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Supply chain network design under uncertainty: A comprehensive review and future research directions

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ABSTRACT

Supply chain network design (SCND) is one of the most crucial planning problems in supply chain management (SCM). Nowadays, design decisions should be viable enough to function well under complex and uncertain business environments for many years or decades. Therefore, it is essential to make these decisions in the presence of uncertainty, as over the last two decades, a large number of relevant publications have emphasized its importance. The aim of this paper is to provide a comprehensive review of studies in the fields of SCND and reverse logistics network design under uncertainty. The paper is organized in two main parts to investigate the basic features of these studies. In the first part, planning decisions, network structure, paradigms and aspects related to SCM are discussed. In the second part, existing optimization techniques for dealing with uncertainty such as recourse-based stochastic programming, risk-averse stochastic programming, robust optimization, and fuzzy mathematical programming are explored in terms of mathematical modeling and solution approaches. Finally, the drawbacks and missing aspects of the related literature are highlighted and a list of potential issues for future research directions is recommended.

Contents

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1. Introduction

In the early 1980s, SCM was introduced in order to respond to fierce competition among companies (Oliver & Webber, 1982). Over time, a growing number of corporations realized the significance of integrating their operations into key supply chain (SC) processes instead of managing them separately, thus extending the SCM evolution (La Londe, 1997). As pointed out by Handfield and Nichols (1999), SCM is "The holistic management approach for integrating and coordinating the material, information and financial flows along a supply chain." In accordance with Simchi-Levi, Kaminsky, and Simchi-Levi (2004) and the Council of Supply Chain Management Professionals, Melo, Nickel, and Saldanha-Da-Gama (2009) also defined SCM to be "The process of planning, implementing and controlling the operations of the supply chain in an efficient way." Several issues, such as appearance of short-life products, fierce competitions in today's markets, increasing expectations and changing customers' preferences, the development of new technologies, and globalization have led business enterprises to make large investments in their SCs (Simchi-Levi et al., 2004).

A SC, a complex network of organizations and facilities which are mostly settled in a vast geographical area or even the globe, synchronizes a series of interrelated activities through the network (Christopher, 1999). The SC network is also referred to as the logistics network by Simchi-Levi et al. (2004), and Ghiani, Laporte, and Musmanno (2004) defines the SC as "a complex logistics system in which raw materials are converted into finished products and then distributed to final users (consumers or companies)." On the other hand, Hugos (2011) points out that some differences exist between logistics management and SCM. In essence, logistics management, as a portion of SCM, focuses on activities such as inventory management, distribution, and procurement that are usually made on the boundaries of a single organization, while SCM includes other activities such as marketing, customer service, and finance as well.

SCND, also called *strategic supply chain planning*, is a part of the planning process in SCM, which determines the infrastructure and physical structure of a SC. Over the last two decades, SCND has been considered as a suitable application for *facility location* (FL) models. Revelle, Eiselt, and Daskin (2008) characterized existing FL models into four main types: *continuous*, *network*, *analytic*, and *discrete*. In spite of many differences among these models, they all include a set of customers with known locations and a set of facilities whose locations should be specified. Most SCND models belong to the category of discrete location models (Melo et al., 2009).

Several review papers exist on FL models, (e.g., Daskin, 2011; Owen & Daskin, 1998) and some surveys focus particularly on discrete location models (e.g., Klose & Drexl, 2005; Mirchandani & Francis, 1990; Revelle et al., 2008). However, FL models in the context of SCM have been reviewed by only a few papers, including Daskin, Snyder, and Berger (2005), Shen (2007b), and Melo et al. (2009). Therefore, there is still ample room to survey SCND models and methods.

Large investments are usually required to make strategic decisions in SCND. These decisions are very difficult to change and have long-term effects on SC's performance. The most common strategic decisions consist of determining locations and number of facilities, capacities and sizes of facilities, technology and area allocation for production and process of products at different facilities, selection of suppliers, and so on (Simchi-Levi et al., 2004). Over time (generally between three and five years), when a company has been influenced by these decisions, many parameters, including demand, capacity, and costs of its SC network, can have major fluctuations. Further, the parameters associated with SCND involve an enormous volume of data, often resulting in wrong estimations due to inaccurate forecasts and/or poor measurements in the modeling process (e.g., aggregation of demand points and products). Thus, SCND under uncertainty has obtained significant attention in both practice and academia over recent years.

Designing *reverse logistics* (RL) networks is another type of optimization problem based on the FL models. The RL networks are often designed for the purpose of collecting used, refurbished, or defective products from customers and then carrying out some recovery activities. Due to the stringent pressures from environmental regulations, many companies have been confronted with the challenge of designing RL networks. Locating facilities to perform recovery activities is one of the key strategic decisions to be made in this problem. Indeed, these facilities should operate properly over many years under uncertain business environments. Thus, the task of dealing with existing uncertainty in the return quantities and other parameters of RL networks plays a significant role in designing them. RL network design under uncertainty has attracted a great deal of attention and, as a result, an investigation into this problem is included in our review paper as well. It is noteworthy that this problem has many similarities to the SCND in terms of optimization approaches. Further, the forward and reverse logistics networks are often integrated, also known as closed-loop supply chain (CLSC) network.

The main purpose of this paper is to review the studies and optimization approaches developed for designing SC, CLSC, and RL networks under uncertainty. Briefly, our major research questions in this field are:

i. Which SCM paradigms and issues are addressed?
ii. What sources of uncertainty are considered?
iii. How are uncertain parameters modeled and integrated into the existing mathematical formulations?
iv. Which optimization techniques and tools are mostly utilized?
v. Which real-world case studies are investigated?

In this regard, Snyder (2006) represented a survey on stochastic and robust FL problems without consideration of SCM aspects. Reliable FL models for SCND with disruptions were studied by Snyder and Daskin (2007) . Furthermore, a critical review on optimization models for robust design of SC networks was represented by Klibi, Martel, and Guitouni (2010). They categorized existing uncertainties in the SCND problem and investigated their impacts on the network as well. Moreover, SCND has been the subject of many recent review papers focusing on other SC features (e.g., Farahani, Rezapour, Drezner, & Fallah, 2014; Eskandarpour, Dejax, Miemczyk, & Péton, 2015). However, to the best of our knowledge, there has not been any review paper in the area of SC and RL network design under uncertainty that focused on both SCM aspects and optimization techniques. Therefore, in the presented survey on this area:

- A comprehensive and categorized review is provided in accordance with network structure, planning decisions and main SCM issues.
- Various uncertainty sources and different uncertainty modeling approaches for developing an optimization model are studied.
- Optimization techniques, including modeling and solution approaches to deal with uncertainty, are investigated as a general framework.
- Relevant real-life applications and case studies are explored.
- Finally, significant research gaps are introduced to be investigated as future studies by scholars and researchers.

The remainder of this paper is organized as follows: In Section 2, the scope and our research procedure are introduced. In Section 3, different related decision-making environments are discussed. The associated papers are categorized consistent with the SCM issues in Section 4. Optimization aspects in the related literature are investigated in Section 5. The studies addressing real-world applications are introduced in Section 6. Finally, in Section 7, a discussion, conclusions and possible future research directions are explicated.

2. Scope and review methodology

In this paper, peer-reviewed articles published over the last two decades in ISI indexed journals in the context of SCND (including RL and CLSC network design as well) under uncertainty are studied. We consider three criteria for these papers, including: (1) the paper must be written in English; (2) one of the decision variables is location or selection of facilities from potential candidates for at least one layer of SC; and finally, (3) at least one of the problem's parameters is uncertain. Published papers in international journals among electronic bibliographical sources including *Scopus* and *Web of Science* have been searched by using a combination of different keywords.

Firstly, we searched on 12 June 2015 by using keywords (*supply chain network design* OR *strategic supply chain planning*) AND (*stochastic* OR *uncertain* OR *robust* OR *risk* OR *fuzzy* OR *reliable* OR *resilient*), and we came up with 33 and 24 journal papers from *Scopus* and *Web of Science*, respectively. Then, using wider combinations of keywords, (*Supply chain* OR *logistic* OR *supply network* OR *recovery network* OR *distribution network*) AND (*design* OR *planning*) AND (*stochastic* OR *uncertain* OR *robust* OR *risk* OR *fuzzy* OR *reliable* OR *resilient*), we obtained 259 journal papers from *Scopus.* However, many of them were not published in ISI indexed journals or more specifically, they did not satisfy the second or third criteria, which are the key considerations in this study. Further, the scope of this survey was addressed with other keywords such as transportation–production, and transportation–inventory networks by a few studies in the past. Therefore, to resolve the limitations of our search keywords and provide a comprehensive review, we have completed our survey by utilizing other survey and review papers in the area of SCND, FL, and SCM.

Using all afore-mentioned search strategies, 170 journal papers, published from 2000 up to now, are explored. We refer to them as reference papers from now on. The distribution of these reference papers in terms of their publication date is shown in Fig. 1. In Fig. 1, more than 50% of these papers were published from 2012 up to now where many developments and much progress have been made in the area of optimization, and this recent trend reveals the importance of uncertainty in the area of SCND problem.

In addition, Fig. 2 elucidates the share of international journals that have the highest contributions in publishing the reference papers: *European Journal of Operational Research* and *Transportation Research Part E: Logistics and Transportation Review* occupy first and second rank by publishing 17 and 15 papers, respectively.

Additionally, Table 1 displays existing review papers in the relevant literature. Note that all these papers are in the area of SCM, but some of them explored the FL or logistics network design models in SCM, specifically. Their scope and special features are reported in Table 1. Moreover, the numbers of reference papers that have some overlapping with our review paper are put in the last column of Table 1.

As shown by Table 1, while there are overlapping areas between other review papers and ours, to our knowledge, no review paper has examined the aspects taken into account in this paper. In summary, the purpose of this paper is to explore the studies that have been made in the area of SCND (including CLSC and RL network design as well) under uncertainty to highlight the research gaps and future research directions. Therefore, the reference papers are investigated in terms of different uncertain decision-making environments, network structures, planning decisions, various paradigms and aspects of SCM. Further, we examine different optimization approaches to deal with uncertainty in these studies. The papers that have addressed a SC of a real-life case study or specific industry are also discussed.

3. Decision-making environments for SCND under uncertainty

Several parameters of a SCND problem, such as costs, demand, and supply, have inherent uncertainty. Moreover, SC networks can be affected by major man-made or natural disruptions such as floods, terrorist attacks, earthquakes, and economic crises. However, these kinds of disruptions usually have a low likelihood of occurrence, but their impacts on SC network are prominent.

The objective of SCND under uncertainty is to achieve a configuration so that it can perform well under any possible realization of uncertain parameters. But, this measure of performing well for different SC networks under uncertain environments could be quite different according to the viewpoints of decision makers.

Based on the definition of different decision-making environments by Rosenhead, Elton, and Gupta (1972) and Sahinidis (2004), uncertain environments for the SCND problem can be categorized according to the following groups:

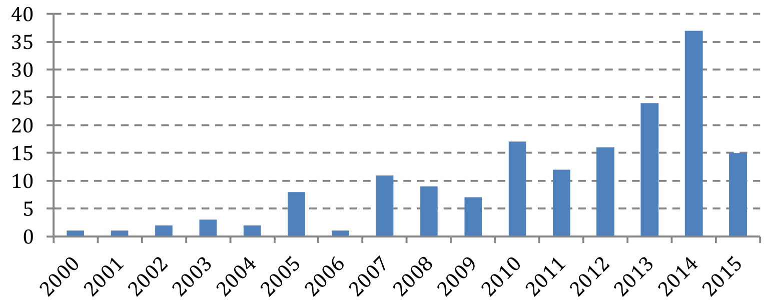

Fig. 1. Publication date distribution of reference papers.

