning.

The results presented in this study suggest some fruitful avenues for future research. For instance, incorporating routing decisions into the RO model can provide more managerial insights. Additionally, our model can be extended by considering different types of quantity discount when acquiring raw materials. Future research can also consider the nexus of resilience and sustainability in the problem. Last but not least, other acceleration methods can be developed to enhance the convergence of the BDA.

Appendix A

Here, to formulate the proposed unified DEA model, we utilize the following notations. For more details about the unified DEA, one can refer to (Sueyoshi & Goto, 2012).

Sets:

M	Set of suppliers (DMUs),$m \in M$
J	Set of inputs,$j \in J$
R^g	Set of desirable outputs,$r \in R^g$
F^b	Set of undesirable outputs,$f \in F^b$

Parameters:

χ_{jm}	Amount of input j used by supplier m
ξ_{rm}	Amount of desirable output r produced by supplier m
ϖ_{fm}	Amount of undesirable output f produced by supplier m

ρ_j^x	Range of input j in OF
ρ_r^g	Range of desirable output r in OF
ρ_f^b	Range of undesirable output f in OF

Decision variables:

d_r^g	Slack variable for desirable output r
d_f^b	Slack variable for undesirable output f
d_j^{xg}	Input-related slack variables j on desirable outputs
d_j^{xb}	Input-related slack variables j on undesirable outputs
λ_m^g	Intensity or structural variable m for desirable outputs
λ_m^b	Intensity or structural variable m for undesirable outputs
α_m	Efficiency score for supplier m

The following unified DEA model is solved for each supplier as given in (62)-(69). Index 0 denotes the supplier under investigation.

$$Max\ \alpha_0 = 1 - \left[\sum_j \rho_j^x (d_j^{xg} + d_j^{xb}) + \sum_r \rho_r^g d_r^g + \sum_f \rho_f^b d_f^b \right] \tag{62}$$

$$\sum_m \chi_{jm} \lambda_m^g + d_j^{xg} = \chi_{j0} \qquad \forall j \tag{63}$$

$$\sum_m \xi_{rm} \lambda_m^g - d_r^g = \xi_{r0} \qquad \forall r \tag{64}$$

$$\sum_m \chi_{jm} \lambda_m^b - d_j^{xg} = \chi_{j0} \qquad \forall j \tag{65}$$

$$\sum_m \varpi_{fm} \lambda_m^b + d_f^b = \varpi_{f0} \qquad \forall f \tag{66}$$

$$\sum_m \lambda_m^b = 1 \tag{67}$$

$$\sum_m \lambda_m^g = 1 \tag{68}$$

$$\lambda_m^g,\ \lambda_m^b,\ d_j^{xg},\ d_j^{xb},\ d_r^g,\ d_f^b \geq 0 \qquad \forall m,\ j,\ f,\ r \tag{69}$$

Parameters ρ_j^x, ρ_r^g and ρ_f^b in Equation (58) are written as below.

$$\rho_j^x = \frac{1}{(|J| + \left|F^b\right| + |R^g|)\left[max_m\left\{\chi_{jm}\right\} - min_m\left\{\chi_{jm}\right\}\right]} \tag{70}$$

$$\rho_r^g = \frac{1}{(|J| + \left|F^b\right| + |R^g|)\left[max_m\{\xi_{rm}\} - min_m\{\xi_{rm}\}\right]} \tag{71}$$

$$\rho_f^b = \frac{1}{(|J| + \left|F^b\right| + |R^g|)\left[max_m\left\{\varpi_{fm}\right\} - min_m\left\{\varpi_{fm}\right\}\right]} \tag{72}$$

Appendix B

$$\begin{aligned} Max\ DSP = & \sum_s (SC + FC + EC + AC + HC - \phi_s^*)\ a_s^1 + \varepsilon\, a^2 \\ & - \sum_k \sum_m \sum_s \sum_u (1 - \sigma_{mus})\, \tau_{km}\, \overline{X}_{mu} a_{kms}^3 - \sum_n \sum_s \sum_{u'} (1 - \nu_{nu's})\, (\varphi_n\, \overline{C}_{nu'} + \overline{\Gamma}_{nu'})\, a_{ns}^4 \\ & - \sum_{n'} \sum_s \sum_{v'} \sum_{u'} (1 - \nu_{n'u's})\, \theta_{v'n'}\, \overline{T}_{v'n'u'} a_{n's}^5 + \sum_n \sum_s \varphi_n^{min} \sum_{u'} (1 - \nu_{nu's})\, \overline{C}_{nu'} a_{ns}^6 \\ & - \sum_v \sum_s \sum_w \sum_{w'} \delta_{vw}\, \overline{Z}_{vww'}\, (1 - \gamma_{ww's})\, a_{ws}^7 + \sum_i \sum_f \sum_s d_{ifs}\, a_{ifs}^{11} - \sum_l \sum_w \sum_s \overline{H}_{lw}\, a_{lws}^{12} \end{aligned} \tag{73}$$