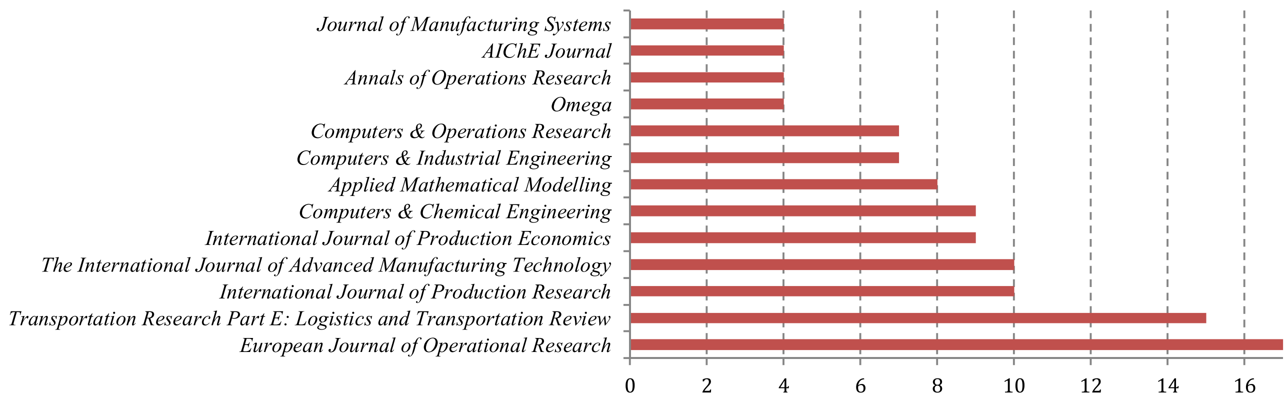

Fig. 2. Share of international journals with the highest contributions in publishing the reference papers.

Table 1
Scope and special features of relevant review papers.

Articles	Facility location/ logistics network design focus	Scope and special features	Number of shared reference papers
Akçalı, Çetinkaya, and Üster (2009)	×	Network design for Reverse and Closed loop supply chains	2
Melo et al. (2009)	×	Facility location models in the context of SCM	16
Klibi et al. (2010)	×	Optimization approaches, key random environmental factors and disruptive events in SCND under uncertainty	7
Elbounjimi, Abdulnour, and Ait-Kadil (2014)	×	Green closed loop supply chain network design	5
Farahani et al. (2014)	×	Competitive SCND	26
Eskandarpour et al. (2015)	×	Sustainable SCND	7
Heckmann et al. (2015)		Supply chain risk	6
Govindan, Soleimani, and Kannan (2015)		Reverse logistics and Closed loop supply chains	16

Group 1* (G1)*: Decision-making environments with random parameters in which their probability distributions are known for the decision maker. Here, these parameters are called stochastic parameters. Stochastic parameters in SCND are described by either continuous or discrete scenarios.

In a smaller part of Group 1, the stochastic parameters are described using a known continuous probability distribution. This type of SCND problem – except for simple networks with one location layer – engenders intractable optimization models. Additionally, the customers' demand is the most popular stochastic parameter in these studies, which is modeled through the normal distribution with known mean and variance. A discussion about these studies is provided in Section 5.2.

Sheppard (1974) was one of the seminal authors who used a scenario approach for a FL problem; gradually, this approach has been exploited for SCND. The scenario approach leads to tractable optimization models. By this approach, we can describe various stochastic parameters having different probability distributions with consideration of dependency among them. Therefore, this approach is quite common for describing stochastic parameters (Snyder, 2006). A complete review of this group of uncertain decision-making environments is provided in Section 5.4.

Group 2* (G2)*: Decision-making environments with random parameters in which the decision maker has no information about their probability distributions. Under this setting, robust optimization models are usually developed for SCND with the purpose of optimizing the worst-case performance of SC network. The random parameters in this decision-making group are divided into either continuous or discrete. To model discrete uncertain parameters, the scenario approach has been used. However, for continuous uncertain parameters, some pre-specified intervals are defined. This approach is also called interval-uncertainty modeling. Optimization models for SCND under this group of decision-making environments are studied in detail in Section 5.6.

Group 3* (G3)*: Fuzzy decision-making environments. In general, there exist two types of uncertainties including *ambiguity* and *vagueness* under the fuzzy decision-making environment. *Ambiguity* denotes the conditions in which the choice among multiple alternatives is undetermined. However, *vagueness* states the situations in which sharp and precise boundaries for some domains of interest are not delineated. In this context, fuzzy mathematical programming handles the planner's expectations about the level of objective function, the uncertainty range of coefficients, and the satisfaction level of constraints by using membership functions

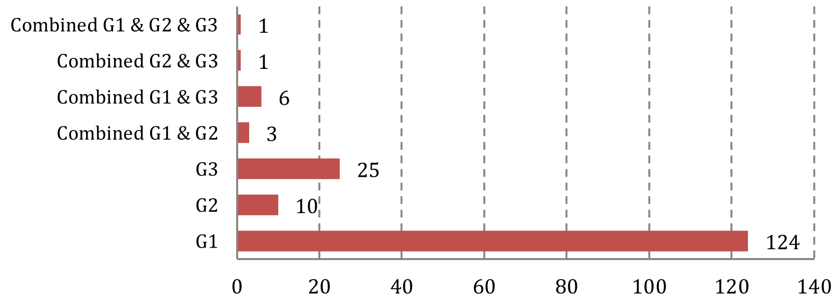

Fig. 3. Frequency of reference papers with respect to different uncertain decision-making environments.

(see Inuiguchi & Ramık, 2000; Sahinidis, 2004). The studies belonging to this group are discussed in Section 5.7.

Fig. 3 presents the frequency of reference papers according to the above-mentioned uncertain decision-making environments.

4. SCM issues in designing SC networks

In this section, the relevant papers are categorized based on the main aspects of SCM including the structure of network, decision variables, and SCM's paradigms.

4.1. Network structure and uncertain parameters

A SC network converts raw materials into final products and then delivers them to customers. It includes various types of facilities, and each type plays a specific task in the network. A set of facilities with the same task and type is called a layer or echelon. A crucial aspect of SCND studies is the number and type of layers and the layers in which location decisions are determined. The usual layers of SC networks are composed of suppliers, plants, distribution centers, warehouses, and customers and the typical material flows are often from suppliers to customers. It is noteworthy that another issue driven by real-life applications is the necessity to deal with multi-product problems.

Regarding the material and product flows in a SC network, some studies have the assumption of being single-sourcing, which means a facility or a customer can be served by only one facility from its upstream layer (e.g., Georgiadis, Tsiakis, Longinidis, & Sofioglou, 2011; Shen & Daskin, 2005). Moreover, some studies have regarded the material/product flows in one layer of SC, called intra-layer flows (e.g., Aghezzaf, 2005; Mousazadeh, Torabi, & Zahiri, 2015). Furthermore, direct flows from upper layers to customers have been taken into account in the literature (e.g., Govindan, Jafarian, & Nourbakhsh, 2015; Vila, Martel, & Beauregard, 2007). In Fig. 4, different types of these material flows for a typical SC network are shown.

In this paper, the studies related to RL network design under uncertainty are also reviewed. Several studies in the relevant literature have focused on designing only a RL network (also called a recovery network) and some others have integrated forward and reverse networks, named a CLSC network. As stated by Melo et al. (2009), the strategic planning for RL networks has many similarities with forward logistics networks. The main differences are the type of facilities they use and the direction of flows. In RL networks, the reverse flows are often started by collecting used and defective products from customers and their final destination is usually recovery, remanufacturing, disposal centers, or secondary markets (Keyvanshokooh, Fattahi, Seyed-Hosseini, & Tavakkoli-Moghaddam, 2013).

Table 2
Defined abbreviations for uncertain parameters.

Uncertain parameter	Abbreviation
Demand	D
Cost of activities (e.g., transportation, production)	C
Capacity of network facilities/ transportation links	CA
Supply quantity for network facilities	S
Required capacity for producing products	CR
Capacity coefficients for holding products/materials in SC facilities	CS
Parameters of demand distribution function	DP
Selling price of finished products	P
Buying price of raw materials	PR
Conversion rates of materials/components/products to process other materials/components/products in network facilities.	CP
Safety-stock levels for products in SC facilities	SS
Processing/production time for network facilities	PT
Transportation time through entities of SC network	TT
Supply time for network facilities	ST
Fuzzy goals to represent aspiration levels of multiple objectives	FG
Availability of network facilities	AF
Availability of transportation links/modes between network's entities	AT
Disrupted products/supply/commodities in SC facilities	DC
Return quantities in a RL or CLSC network	R
Disposal rate of returns in a RL or CLSC network	DR
Buying price of returns in a RL or CLSC network	BP
Proportion of returned products/components for different activities (e.g., remanufacturing, recycling, refurbishing) in a RL or CLSC network	PA
Profit of recycling/remanufacturing returned products in RL or CLSC network	PP
Selling price of RL outputs (products/components/raw materials) to customers in a RL or CLSC network	SP
Demand for RL outputs (products/components/raw materials) in a RL or CLSC network	DS
Financial parameters such as tax, exchange, and interest rate	FP
Environmental parameters such as environmental impacts of SC's activities and facilities	EP
Social parameters related to designing logistics networks	PS

Another important feature of SCND problem is that it is sometimes assumed that there is a primary structure for a SC network and then the goal is to redesign it (e.g., Aghezzaf, 2005).

The most uncertain parameters that have been assumed in designing logistics networks in the reference papers are listed in Table 2. Here, we present some abbreviations for these parameters, which are used in the following sections of the paper.

In Appendix A, the reference papers are characterized based on the structure of the forward SC network in Table A.1. CLSC and RL network design models are categorized according to the structure of RL network in Table A.2. The uncertain parameters and their classification on the basis of different decision-making environments are also illustrated in Tables A.1 and A.2. In these tables, we assign numbers to the reference papers, which have been utilized in the following sections to analyze them.

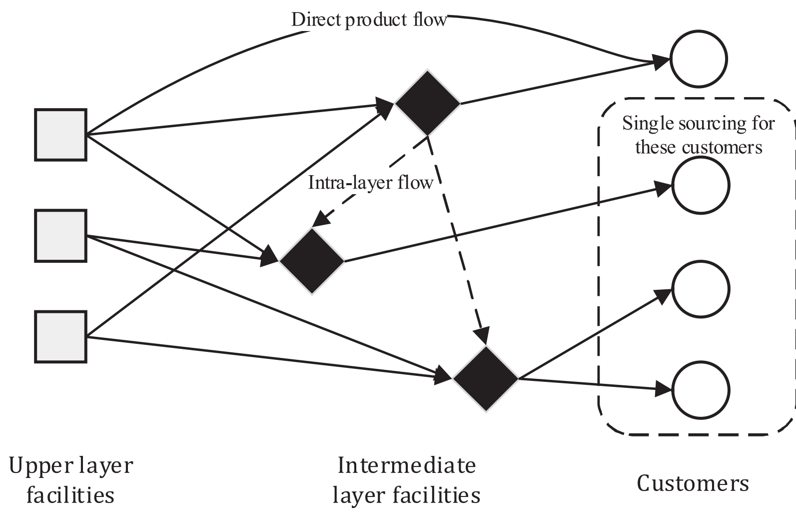

Fig. 4. A SC network structure with different types of product flows.

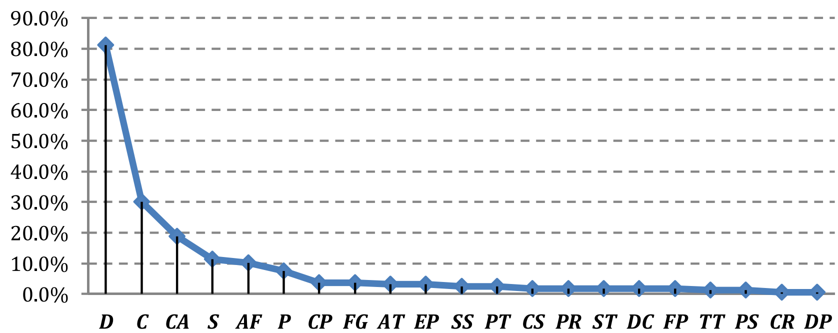

Fig. 5. Frequency of uncertain parameters in the forward logistics network of reference papers.

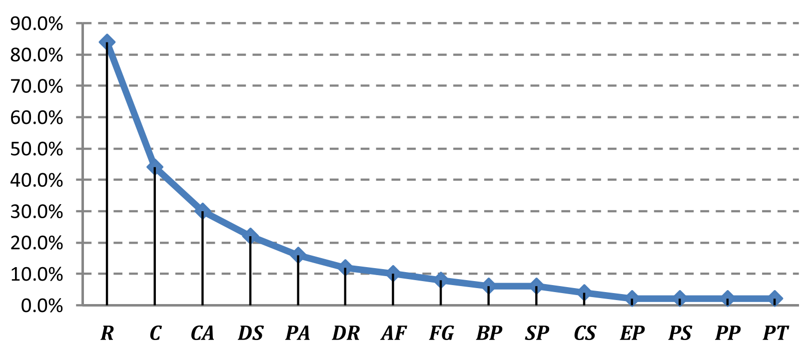

Fig. 6. Frequency of uncertain parameters in the RL network of reference papers.

By analyzing tables in Appendix A, we highlight many key facts about logistics network design models under uncertainty. One of the most significant factors is the frequency of uncertain parameters assumed in designing forward and RL networks, which is illustrated by Figs. 5 and 6, respectively.

In Table 3, the forward SC and CLSC network design models are categorized according to the forward network structure and the type of decision-making environment under uncertainty. Table 4 represents this classification for the reverse and CLSC network design models based on the RL network features. Here, the network features include the number of commodity and the number of layers in which location decisions are specified. This idea of classification has been gained from Melo et al. (2009).

From Tables 3 to 4, we can conclude that most reference papers have considered single or two location layers. A few papers have dealt with RL or CLSC network design problem under uncertainty and about 70% of them have explored SCND problem without consideration of RL activities.

In optimization problems under uncertainty, decision-making environments depend on available information for uncertain parameters and their source of uncertainty. Klibi et al. (2010) investigated different existing uncertainties in SC as well as their sources and impacts. Here, G1 and G2 have the highest and lowest frequencies among the reference papers' decision-making environments, respectively. Moreover, a few papers have assumed combined uncertain decision-making environments to model their SC network on the basis of type and features of their uncertain parameters (e.g., Keyvanshokooh, Ryan, & Kabir, 2016; Sadghiani, Torabi, & Sahebjamnia, 2015; Torabi, Namdar, Hatefi, & Jolai, 2016; Vahdani, Tavakkoli-Moghaddam, Modarres, & Baboli, 2012).

Among the reference papers, about 19% of them have addressed SCND problem with disruption. The influences of disruptions on

Table 3
Classification of SC and CLSC network design models based on the decision-making environment and features of forward logistics network.

		G1	G2	G3
1 location layer	Single commodity	[3,4,5,8,9,10,11,13,15,18,19,20,21,22,23,24,29,33,34,42,44,45,50, 54,55,57,61,62,63,67,70,72,73,75,86,87,88,90,96, 100,101,104,105,107,112,113,121,122,130,143]	[66]	[53,81,128]
	Multiple commodities	[6,17,25,28,35,38,51,68,69,71,78,80,84,89,99,108, 124,139,144,145,153]	[79,152,154]	[99,138,139,153]
2 location layers	Single commodity	[36,40,46,74,85,114,115,118,120,126,127,137,149,150,156]	[133,137,146,156]	[27,77,82,94,110,146,149,150,151]
	Multiple commodities	[1,2,7,12,26,32,37,43,47,48,52,56,58,59,60,64,91,93,95,98, 109,125,136,159]	[92,159]	[31,65,116,123,131]
3 location layers	Single commodity	[106,155]		[41,103]
	Multiple commodities	[14,16,30,39,76,97,111,132,134,157]	[141,148,157]	[140,142]
>3 location layers	Single commodity	[49]		
	Multiple commodities	[129]		[158]

Table 4
Classification of RL and CLSC network design models based on the decision-making environment and features of RL network.

		G1	G2	G3
1 location layer	Single commodity	[23,70,162,164]		[81,128,135,163]
	Multiple commodities	[25,38,83]	[79, 83,148, 160]	[65,83,167]
2 location layers	Single commodity	[85,156, 161,165]	[156]	[110]
	Multiple commodities	[26, 28,47,84,91,99,102,139,147,168]	[92,154]	[99,102,123,138, 139]
3 location layers	Single commodity	[40,137, 149, 150]	[137,146, 166]	[53, 119,146,149,150,151]
	Multiple commodities	[97,169, 170]		[117]
>3 location layers	Single commodity			
	Multiple commodities	[129,134]		

the physical structure of a SC network may result in having uncertainty in some parameters. Facilities' capacity, availability of facilities and their connections, and amount of disrupted products in SC facilities are the most frequent parameters, which have been assumed uncertain because of disruption events. It must be noted that disruptions can deeply fluctuate costs, demand and supply parameters, which should be of more interest to future researchers.

4.2. Planning horizon and decisions for SCND

Due to the complexity of SC networks in today's business environment, it is important to consider several planning decisions along with the classical location-allocation decisions to achieve an integrated system. These planning decisions remain constant for different time spans and may be divided into three categories, including strategic (long-term), tactical (mid-term), and operational (short-term) level decisions according to their time spans.

In the strategic level, there are usually several crucial SC decisions to be made such as the number, locations, and capacity of facilities. While it depends entirely on the nature of the SC, strategic decisions typically hold for about three to five years. Tactical decisions are usually made for three months to three years and operational decisions (e.g., vehicle routing decisions) are often constant for one hour to one trimester (Vidal & Goetschalckx, 1997). It should be noted that holding these decisions for a certain time span is mostly dependent on the nature of SC and thus it can vary for different SCs.

Fig. 7 illustrates different SC decisions (except location-allocation, production, and inventory decisions that are considered in the majority of the related literature), which have been determined in SCND problems.

As shown by Fig. 7, the decisions associated with different planning levels are taken into account in the related literature. However, several decisions such as products' price and routing decisions have been addressed by a few studies. Pricing decisions are usually put at the tactical planning level and routing decisions belong to the operational planning level, which are rarely integrated with SCND under uncertainty in the related literature.

Distribution networks, often the ending part of a SC network, consist of products flows from depots to customers or retailers. The design of such network requires solving two hard combinatorial optimization problems including determining the depots' locations and vehicle routes to serve customers. For the first time, Salhi and Rand (1989) revealed numerically that solving the FL and routing problems separately leads to suboptimal solutions. Then, the location-routing problem gained substantial attention. Recently, Prodhon and Prins (2014) presented a survey paper in this area. In the context of SCND under uncertainty, Ahmadi-Javid and Seddighi (2013), Javid and Azad (2010), and Azad and Davoudpour (2013) addressed the FL and routing decisions simultaneously under uncertainty.

In the majority part of literature, the decisions have been made for a single period. As explained by Melo et al. (2009), these single-period SCND models may be enough to obtain a robust configuration for a network and also a robust set of operational and tactical decisions. Moreover, another part of the literature has addressed SCND problem with a planning horizon including multiple periods. In these studies, the periods can be divided into (1) tactical/operational time periods, or (2) strategic time periods.

In the studies with multiple tactical or operational periods (e.g., Schütz, Tomasgard, & Ahmed, 2009; Tsiakis, Shah, & Pantelides, 2001), strategic decisions are made at the beginning of planning horizon while tactical or operational decisions, such as products allocation to customers and inventory levels, are able to be changed in different periods throughout the planning horizon.

In addition, some studies consider the possibility of applying future adjustments in the SC strategic decisions. These kinds of adjustments are typically made for location and/or capacity of facilities, for example, due to unstable condition of target markets, expansion opportunities for new markets, and budget limitations for investments. Thus, a planning horizon divided into several strategic periods is assumed (e.g., Aghezzaf, 2005; Nickel, Saldanha-da-Gama, & Ziegler, 2012).

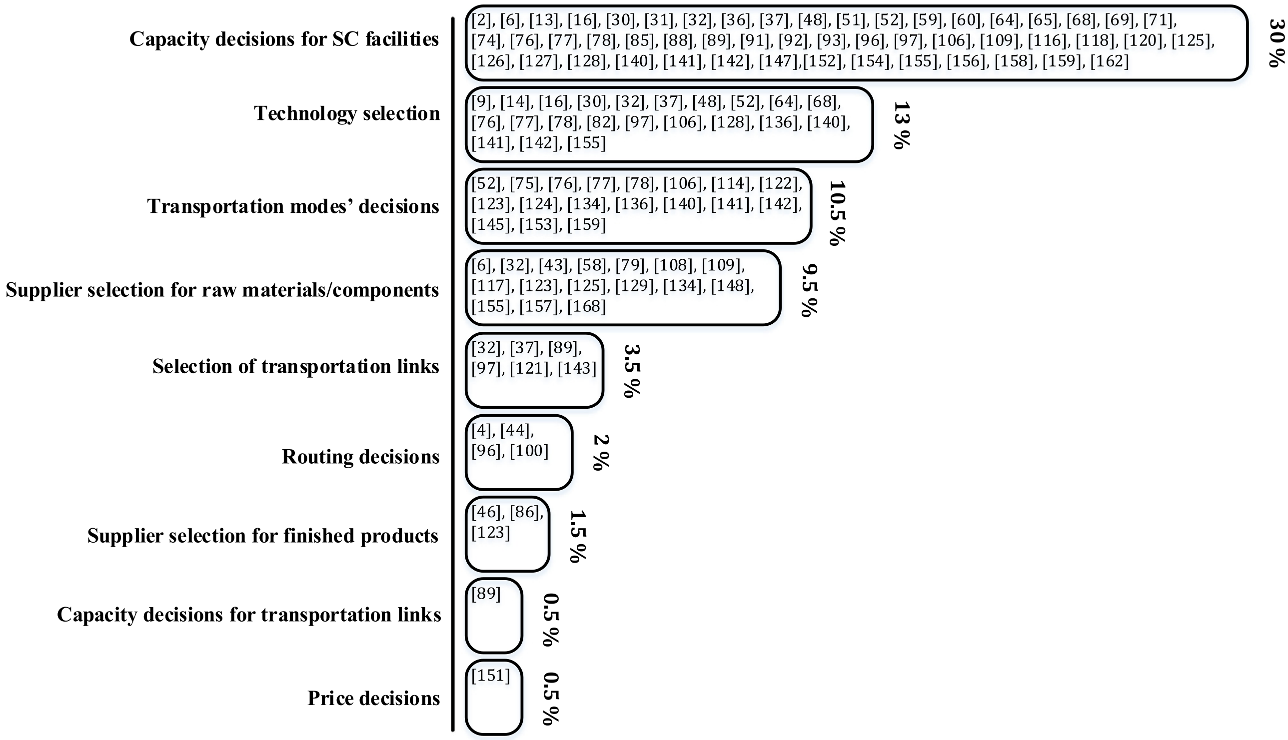

Fig. 7. Main planning decisions (except location-allocation, production, and inventory) in the reference papers.

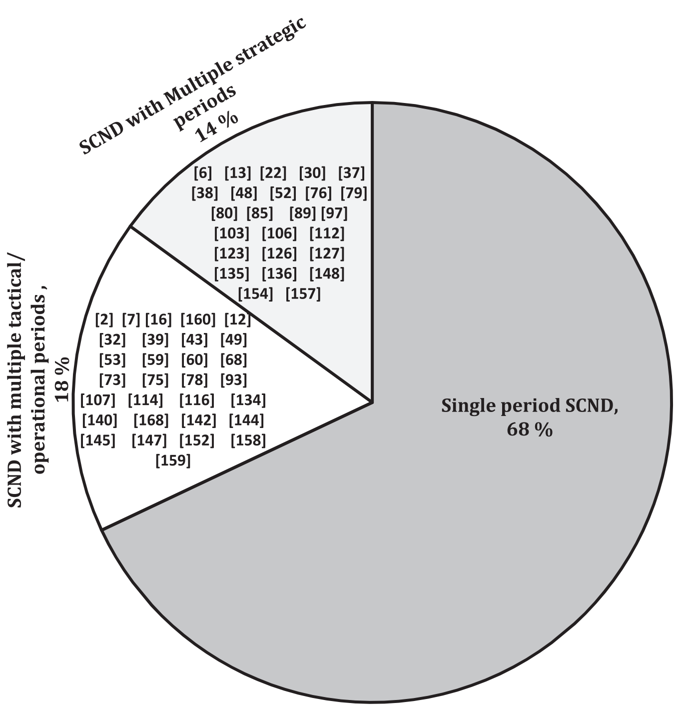

Fig. 8. Frequency of reference papers in terms of their planning horizon.

Fig. 8 classifies the SCND models under uncertainty that considered a planning horizon with multiple strategic periods or multiple tactical/operational periods. It also compares the frequency of single-period SCND models with multiple-periods ones. It can be drawn from Fig. 8 that most SCND models under uncertainty are single-period.

There exist some practical features related to SCND problems with multiple strategic periods. Sometimes, it is presumed that facilities can be closed, opened, or reopened more than once over a planning horizon. Further, expanding, reducing, or relocating facilities' capacities are another key issue. Melo, Nickel, and Da Gama (2006) investigated different approaches to make capacity planning for a deterministic dynamic FL problem. However, the papers that addressed these concerns in multi-period SCND problem under uncertainty are still scarce. It is worth mentioning that a limited number of studies in deterministic SCND problems (e.g., Correia & Melo, 2016; Fattahi, Mahootchi, & Husseini, 2016; Fattahi, Mahootchi, Govindan, & Husseini, 2015; Salema, Barbosa-Povoa, & Novais, 2010) have used a planning horizon including interconnected strategic and tactical periods, but no study has yet regarded this issue under an uncertain environment.