$$-q_{kmos} a_s^1 + \pi_s \alpha_m a^2 - a_{kms}^3 + \tau_{km} a_{kos}^8 \leq \eta\, \pi_s\, q_{kmos} \qquad \forall\, m,\ o,\ k,\ s \tag{74}$$

$$-p_{fns} a_s^1 - a_{ns}^4 + a_{ns}^6 - \sum_k \mu_{kf} a_{kns}^8 + a_{nfs}^9 \leq \eta \pi_s\, p_{fns} \qquad \forall\ f,\ n,\ s \tag{75}$$

$$-p_{fn's} a_s^1 - a_{n's}^5 - \sum_k \mu_{kf} a_{kn's}^8 + a_{n'fs}^9 \leq \eta \pi_s\, p_{fn's} \qquad \forall\ f,\ n',\ s \tag{76}$$

$$-g_{fows}\, a_s^1 - a_{ws}^7 - a_{ofs}^9 + \sum_l a_{lws}^{10} \leq \eta\, \pi_s\, g_{fows} \qquad \forall\, o,\ f,\ w,\ s \tag{77}$$

$$-y_{lwis} a_s^1 - \beta_{fl} a_{lws}^{10} + \beta_{fl} a_{ifs}^{11} \leq \eta\, \pi_s\ y_{lwis} \qquad \forall\, l,\ s,\ w,\ i,\ f \tag{78}$$

$$-y_{lwis} a_s^1 + \beta_{fl} a_{ifs}^{11} - \beta_{fl} a_{lws}^{12} \leq \eta\, \pi_s\ y_{lwis} \qquad \forall i,\ l,\ w,\ s,\ f \tag{79}$$

$$-b_{ifs}\, a_s^1 + a_{ifs}^{11} \leq \eta\, \pi_s\, b_{ifs} \qquad \forall\, f,\ s,\ i \tag{80}$$

$$\sum_s a_s^1 \leq (1 - \eta) \tag{81}$$

$$\sum_s a_s^1 \leq (1 - \eta) \qquad \forall m,\ l,\ k,\ w,\ n',\ n,\ s \tag{82}$$

Appendix C

$$Min\, MP = \Omega + \eta(SC + FC + EC + AC + HC) \tag{83}$$

Subject to:

$$\Omega \geq \sum_{s} (SC + FC + EC + AC + HC - \phi_s^*)\, \hat{a}_s^1 + \varepsilon\, \hat{a}^2$$

$$- \sum_{k} \sum_{m} \sum_{s} \sum_{u} (1 - \sigma_{mus})\, \tau_{km}\, X_{mu} \hat{a}_{kms}^3 - \sum_{n} \sum_{s} \sum_{u'} (1 - \nu_{nu's})\, (\varphi_n\, C_{nu'} + \Gamma_{nu'})\, \hat{a}_{ns}^4$$

$$- \sum_{n'} \sum_{s} \sum_{v'} \sum_{u'} (1 - \nu_{n'u's})\, \theta_{v'n'}\, T_{v'n'u'} \hat{a}_{n's}^5 + \sum_{n} \sum_{s} \varphi_n^{min} \sum_{u'} (1 - \nu_{nu's})\, C_{nu'} \hat{a}_{ns}^6$$

$$- \sum_{v} \sum_{s} \sum_{w} \sum_{w'} \delta_{vw} Z_{vww'} (1 - \gamma_{ww's})\, \hat{a}_{ws}^7 + \sum_{i} \sum_{f} \sum_{s} d_{ifs}\, \hat{a}_{ifs}^{11} - \sum_{l} \sum_{w} \sum_{s} H_{lw}\, \hat{a}_{lws}^{12} \tag{84}$$

Constraints (17), (22)-(26), (28) to (30), (33)-(36).

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