4.3. Risk management in SCND problem

Risk management in SCM has gained considerable attention in both practice and academia recently. Unfortunately, there is not a clear and comprehensive consensus for definition of *supply chain risk*. Sodhi, Son, and Tang (2012) explored researchers' perspectives in this area and emphasized that their perspectives are widely diverse. Moreover, Heckmann, Comes, and Nickel (2015) asserted that no unique definition has been provided for the SC risk. Further, the term *risk* is still a rather vague concept and generally, risk comprehension is based on the fear of losing (business) value. Heckmann et al. (2015), after examining various relevant research works, defined the supply chain risk as the potential loss for a SC in terms of its objectives caused by uncertain variations in SC features due to occurrence of triggering-events. Further, they provided some major characteristics of SC risk that one can refer to this study for more details.

In SCND problem under uncertainty, consistent with a presented classification by Tang (2006a), SC risks can be divided into *operational* and *disruption risks* based on the source of uncertainties. As pointed out by Behdani (2013) and Snyder, Atan, Peng,

Table 5
Reference papers dealing with operational or disruption risks in SCND problem under uncertainty.

	Reference papers	Share (%)
Operational risks	Azad and Davoudpour (2013), Azaron, Brown, Tarim, and Modarres (2008), Baghalian et al. (2013), Franca et al. (2010), Gebreslassie, Yao, and You (2012), Goh et al. (2007), Guillén et al. (2005), Guillén, Mele, Bagajewicz, Espuña, and Puigjaner (2003), Huang and Goetschalckx (2014), Jabbarzadeh et al. (2014), Jin et al. (2014), Kara and Onut (2010b), Kazemzadeh and Hu (2013), Madadi, Kurz, Taaffe, Sharp, and Mason (2014), Nickel et al. (2012), Pan and Nagi (2010), Pasandideh, Niaki, and Asadi (2015), Ramezani, Bashiri, and Tavakkoli-Moghaddam (2013a), Sabio, Gadalla, Guillén-Gosálbez, and Jiménez (2010), Sadghiani et al. (2015), Soleimani and Govindan (2014), Soleimani, Seyyed-Esfahani, and Kannan (2014), and Govindan and Fattahi (2017)	**14%**
Disruption risks	Jabbarzadeh, Naini, S., Davoudpour, and Azad (2012), Mak and Shen (2012), Ahmadi-Javid and Seddighi (2013), Azad et al. (2014), Baghalian et al. (2013), Jabbarzadeh et al. (2014), Klibi and Martel (2012a), Klibi and Martel (2013), Noyan (2012), and Sadghiani et al. (2015)	**5%**

Rong, Schmitt, and Sinsoysal (2016), supply chain disruption is an event that may occur in a part of SC due to natural disasters (e.g., earthquakes and floods) or through intentional/unintentional human actions (e.g., war and terrorist attacks), which have undesired effects on SC's goal and performance. Moreover, the operational risks are rooted in intrinsic uncertainties of SC, such as uncertainty in supply, demand, lead-time, transportation times and costs. This risk type usually has no influence on functionality of SC's elements, while it affects the operational factors, which are basically assumed to be uncertain. However, the disruption risks evoked by SC disruptions can affect functionality of SC's elements either completely or partially for uncertain time duration.

In Table 5, the studies that dealt with risk management (either operational or disruption risk) in the context of SCND problem under uncertainty are classified.

In most studies in Table 5, risk measures have been utilized in an optimization problem to cope with the existing risk. We discuss these risk measures in detail in Section 5.5.

4.4. Resilient SCND

It is crucial to regard SC disruptions while designing a SC network since there are a few recourses for making strategic decisions when a disruption happens. However, firms can adjust their tactical and operational decisions under disruptions. Planning for SC networks with disruptions was studied by Snyder, Scaparra, Daskin, and Church (2006) in terms of mathematical modeling. This issue is discussed on Section 5.8.

For a SC under uncertainty, there exist a number of strategies that can be utilized to manage the risk associated with disruptions. In accordance with Tomlin (2006), *mitigation* strategies are those where a SC takes some preventive actions in advance of a disruption and also pays their related costs regardless of whether a disruption takes place, while *contingency* strategies are those where a SC takes several actions merely when a disruption happens with the aim of returning SC to its original condition. As pointed out by Christopher and Peck (2004) and Tang (2006a), *resilience* is a system or firm's capability to return to its initial condition or even to a more desirable state after disruption. In SCM, this ability is directly affected by SC resources and design of its network. Indeed, a *resilient supply chain network* should operate efficiently both normally and in the face of a disruption. Regarding resilient SCND under disruption events, a few papers employed mitigation strategies. These strategies are discussed in detail on Section 5.8.

Measuring the resiliency of SCs is still a questionable task and different resilience indicators have been defined in the existing literature. In this regard, Cardoso, Barbosa-Póvoa, Relvas, and Novais (2015) investigated the performance of different resilience metrics and indicators for various types of SC networks and Spiegler, Naim, and Wikner (2012) presented an assessment framework of resilience. In fact, the choice of approaches for designing resilient SC networks is contingent upon many factors such as availability of financial resources, network structure, risk preference of decision maker, and so on.

4.5. Different paradigms in SCM

In a SC, the initial goals include meeting demand of customers, functionality of SC's processes, and accessibility of SC's resources (Heckmann et al., 2015). SCND was seeking traditionally to achieve these goals economically. However, the business goals of a company affect its SCND problem and, in fact, a suitable design of SC network enables the company to attain its goals and competitive advantages. If a corporation wants to become successful in today's market, both its SC and competitive strategies should fit together to have aligned goals. Over the last decade, various paradigms have been proposed in SCM that influence designing a SC network. In this section, we explore these paradigms briefly.

4.5.1. Responsive SCND

Besides economic goals, several companies consider responsiveness of their SC as another goal to attain competitive advantages. Different definitions exist for the SC responsiveness: the ability of a SC to produce innovative products, meet short lead-times, cope with a wide range of products, and meet a high service level (Chopra & Meindl, 2013). Gunasekaran, Lai, and Cheng (2008) defined the SC responsiveness as a paradigm that has emerged in response to the volatile and competitive business environment; thus, a responsive SC has to be highly flexible to changes of market or customer requirements.

In a optimization problem for designing responsive SC networks, several studies considered objective functions such as minimizing service time of customers (e.g., Cardona-Valdés, Álvarez, & Ozdemir, 2011; Mirakhorli, 2014; You & Grossmann, 2011), maximizing fill rate of customers' demands (e.g., Shen & Daskin, 2005), and minimizing lateness of products' delivery to customers (e.g., Pishvaee & Torabi, 2010). Fig. 9 represents the studies that dealt with responsive SCND models under uncertainty. Recently, Fattahi, Govindan, and Keyvanshokooh (2017) presented a stochastic model for designing responsive and resilient supply chain networks with delivery lead-time sensitive customers.

4.5.2. Green SCND

The increasing importance of environmental issues for SCs has resulted in integrating different environmental factors in SCND models instead of only focusing on pure economic models. This integration can be applied as either environmental measures in objective functions or environmental constraints in the mathematical model. Green SCND is another paradigm that aims to merge economic and environmental goals/factors in designing SC networks. Fig. 9 specifies studies that regarded environmental concerns. It is worth noting that the effects of SC activities on the environment have been considered as uncertain parameters in Guillén-Gosálbez and Grossmann (2010), Guillén-Gosálbez and Grossmann (2009), Pishvaee, Razmi, and Torabi (2014), Pishvaee, Torabi, and Razmi (2012), and Babazadeh, Razmi, Pishvaee, and Rabbani (2017).

Furthermore, mitigating the environmental disruptions via wastes of used products is another significant environmental issue

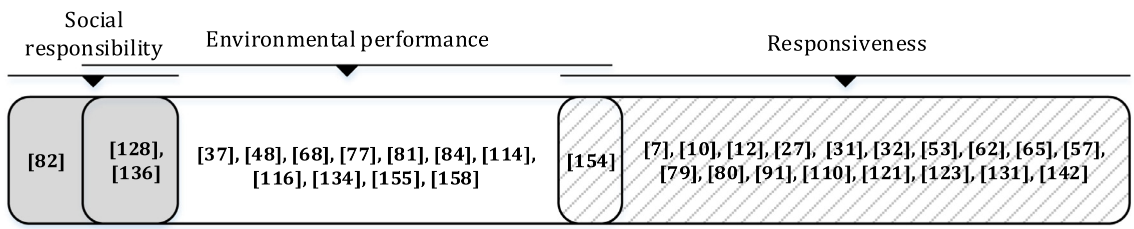

Fig. 9. Classification of different paradigms in SCND problem under uncertainty.

(Farahani et al., 2014). In this regard, many researchers (see studies in Table A.2 of Appendix A) have studied designing RL networks for recovery of used products.

4.5.3. Sustainable SCND

A definition for *sustainable development* was made by the World Commission on Environment and Development (WCED) as "a development that satisfies present needs without compromising the capability of future generations to meet their own resources and needs" (Brundtland, 1987). As mentioned by Farahani et al. (2014), sustainable SCs play an essential role in conserving natural resources for the next generation and gaining the attention of many researchers over recent years. Based on this paradigm, several scholars have tried to design SC networks consistent with economic aspects, environmental performance, and social responsibility that are called *sustainable SCND* (Eskandarpour, et al., 2015). We have identified that the majority of studies in this area presumed a deterministic decision-making environment such as Mota, Gomes, Carvalho, and Barbosa-Povoa (2015) and You, Tao, Graziano, and Snyder (2012). Recently, Eskandarpour et al. (2015) have presented a survey on sustainable SCND and investigated existing approaches for assessment of the environmental impact and social responsibility performance of SCs.

In Fig. 9, the reference papers based on the above-mentioned paradigms are categorized. It should be noted that in Fig. 9, the studies that have considered environmental issues directly in their constraints or objective function(s) are reported and we do not report all studies related to RL and CLSC.

From Fig. 9, a small percentage of papers (about 19%) have addressed the responsiveness goals, environmental performance or social responsibility. Further, Pishvaee et al. (2014) and Dayhim, Jafari, and Mazurek (2014) among the reference papers of our study regarded the social responsibility and environmental performance concurrently for designing a sustainable SC network under uncertainty.

4.6. Humanitarian SCND

Studies in SCND are not limited only to business SCs. Non-business SCs such as public and governmental ones have been much attracted over recent years (e.g., Jabbarzadeh, Fahimnia, & Seuring, 2014; Jeong, Hong, & Xie, 2014; Liu & Guo, 2014; Noyan, 2012). A *humanitarian SC*, also called *relief SC*, often designed to alleviate suffering of vulnerable people in the event of a disaster or even after that, is one of the most popular non-business SCs. As pointed out by Najafi, Eshghi, and Dullaert (2013), a *disaster* is an event that often leads to destruction, damage, human suffering, loss of human life, and/or deterioration of health service. Humanitarian logistics network design is usually placed in the category of pre-disaster planning; naturally, it is under uncertainty associated with the impact of different types and magnitude of disasters (Özdamar & Ertem, 2015) . It should be noted that optimization approaches for pre-disaster FL are reviewed by Caunhye, Nie, and Pokharel (2012).

4.7. Other SC characteristics

In this section, two important issues regarding SCND problem are briefly discussed. It should be emphasized that these presented facets have not been widely investigated in the related context.

Financial factors: There are a limited number of papers in the area of SCND under uncertainty in which financial factors are taken into account. International financial factors have strong impact on the structure of global SCs and several studies, such as Goh, Lim, and Meng (2007) and Hasani, Zegordi, and Nikbakhsh (2015), dealt with this issue. As the second category, a few studies such as Longinidis and Georgiadis (2013) and Longinidis and Georgiadis (2011) assumed that the financial cycle of a corporation is also affected by the operations related to its SC; hence, they presented financial operation constraints to model the financial cycle. In the last category, budget constraints are embedded into SCND problem to limit investment on designing SCs. In this regard, Nickel et al. (2012) considered budget constraints for designing a SC under stochastic demand and interest rates. They also presumed that there are different alternative investment options and thereby imposing a target for the return on investment.

Moreover, there are a few reference papers in which financial parameters such as tax, exchange, and interest rates are assumed to be uncertain. These studies include Goh et al. (2007), Nickel et al. (2012), and Longinidis and Georgiadis (2013).

Competition: Recently, Farahani et al. (2014) presented a survey paper on competitive SCND. In general, the competitive environments for designing a SC network can be categorized into three primary groups: (1) competition among facilities in the same echelon of SC, (2) competition among facilities in different echelons of SC, and (3) competition among multiple SCs. However, the uncertain models that addressed FL under a competitive environment are presented only in the context of pure FL, so this area has a high potential for future research directions.

5. Optimization under uncertainty for SCND

In this section, optimization aspects of the related literature are investigated in separate subsections. Moreover, the reference papers belonging to Groups 1, 2, and 3 (based on the definitions in Section 3) are studied in terms of mathematical modeling, solution methods, and optimization techniques.

5.1. Optimization criteria for evaluation of SC networks' performance

To design a SC network under uncertainty, single or multiple objectives are often considered for a numerical optimization procedure based on SC goals. Heckmann et al. (2015), in accordance to Borgström (2005), defined *efficiency* as "a way to attain the SC's goals through taking minimal resources and thereby achieving the cost-related advantages." Further, they defined *effectiveness* as "obtaining pre-determined SC goals even in the face of inverse conditions or unexpected events."

In SCND, most studies have assumed a single objective function for their optimization models, which usually seeks to achieve eco-

Table 6
Objective function's terms in logistics network design under uncertainty.

Objective function terms	Explanation	Abbreviation
Location costs of facilities	The fixed costs of opening/closing facilities. The fortification costs of facilities are put in this category as well. Further, some papers utilized a single parameter for both opening and operating costs of facilities, and so we have also used **C1** for this case. In a few studies, closing facilities led to cost saving in the objective function that are represented by **C1'**.	**C1**
Operating costs of active facilities	The operating costs of facilities after opening them. In some studies, facilities' operating cost is assumed as a fixed cost and in some others, it depends on the volume of products, which a facility can handle based on its capacity. Moreover, in some studies some fixed costs for active facilities are considered based on the products they handle or the processes they perform. We put these fixed costs in this category as well.	**C2**
Inventory costs	The holding costs of working inventory, safety stock, or extra inventory in SC facilities are regarded as inventory costs.	**C3**
Transportation/shipment costs	The transportation or shipment costs of products among different entities of a SC network. Moreover, the fixed shipment costs are considered in some studies.	**C4**
Production/manufacturing costs	The costs of producing or manufacturing products in entities of a SC network.	**C5**
Processing costs in facilities	The costs of handling products in warehouses, distribution centers, or other facilities of a SC network.	**C6**
Capacity costs of facilities	The costs of establishing, expanding, or relocating the capacity of different facilities in a SC network.	**C7**
Procurement costs	The costs of procuring raw materials, required components or finished products from corresponding suppliers. Further, the buying costs of used products in a CLSC or RL network are put in this category.	**C8**
Fixed ordering costs	The fixed costs of placing an order from a SC facility to another one.	**C9**
Supplier selection costs	The fixed costs for selecting the suppliers, which include establishing business with them.	**C10**
Technology selection costs	The costs of selecting the technology for SC's facilities.	**C11**
Costs of selection/establishment transportation links	The costs of establishing transportation links.	**C12**
Capacity costs of transportation links	The costs of establishing or expanding capacity of transportation links in a SC network.	**C13**
Shortage/backorder costs	The penalty costs related to not satisfying the customers' needs. Back order costs are also considered in this category.	**C14**
Sales tax costs	The costs related to the tax of sales' products.	**C15**
Recovery activities costs	The costs related to recovery activities in a RL network, which may include inspection, recycling, remanufacturing, repairing, or disposal costs. These costs are dependent on the type of activities in a RL network.	**C16**
Routing costs	The costs related to transporting the products from one layer of a SC network to another one, which are calculated based on routing decisions.	**C17**
Penalty costs in RL networks	The penalty costs related to not collecting the returned products in a RL network.	**C18**
Cost saving from integrating facilities	The cost saving due to integrating some facilities in a CLSC network.	**C19**
Penalty costs for not utilizing installed capacities	The penalty costs related to not utilizing the existing capacity in SC's facilities	**C20**
Salvage values of products	The salvage values of unsold products in SC's facilities.	**SA**
SC's income	The income of SC network, usually calculated as multiplication of the amount of sold products and their related prices.	**I**
SC's responsiveness	Different criteria exist for defining the responsiveness of a SC network, which has been discussed in Section 4.5.1. We put all these criteria in this category.	**R**
SC's flexibility	There are many criteria for measuring the flexibility of a SC network in the related literature. We put all these criteria in this category.	**F**
SC's environmental impacts	The effects of a SC network on the environment are often measured as its environmental impacts, which may include different terms.	**E**
SC's social responsibility	The influences of a SC network on the social issues are measured as its social responsibility, which may include different terms.	**S**
Risk/Robustness measures	Some studies have regarded the risk or robustness measures in their objective functions.	**M**

nomic goals for SC in terms of either cost minimization or profit maximization (Melo et al., 2009). In the profit maximization, a SC's profit is calculated based on revenues minus costs. Sometimes, particularly for designing a global SC, the after-tax profit is presumed as an objective function (e.g., Goh et al., 2007). Moreover, for a profit-maximization problem, it is often not necessary to serve all potential customers; indeed, SC prefers to lose some potential customers whose service costs are high compared with their revenues (Melo et al., 2009).

To measure SC's performance in terms of economic goals, a SC's costs are usually made of some components like inventory costs, transportation costs, FL costs and so on. These components can be different in various optimization problems and have direct relation with the planning decisions. We provide a list of these components used in the objective functions of reference papers in Table 6.

Besides the economic goals, some studies consider other objectives in this area. Usually, these studies result in multi-objective optimization problems. In Table 6, other types of common objectives are also listed. In the following sections, we present objective function(s) of reference papers based on Table 6**.**

5.2. SCND problems with continuous stochastic parameters

Daskin, Coullard, and Shen (2002) developed a location-inventory model for the situation where retailers' demands have normal distribution with known daily mean and variance. In response to the retailers' demands, distribution centers (DCs) follow the inventory policy (Q, r) for ordering their required products from a plant. Both the reorder point and safety stock are specified so that the stock-out probability is not greater than a predetermined value. The final mixed-integer nonlinear programming (MINLP) model is solved by Lagrangian Relaxation (LR) embedded into the Branch and Bound (B&B) algorithm. This problem is also solved using column generation by Shen, Coullard, and Daskin (2003). The paper presented by Daskin et al. (2002) has been put as a foundation for many studies in the area of SCND where the retailers' demands have normal distribution with known mean and variance (e.g., Park, Lee, & Sung, 2010; Shen & Daskin, 2005).

In complex SCND models with more than one location layer, where location decisions are made along with other strategic or tactical planning decisions, assuming continuous distribution function for stochastic demand often results in intractable nonlinear problems. In such a SCND problem, the solution approaches proposed by Daskin et al. (2002) and Shen et al. (2003) based on the structure of mathematical models are not applicable. In fact, few papers coped with this issue.

Another popular situation of modeling continuous stochastic parameters is the case where the availability or reliability of facilities (e.g., Cui, Ouyang, & Shen, 2010; Qi & Shen, 2007) or transportation links (e.g., Azad, Davoudpour, Saharidis, & Shiripour, 2014) are considered with a pre-determined probability. Typically, the aim of these studies is to design a reliable or resilient SC network against disruption events. Several models in this area are investigated by Snyder and Daskin (2007) and Snyder et al. (2006). In Table 7, SCND models with continuous stochastic parameters are categorized according to their solution approaches, mathematical models, and objective functions.

It is worth noting that, the LR algorithm is categorized as a heuristics approach in this paper. However, some studies utilized the LR algorithm embedded in the B&B algorithm (e.g., Daskin et al., 2002), which guarantees achieving the optimal solution; thus, this method, called LR-based exact algorithm, is characterized as an exact solution approach.

As shown by Table 7, the variety of stochastic parameters that have been modeled continuously in SCND is limited. Further, most existing models are MINLP and due to the structure of the mathematical models, the LR algorithm has been widely used compared with other solution approaches.

5.3. Chance-constrained programming for SCND

Sometimes, in optimization problems, one or multiple constraints are not required to be always satisfied. Indeed, these constraints need to be held with some probability or reliability level. Probabilistic or chance-constrained programming is usually applied to model such a situation and it is often employed when the distribution probabilities of the uncertain parameters are known for decision makers. Consider A, x, and b are $m \times n$ matrix, n-vector, and m-vector, respectively. Let $Ax \geq b$ be a deterministic linear constraint in which x is decision variables vector. Assuming uncertainty for matrix A and right-hand side vector b, then $P(Ax \geq b) \geq \alpha$ is a probabilistic linear constraint saying that $Ax \geq b$ should be satisfied with a pre-specified probability $\alpha \in (0, 1)$.

As pointed out by Laporte, Nickel, and da Gama (2015), there exists a particular case of chance-constrained FL problem with stochastic demand. Let I and J be sets of potential locations for facilities and demand nodes, respectively. The decision variable $x_{ij} (i \in I,\ j \in J)$ equals to one if customer j is assigned to facility i, and $y_i (i \in I)$ equals to one if facility i is opened. The stochastic demand of customer j (d_j) follows a pre-specified probability distribution. To guarantee that the amount of demand assigned for each facility i with known capacity q_i does not exceed the facility's capacity with a pre-determined probability α_i, the following probabilistic constraints should be considered:

$$\mathrm{P}\left(\sum_{j \in J} d_j x_{ij} \leq q_i y_i\right) \geq \alpha_i, \quad i \in I$$

The most challenging issue is to attain a deterministic equivalent formulation for chance-constrained programs. For example, Lin (2009) obtained a deterministic equivalent formulation for a FL problem with the above type of probabilistic constraints in which customers' demands are independent and follow Poisson or Gaussian probability distribution.

Note that it is not always straightforward to convert probabilistic constraints into their equivalent deterministic ones (see Birge and Louveaux (2011) and Sahinidis (2004) for more details about this issue). In SCND problem, these probabilistic constraints have been developed in a few research studies, such as Guillén-Gosálbez and Grossmann (2009), You and Grossmann (2008a), and Vahdani et al. (2012).

5.4. Scenario-based stochastic programs for SCND

In this category of SCND problem under uncertainty, stochastic parameters are usually modeled via a set of discrete scenarios with known probabilities. Here, the problems are divided into two main groups: (1) two-stage stochastic programs and (2) multi-stage stochastic programs (Birge & Louveaux, 2011). Both approaches have been employed for SCND problems. As stated by Snyder (2006), there are some difficulties in using these approaches to design a SC network. First, creating scenarios and obtaining their associated probabilities could be a problematic and cumbersome task, especially in real-life SCND problems. Second, an adequate number of scenarios could lead to a large-scale optimization problem.

5.4.1. Two-stage stochastic programs

Two-stage stochastic programs are quite popular due to the two-stage nature of decisions in SCND problems. Indeed, SC strategic or long-term decisions such as location and capacity should be made before knowing the realization of random parameters as the first-stage decisions. However, when random parameters are disclosed, the operational and tactical decisions such as inventory, production, transportation and routing have to be determined as the second-stage decisions. The general formulation of a two-stage stochastic program can be presented as:

$$\underset{\mathbf{x} \in X}{\mathrm{Min}}\ \mathbf{c}^{\mathrm{T}}\mathbf{x} + \mathcal{Q}(\mathbf{x}), \tag{1}$$

where $\mathbf{c} \in \mathrm{R}^{n_1}$ is a known vector, $\mathbf{x} \in \mathrm{R}^{n_1}$ is first-stage decisions vector, $X \subset \mathrm{R}^{n_1}$ is a non-empty set of feasible combinations for first-stage decisions, and $\mathcal{Q}(\mathbf{x})$ is a recourse function. Here, first-stage decisions are made by considering the effect of stochasticity, measured by this recourse function.

In two-stage stochastic program (1), if we assume ζ as the stochastic parameters vector with finite and discrete support, it can be expressed as a finite number of realizations, called scenarios. Here, S is a set of all scenarios and $|S|$ is the number of scenarios. Then, $\zeta^s, \forall s \in S$, is a given realization of stochastic parameters, and set $\{\zeta^1, \zeta^2, ..., \zeta^{|S|}\}$ is the sample space for stochastic parameters with corresponding probabilities $\pi^1, \pi^2, ..., \pi^{|S|}$. The recourse function can be defined as:

$$\mathcal{Q}(\mathbf{x}) = E_\zeta\left(Q(\mathbf{x}, \zeta^s)\right) = \sum_{s \in S} \pi^s \times Q(\mathbf{x}, \zeta^s). \tag{2}$$

For a given scenario s, the optimal objective function value of the second-stage problem is:

$$Q(\mathbf{x}, \zeta^s) = \min_{\mathbf{y}^s} \left\{ (\mathbf{q}^s)^{\mathrm{T}}\mathbf{y}^s : W^s\mathbf{y}^s = \mathbf{h}^s - T^s\mathbf{x},\ \mathbf{y}^s \geq 0 \right\}. \tag{3}$$

where $\mathbf{y}^s \in \mathrm{R}^{n_2}$, $\forall s \in S$ is the second-stage decisions vector for scenario s. Further, for each scenario s, $\mathbf{q}^s \in \mathrm{R}^{n_2}$, $W^s \in \mathrm{R}^{m_1 \times n_2}$, $T^s \in \mathrm{R}^{m_1 \times n_1}$, and $\mathbf{h}^s \in \mathrm{R}^{m_1}$ are a realization of stochastic components, which can be pieced together as $\zeta^s = (\mathbf{q}^s, W^s, T^s, \mathbf{h}^s)$ (Birge & Louveaux, 2011).

Here, second-stage problem (3) is written for a general case where all components $\mathbf{q}$, W, T, and $\mathbf{h}$ are assumed to be stochastic. Nonetheless, in a SCND problem, only one or multiples of these components may be stochastic consistent with its assumptions. In Table 8, scenario-based stochastic programs in the area of SCND problems are investigated in terms of optimization aspects.

It is worth mentioning that several studies (e.g., Georgiadis et al., 2011; Schütz et al., 2009) modeled their stochastic problems in such a way that the second stage includes multiple periods and,

Table 7
Solution approach and specifications of the mathematical model for problems with continuous stochastic parameters.

Articles	Solution approach				Mathematical model	Continuous stochastic parameters	Objective
	Exact algorithm	Heuristic algorithm	Meta-heuristic	Commercial solver			
Sabri and Beamon (2000)		An iterative approach by solving two sub-models			MINLP	D, ST, PT	Max F, Min (C1+C3+C4+C6+C8)
Daskin et al. (2002)	LR-based exact algorithm				MINLP	D	Min (C1+C3+C4+C9)
Hwang (2002)			Improved Genetic Algorithm (GA)		MILP	AF	Min C1+ Min C17
Shen et al. (2003)	Column generation				MINLP	D	Min (C1+C3+C4+C9)
Miranda and Garrido (2004)		LR algorithm			MINLP	D	Min (C1+C3+C4+C9)
Shen (2005)	LR-based exact algorithm				MINLP	D	Min (C1+C3 *or* C11+C4+C9)
Shen and Daskin (2005)			GA		MINLP	D	Min(C1+C3+C4+C9), Max R
Avittathur, Shah, and Gupta (2005)				GAMS [1]	MINLP	D	Min(C1+C3+C4+C15)
Shu, Teo, and Shen (2005)	Column generation				MINLP	D	Min(C1+C3+C4+C9)
Romeijn, Shu, and Teo (2007)	Branch & Price algorithm				MINLP	D	Min (C1+C2+C3+C4+C9)
Lieckens and Vandaele (2007)			GA		MINLP	Inter-arrival time of returns, PT	Max(I-C1-C3-C4-C14-C16-C18)
Qi and Shen (2007)		LR algorithm[2]			MINLP	D, AF	Max(I+SA-C1-C3-C4-C9-C14)
Shen and Qi (2007)	LR-based exact algorithm				MINLP	D	Min(C1+C3+C4+C9)
Shen (2007a)[3]	Column generation				MINLP	D	Min(C1+C3+C4+C9)
Miranda and Garrido (2008)		LR algorithm			MINLP	D	Min(C1+C3+C4+C9)
You and Grossmann (2008a)		A heuristic based on the model's convexification			MINLP	D	Max(I -C1-C3-C4 -C6-C7-C8-C11-C12), Max R
You and Grossmann (2008b)		LR algorithm			MINLP	D	Min(C1+C3+C4+C9)
Tanonkou, Benyoucef, and Xie (2008)		LR algorithm			MINLP	D, ST	Min(C1+C3+C4+C9)
Rappold and Van Roo (2009)		A two-step heuristic by fixing binary variables			MINLP	D, PT	Min(C1+C3+C4+C7+C14)
Guillén-Gosálbez and Grossmann (2009)		A decomposition method based on outer approximation			MINLP	EP	Max(I-C1-C3-C4-C6-C7-C8-C11-C12), Min E
You and Grossmann (2009)		LR algorithm			MINLP	D	Min(C1+C3+C4+C9)
Javid and Azad (2010)			Hybrid tabu search (TS) & simulated annealing (SA)		MINLP	D	Min(C1+C3+C4+C9+C17)
Qi et al. (2010)	LR-based exact algorithm				MINLP	D, AF	Min(C1+C3+C4+C9+C14)
Park et al. (2010)		LR algorithm			MINLP	D	Min(C1+C3+C4+C9)
Guillén-Gosálbez and Grossmann (2010)		A heuristic by using spatial B&B			MINLP	EP	Max (I-C1 -C3-C4-C6-C7-C8 -C11-C12), Max (Environmental performance)
You and Grossmann (2010)		Piece-wise linear approximation & LR algorithm			MINLP	D	Min(C1+C3+C4)
Nasiri, Davoudpour, and Karimi (2010)		LR algorithm			MINLP	D	Min(C1+C3+C4+C7 +C9)
Cui et al. (2010)	LR-based exact algorithm				MINLP[4]	AF	Min(C1+C4)
You and Grossmann (2011)				GAMS	MINLP	D	Min (C1+C3+C4), Min (Customers' service time)
Abdallah, Diabat, and Simchi-Levi (2012)				GAMS	MINLP	D, R	Min(C1+C3+C4+C9)
Vahdani et al. (2012)				GAMS	MILP	AF	Min(C1+C4+C5+C6+C16), Min(Disruption cost)

(*continued on next page*)

Table 7 (*continued*)

Articles	Solution approach				Mathematical model	Continuous stochastic parameters	Objective
	Exact algorithm	Heuristic algorithm	Meta-heuristic	Commercial solver			
Benyoucef et al. (2013)		LR algorithm			MINLP	D, ST	Min(C1+C3+C4+C8+C9)
Kumar and Tiwari (2013)		LR algorithm			MINLP	D	Min(C1+C3+C4+C5+C9)
Azad and Davoudpour (2013)			Hybrid TS & SA		MINLP	D	Min(C1+C4+C6+C7+C17), Min M
Baghalian et al. (2013)				LINGO	MINLP[5]	D	Max(I-C1-C3-C4-C5-C6-C14+S), Min M
Vahdani, Tavakkoli-Moghaddam, and Jolai (2013)				GAMS	MILP	AF	Min(C1+C4+C5+C6+C16), Min(Disruption cost)
Vahdani, Tavakkoli-Moghaddam, Jolai, and Baboli (2013)				GAMS	MILP	AF	Min(C1+C4+C5+C6+C16), Min(Disruption cost)
Li et al. (2013)		LR algorithm			MINLP	AF	Min(C4)
Azad et al. (2013)	Benders' decomposition				MILP	CA, AT	Min(C1+C4+ Disruption cost)
Nasiri, Zolfaghari, and Davoudpour (2014)		LR algorithm			MINLP	D	Min(C1+C3+C4+C9)
Mari, Lee, and Memon (2014)				LINGO	MILP	AF	Min(C1+C4+C5+C6+C8), Min E, Min (Disruption cost)
Jeong et al. (2014)				CPLEX	MILP	AF	Min C4, Min (Disruption cost)
Marufuzzaman et al. (2014)	Benders' decomposition				MILP	AF	Min (C1+C4+C7+C12)
Azad et al. (2014)			Hybrid TS & SA		MINLP	CA,AT	Min(C1+C4+ Disruption cost)
Rodriguez, Vecchietti, Harjunkoski, and Grossmann (2014)		Piece-wise linear approximation			MINLP	D	Min(C1+C2+C3+C4+C5 +C6+C7+C14)
Yongheng, Rodriguez, Harjunkoski, and Grossmann (2014)		LR algorithm			MINLP	D	Min(C1+C2+C3+C4+C5 +C6+C7+C14)
Li and Savachkin (2016)		Piece-wise linear approximation & LR algorithm			MINLP	AF	Min(C1+C4)
Pasandideh et al. (2015)			NSGA II & NRGA		MINLP	D, C, PT	Min(C1 +C2+C3+C4+C14), Min M
Hatefi et al. (2015a)				CPLEX	MILP	CA	Min (C1+C4+C5+C6+C16 +Disruption cost)
Hatefi et al. (2015b)				CPLEX	MILP	CA	Min (C1+C4+C5+C6+C16 +Disruption cost)
Table's summary:	Exact algorithms: **22%**, Heuristic algorithms: **42%**, Meta-heuristics: **14%**, Commercial solvers: **22%**		MILP: **20%** MINLP: **80%**		Single objective (Minimization: **66%**, Maximization: **8 %**) Multiple objectives: **26%**		

[1] In this study, MINLP model is approximated by an MILP model. **[2]** In designing the algorithm, insights from bidirection search algorithm and outer approximation algorithm were drawn.
[3] This study presented different models for integrated SC netwrok design under uncertainty. Furthermore, the author extended the model for the situation in which mean and variance of demand are dependent to scenarios. **[4]** In this study the MINLP model is linearized. **[5]** The MINLP model is linearized by using regression.

hence, the variation of stochastic parameters over a planning horizon is captured. Additionally, first stage decisions are determined for a planning horizon with multiple periods in some papers (e.g., Aghezzaf, 2005; Poojari, Lucas, & Mitra, 2008).

In most two-stage stochastic SCND problems, the second stage decisions are continuous and positive variables; therefore, the value of recourse function for each feasible solution of first stage decisions can be obtained through solving a linear program for each scenario. Thus, as shown by Table 8, decomposition techniques such as Benders' decomposition have been widely applied for solving them.

5.4.2. Multi-stage stochastic programs

SCND problems with stochastic parameters and a multi-period setting can result in a multi-stage stochastic program. There are a limited number of studies in this area such as Albareda-Sambola, Alonso-Ayuso, Escudero, Fernández, and Pizarro (2013), Goh et al. (2007), Nickel et al. (2012), Fattahi et al. (2017), and Pimentel, Mateus, and Almeida (2013). In general, a stochastic problem with T stages includes a sequence of random parameters $\zeta_1, \zeta_2, \ldots, \zeta_{T-1}$ defined on a probability space (refer to Billingsley (2012) for a rigorous definition of a probability space). In a SCND problem, $\zeta_i, i = 1, 2, \ldots, T-1$ is the vector of stochastic parameters, such as costs, demand, supply, capacity and so on, at stage i of a multi-stage stochastic program.

A scenario is defined as a realization of random parameters $\zeta_1, \zeta_2, \ldots, \zeta_{T-1}$ and a scenario tree is exploited for discrete representation of stochastic parameters. Indeed, a scenario tree is an explicit display of branching process for progressive observation of $\zeta_1, \zeta_2, \ldots, \zeta_{T-1}$ under the assumption that these stochastic parameters have a discrete support. Fig. 10 illustrates a scenario tree including nine scenarios for a four-stage stochastic program that can be employed for a stochastic SCND problem over a planning horizon with three periods.

In a multi-stage stochastic program, the realization of random parameters $\zeta_1, \zeta_2, \ldots, \zeta_{t-1}$ at an intermediate stage t has been ob-

Table 8
Solution approach and specifications of the mathematical model for scenario-based stochastic problems (TSSP and MSSP are abbreviations for two-stage stochastic program and multi-stage stochastic program, respectively).

Articles	Solution approach				Mathematical model	Objective
	Exact algorithm	Heuristic	Meta-heuristic	Commercial solver[1]		
Tsiakis et al. (2001)				CPLEX	MILP-TSSP	Min (C1+ C4+C5+ C6)
Alonso-Ayuso, Escudero, Garìn, Ortuño, and Pérez (2003)		Branch and fix coordination algorithm			MILP-TSSP	Max (I-C1-C3-C4-C5-C7-C8)
Guillén et al. (2003)				CPLEX	MILP-TSSP	Max(I-C1-C3-C4-C5-C6-C15), Max R, Min M
Guillén et al. (2005)				CPLEX	MILP-TSSP	Max(I-C1-C3-C4-C5-C6-C15), Max R, Min M
Santoso et al. (2005)	Benders' decomposition				MILP-TSSP	Min(C1+C4+C6 +C11)
Listeş and Dekker (2005)				CPLEX	MILP-3SSP[2]	Max(I-C4-C16)
Guillen, Mele, Espuna, and Puigjaner (2006)			GA		MILP-MSSP	Max(I-C1-C2-C3-C8-C14)
Vila et al. (2007)				CPLEX	MILP-TSSP	Max(I-C1-C3-C4-C5-C6 -C15)
Snyder, Daskin, and Teo (2007)	LR-based exact algorithm				MINLP-TSSP	Min(C1+C3+C4+C9)
Goh et al. (2007)		Newton's method combined with Moreau–Yosida regularization			MILP-MSSP	Max(I-C1-C4-C15)
Listeş (2007)	L-shaped algorithm				MILP-TSSP	Max(I-C1-C4-C5-C12 -C16-C18)
Lee et al. (2007)				CPLEX	MILP-TSSP	Min(C1+C3+C4+C5+C6+C16-I)
Salema, Barbosa-Povoa, and Novais (2007)				CPLEX	MILP-TSSP	Min(C1+C4+C5+C14+C16 +C18)
Chouinard et al. (2008)				CPLEX	MILP-TSSP	Min(C1+C4+C16)
Poojari et al. (2008)	Benders' decomposition				MILP-TSSP	Min(C1+C4+C11+C14)
Azaron et al. (2008)[3]				LINGO	MINLP-TSSP	Min(C1+C6+C15), Min M_1, Min M_2
Lee and Dong (2009)			SA		MILP-TSSP	Min(C1+C2+C4)
Schütz et al. (2009)		LR algorithm			MILP-TSSP	Min(C1+C4+C6+C5+C14)
Pishvaee et al. (2009)				LINGO	MILP-TSSP	Min(C1+C4+C5+C6+C16+C20)
Franca et al. (2010)				√	MILP-TSSP	Max (I-C1-C2-C4-C5-C6-C8), Min (amount of defective raw materials), Min M
Lee et al. (2010)				CPLEX	MILP-TSSP	Min(C1+C4+C6+C16)
Sabio et al. (2010)				CPLEX	MILP-TSSP	Min(C1+C3+C4+C5+C7+ C11+Capital and operating costs of transportation modes), Min M
Shu, Ma, and Li (2010)	Column generation				MINLP-TSSP	Min(C1+C3+C4+C9)
Mo, Harrison, and Barton (2010)				CPLEX	MILP-TSSP	Min(C1+C4+C8)
Kara and Onut (2010a)				CPLEX	MILP-TSSP	Max (I-C1-C2-C4-C16-C18)
Bidhandi and Yusuff (2011)	Benders' decomposition				MILP-TSSP	Min(C1+C4+C5+C6+C8 +C12+C14)
Longinidis and Georgiadis (2011)				CPLEX	MILP-TSSP	Max (Financial performance based on (I-C1-C3-C4-C5-C6-C15))
Georgiadis et al. (2011)				CPLEX	MILP-TSSP	Min(C1+C3+C4+C5+C6)
Shukla, Agarwal Lalit, and Venkatasubramanian (2011)				CPLEX	MILP-TSSP	Min(C1+C4+C6), Min(Disruption cost)
Cardona-Valdés et al. (2011)	L-shaped algorithm				MILP-TSSP	Min(C1+C4+C6), Min(Service time)
Shimizu, Fushimi, and Wada (2011)			TS		MINLP-TSSP	Min(C1+C4+C5+C6+C8), Min M
Kim, Realff, and Lee (2011)				CPLEX	MILP-TSSP	Max(I-C1-C4-C5-C7-C8-C11)
Rajgopal, Wang, Schaefer, and Prokopyev (2011)	L-shaped algorithm				MILP-TSSP	Min(C1+C4+C6+C8 -SA)
Giarola, Shah, and Bezzo (2012)				CPLEX	MILP-TSSP	Max(I-C1-C4-C5-C7-C8-C11)
Kiya and Davoudpour (2012)	Benders' decomposition				MILP-TSSP	Min(C1+C4 +C5+C6+C7-C1')
Noyan (2012)	Benders' decomposition				MILP-TSSP	Min(C1+C4+C7+C8 +C14+SA), Min M
Jabbarzadeh et al. (2012)			GA & LR algorithm		MINLP-TSSP	Max (I-C1-C3-C4-C9)
Mak and Shen (2012)		LR algorithm			MILP-TSSP	Min(C1+C3+C4+C8+C12+C14)
Chen and Fan (2012)		Progressive hedging algorithm			MILP-TSSP	Min(C1+C4+C5+C7+C14)
Klibi and Martel (2012a)				CPLEX	MILP-TSSP	Max(I-C1-C4-C6-C8)

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Table 8 (*continued*)

Articles	Solution approach				Mathematical model	Objective
	Exact algorithm	Heuristic	Meta-heuristic	Commercial solver[1]		
Almansoori and Shah (2012)				CPLEX	MILP-MSSP	Min(C1+C2+C3+C4+C5+C7 +C8+C11+ Capital and operating costs of transportation modes)
Gebreslassie et al. (2012)	L-shaped algorithm				MILP-TSSP	Min(C1+C4+C5+C7 +C8+C11+C14-Governmental incentives), Min M
Nickel et al. (2012)				CPLEX	MILP-MSSP	Max(I-C1-C4+Remained budget), Max R, Min M
Amin and Zhang (2013)				CPLEX	MILP-TSSP	Min(C1+C4+C5+C16-Cost saving from products' recovery), Max (Environmental performance)
Albareda-Sambola et al. (2013)		Fix and relax coordination algorithm			MILP-MSSP	Min(C1+Maintenance costs of facilities+ Assignment costs)
Kazemzadeh and Hu (2013)				CPLEX	MILP-TSSP	Max(I-C1-C4-C5-C6-C7) *or* Min M
Pimentel et al. (2013)		LR algorithm			MILP-MSSP	Min (C1+C2+C4+C5+C7+C12 +C13+C14)
Qin et al. (2013)	Disjunctive decomposition-based Branch and Cut				MILP-TSSP	Min(C1+C3+C4)
Ramezani et al. (2013a)				√	MILP-TSSP	Max(I-C1-C5-C6-C7-C8-C16), Max R, Min (amount of defective raw materials), Min M
Longinidis and Georgiadis (2013)				DICOPT	MINLP-TSSP	Max (Financial performance), Max (Credit solvency)
Cardoso, Barbosa-Póvoa, and Relvas (2013)				CPLEX	MILP-3SSP	Max (I-C1-C3-C4-C6-C7-C8-C12-C16)
Baghalian et al. (2013)				LINGO	MINLP-TSSP	Max(I-C1-C3-C4-C5-C6-C14+SA), Min M
Ahmadi-Javid and Seddighi (2013)			SA		MILP-TSSP	Min(C1+C17+(production and distribution disruption costs)) *or* Min M
Singh, Jain, and Mishra (2013)				LINGO	MILP-TSSP	Min(C1+C3+C6+C14)
Tong, Gong, Yue, and You (2013)				CPLEX	MILP-TSSP	Min(C1+C2 +C4+C5+C7+C8+C11+C14-Governmental incentives)
Klibi and Martel (2013)				CPLEX	MILP-TSSP	Max(I-C1-C2-C4-C6-C8)
Meisel and Bierwirth (2014) [4]			Variable Neighborhood Search (VNS)		-	Min(C1+C2+C4+C5)
Madadi et al. (2014)				GUROBI	MILP-TSSP	Min(C1+C2+C4 +C14+discarding cost of tainted products) *or* Min M
Li and Hu (2014)				GAMS	MILP-TSSP	Max(I-C1-C4-C6-C7-C14)
Cardona-Valdés, Álvarez, and Pacheco (2014)			Hybrid GRASP & TS		MILP-TSSP	Min(C1+C4), Min(maximum travel time through the network)
Liu and Guo (2014)		LR algorithm			MILP-TSSP	Max(Min(fill rate of affected areas)-mismatch among correlated relief supplies), Min (C1+C4+C8+cost of using transportation modes)
Soleimani et al. (2014)				CPLEX	MILP-TSSP	Max(I-C1-C3-C4-C5-C8-C14-C16-C20), Min M
Huang and Goetschalckx (2014)		Branch & reduce algorithm			MINLP-TSSP	Max(I-C1-C4), Min M
Zeballos, Méndez, Barbosa-Povoa, and Novais (2014)				CPLEX	MILP-TSSP	Min(C1+C3+C4)
Dayhim et al. (2014)				CPLEX	MILP-TSSP	Min(C1+ C3+C4+C5+Carbon emission +Energy consumption +Risk costs +Capital cost of transportation modes)

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Table 8 (*continued*)

Articles	Solution approach				Mathematical model	Objective
	Exact algorithm	Heuristic	Meta-heuristic	Commercial solver[1]		
Subulan, Baykasoğlu, Özsoydan, Taşan, and Selim (2014)				CPLEX	MILP	Min(C1+C4+C5+C8+C16-I), Max (Coverage of return products)
Kaya, Bagci, and Turkay (2014)				CPLEX	MILP-TSSP	Min(C1+C3+C8+C9+C16-I)
Soleimani and Govindan (2014)				CPLEX	MILP-TSSP	Min(C1+C3+C4+C8+C14+C16), Min M
Kılıç and Tuzkaya (2015)		Linear relaxation-based heuristic			MILP-TSSP	Max(I-C1-C3-C4-C6-C8-C14)
Khatami et al. (2015)	Benders' decomposition				MILP-TSSP	Min(C1+C2+C3+C4+C5+C6 +C7+C14+C16)
Govindan et al. (2015)			AMOEMA, AMOVNS, NSGA II		MILP-TSSP	Min(C1+C4+C5+C6+C10+C11), Min E
Ayvaz et al. (2015)				CPLEX	MILP-TSSP	Max(I-C1-C4-C16)
Keyvanshokooh et al. (2016)	Benders' decomposition				MILP-TSSP	Max(I-C1-C3-C4-C5-C7-C14-C16)
Hasani and Khosrojerdi (2016)			Memetic algorithm		MINLP-TSSP	Max(I-C2-C3-C4-C5-C8-C10-C15)
Govindan and Fattahi (2017)				CPLEX	MILP-TSSP	Min(C1+C3+C4+C5+C6 +C7+C14), Min M
Table's summary:	Exact algorithms: **18%**, Heuristic algorithms: **13%**, Meta-heuristics: **12%**, Commercial solvers: **57%**		MILP: **88%**, MINLP: **12%**	TSSP: **88%** MSSP:**8%** 3SSP: **2%**	Single objective (Minimization: **42%**, Maximization: **28 %**), Multiple objectives: **30%**	

[**1**]In some papers, the type of commercial solver that has been used is not mentioned and therefore, we have only indicated commercial solver as a solution approach by "√" in these papers.
[**2**] 3-stage stochastic programming model. [**3**] This paper considered two risk measures. [**4**] This paper did not propose a stochastic model for the problem.

served and the residual uncertainty includes the random parameters $\zeta_t, \zeta_{t+1}, \ldots, \zeta_{T-1}$. However, the distribution of these residual stochastic parameters is conditioned upon the realization of random parameters in previous stages (Defourny, Ernst, & Wehenkel, 2011). If we consider a sequence of decision variables from stages 1 to T as $x_1, x_2, \ldots, x_{T-1}, x_T$, then Fig. 11 represents the sequence of decisions and realizations of random parameters for each stage of a T-stage stochastic program.

As pointed out by Dupačová (1995), in T-stage stochastic programs, it is also possible to consider random parameters related to stage T represented by ζ_T. These parameters usually affect only the objective function value.

A policy in a multi-stage stochastic program has to be *non-anticipative*, meaning that the decisions cannot depend on outcome of random parameters in the future. As explained by Dupačová (1995), there are two popular approaches to develop a multi-stage stochastic programming formulation. The first one is based on formulating a multi-stage stochastic program as a sequence of nested two-stage stochastic programs and also inserting the non-anticipativity settings implicitly. In fact, the total objective function is calculated through a recursive evaluation in this approach. However, the second approach imposes the non-anticipativity constraints explicitly.

Generally, multi-stage stochastic programs have been utilized rarely in the related literature. Thus, there is a high potential to develop stochastic SCND models with multiple periods using this approach. For more information about multi-stage stochastic programming, see Kali and Wallace (1994) and Birge and Louveaux (2011). In Table 8, the reference papers that used a scenario-based stochastic programming approach are categorized according to their solution approaches, mathematical models, and objective functions.

As illustrated in Table 8, most studies have employed two-stage stochastic programs. In essence, they assumed that their SCND problem has two-stage nature, which means there is a single moment for uncertain parameters to become known (Laporte et al., 2015). Nonetheless, the uncertainty has been realized progressively in more than one moment in many real-world problems and thus, the multi-stage stochastic program is often utilized. It should be highlighted that all papers that used a multi-stage stochastic program have a planning horizon with multiple periods and the uncertainty related to stochastic parameters has been realized progressively in each period. At each period, some decisions have to be made before uncertainty realization and some others are made afterwards. Notice that not all stochastic SCND problems with multi-period setting result in multi-stage stochastic programs necessarily (e.g., Georgiadis et al., 2011; Schütz et al., 2009).

Furthermore, as shown in Table 8, most stochastic problems have been developed an MILP model, and Benders' decomposition algorithm, called also L-shaped algorithm in stochastic programs, is relatively popular to solve the two-stage stochastic programs. To solve multi-stage stochastic programs in this area, Albareda-Sambola et al. (2013) and Pimentel et al. (2013) proposed a fix-and-relax coordination and the LR algorithm as a heuristic solution approach, respectively.

5.4.3. *Scenario generation for stochastic SCND problems*

Compared with continuous stochastic parameters, scenario approach for modeling stochastic parameters often results in more tractable models. It is also possible to regard dependency among stochastic parameters by using the scenario approach. For multi-stage and two-stage stochastic programs where the parameters are stochastic over multiple periods, a scenario tree and a scenario fan are often used, respectively. In this case, not only the parameters can be correlated with each other, but also they can be correlated across the time units and, therefore, it would be more difficult to generate an appropriate set of scenarios.

A main part of research works in stochastic programming context has been assigned to the task of generating efficient scenarios for stochastic programs. For this aim, the substantial concern is that a scenario generation method has to be evaluated in terms of quality and suitability. In this regard, in-sample and out-of-sample stabilities are two important requirements for an efficient scenario generation procedure. To learn more about quality and stability measures for scenario generation methods, one can refer to Kaut and Wallace (2007).

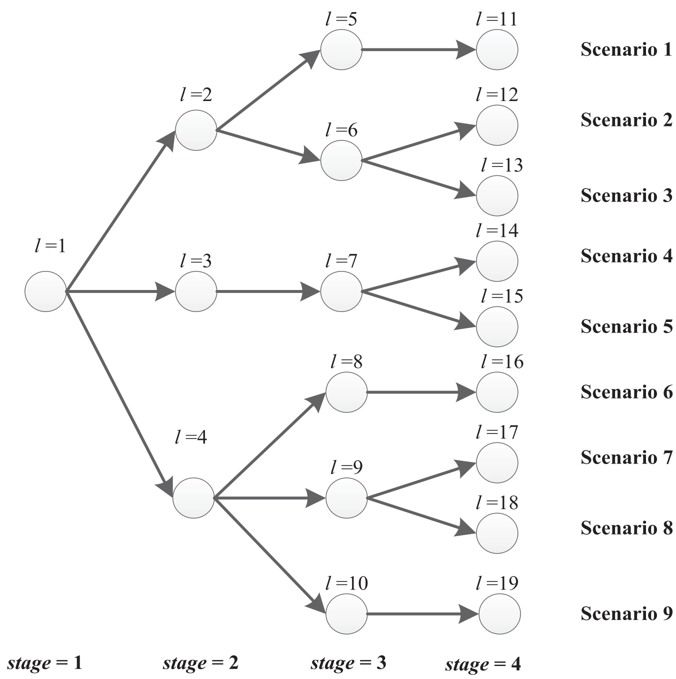

Fig. 10. A scenario tree example (Nodes are indexed by l. The root node is represented by index $l=1$ and the leaf nodes are represented by indexes $l=11$ to $l=19$).

A few studies (e.g., Fattahi & Govindan, 2016; Govindan & Fattahi, 2017; Keyvanshokooh et al., 2016; Klibi & Martel, 2012b; Schütz et al., 2009) developed an appropriate scenario generation procedure to obtain a set of scenarios, and typically most reference papers exploited a pre-determined small set of scenarios with definite probabilities for their stochastic programs. For a single period CLSC network design with stochastic demand and return quantities, Khatami, Mahootchi, and Farahani (2015) used Cholesky's factorization method in their scenario generation approach to deal with dependency of stochastic parameters. In addition, clustering methods have been applied by Khatami et al. (2015) and Pishvaee, Jolai, and Razmi (2009) to reduce the number of generated scenarios although these studies have not investigated the quality of constructed scenarios. Li and Hu (2014) and Poojari et al. (2008) applied the moment matching method to construct a set of scenarios and obtain their corresponding probabilities. Govindan and Fattahi (2017) and Keyvanshokooh et al. (2016) applied the Latin Hypercube Sampling method instead of Monte Carlo to generate a fan of scenarios and then reduced the number of generated scenarios by using backward scenario selection technique. Moreover, there are different types of scenario reduction techniques in the Stochastic Programming community that can be applied in this research area (e.g., Dupačová, Gröwe-Kuska, & Römisch, 2003; Heitsch & Römisch, 2003).

In the related area, sample average approximation (SAA) method has been used broadly to reduce the size of stochastic programs through repeatedly solving the problem with a smaller set of scenarios. These studies include: Bidhandi and Yusuff (2011), Chouinard, D'Amours, and Aït-Kadi (2008), Kiya and Davoudpour (2012), Klibi and Martel (2012a), Klibi and Martel (2012b), Lee and Dong (2009), Lee, Dong, and Bian (2010), Lee, Dong, Bian, and Tseng (2007), Santoso, Ahmed, Goetschalckx, and Shapiro (2005), Schütz et al. (2009), and Ayvaz, Bolat, and Aydın (2015).

5.5. Risk measures in the context of SCND

Traditionally, the stochastic SCND problem is on the basis of the expected value criterion. However, this criterion might be inappropriate specifically when the stochastic parameters vary noticeably. In a stochastic program where we have the random parameters with known probability distributions, the amount of a SC's profit/cost (or more generally SC's outcome) is often a random variable. Its probability distribution depends on the values of decision variables. In a numerical optimization procedure, it is often required to quantify the risk in order to make decisions in such a way that they can limit the level of SC's risk. To this aim, some dispersion statistics are defined as risk measures in the related literature.

A risk measure ρ maps a random outcome Y to a real value $\rho(Y)$. Here, the allowable random outcomes are shown by $\boldsymbol{Y}$. Generally, ρ is a risk mapping function that assigns a certain family of random outcomes to a set of real numbers (Fábián, 2013). Further, a precise definition for the concepts of risk measures and their properties are explicated in terms of a mathematical framework by Ruszczynski and Shapiro (2006).

In a SCND problem, the random objective relies on the values of decision variables. Formally, it can be stated as $Y = F(x),\ F : X \to \mathbf{Y}$ where $x \in \mathrm{R}^n$ is decision variables vector and $X \subseteq \mathrm{R}^n$ is a nonempty set of feasible decisions, and in this case, $\rho(F(x))$ is a risk function. Then, the level of risk aversion can be incorporated into a stochastic program using two main approaches (Fábián, 2013). In a stochastic optimization problem with cost/loss minimization objective, a risk constraint, $\rho(F(x)) \le \theta$, where θ is a constant number, is inserted into the problem as the first approach. The second one is a weighted mean-risk criterion defined for the problem such that the objective function is written as $\underset{x \in X}{Min}\ E(F(x)) + \lambda\rho(F(x))$ where λ is a risk aversion factor.

In SCND literature, many risk measures firstly developed in the area of finance and insurance have been applied. The most widely applicable ones are variance, standard deviation, absolute deviation, conditional value at risk (CVaR), and central semideviation. Another worthwhile approach for incorporating risk into a SCND problem is by assuming a constant target for SC's outcome and then, the risk measure is defined as a semideviation of SC's outcomes from the predetermined target. In Appendix B, Table B.1, the aforementioned risk measures are defined mathematically for a cost/loss minimization problem. In addition, Fig. 12 demonstrates the frequency of applying these risk measures in the reference papers. For more information about computational complexity of different risk measures, one can refer to Ahmed (2006) and Fábián (2013).

Furthermore, Guillén, Mele, Bagajewicz, Espuna, and Puigjaner (2005) and Franca, Jones, Richards, and Carlson (2010) computed the probability of SC's profit being less than a pre-determined target level as a risk measure. Recently, a review paper is represented by Heckmann et al. (2015) in which a variety of risk measures and risk modeling techniques in SCM have been reviewed. It is worth noting that all risk measures introduced in this section are exploited based on economical objective functions, such as SC's cost/profit, in SCND studies.

5.6. Robust optimization in the context of SCND

According to a robust optimization (RO) framework presented by Mulvey, Vanderbei, and Zenios (1995), there exist two kinds of robustness including solution robustness and model robustness meaning that the solution of a RO problem is "nearly" optimal and "nearly" feasible in all possible realizations of uncertain parameters, respectively. The definition of "nearly" is dependent upon the modeler's viewpoint. In an uncertain environment where a decision maker does not know probability distributions of uncertain parameters, it is not possible to use expected value criterion or other ones applied for the studies in Sections 5.4 and 5.5. In such

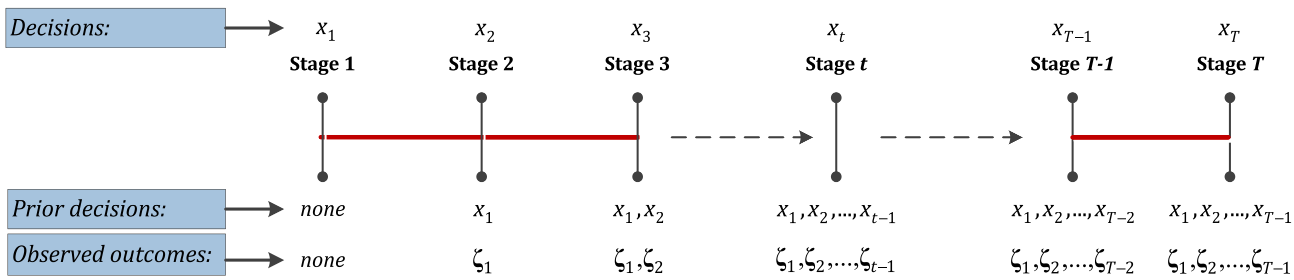

Fig. 11. Order of observations and decisions in a *T*-stage stochastic program.

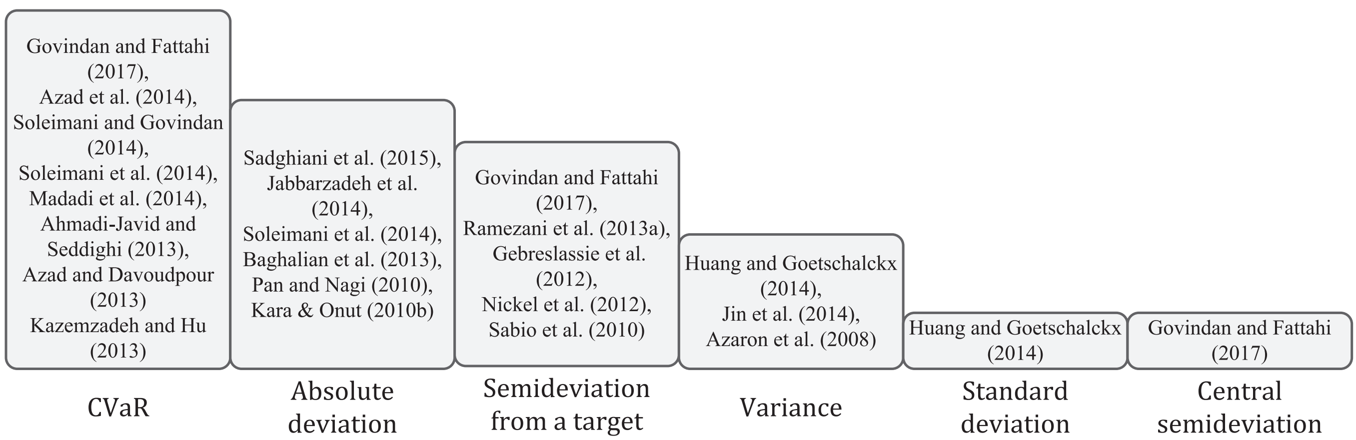

Fig. 12. The frequency of applying different risk measures in the reference papers.

an uncertain environment, RO is applicable through defining different robustness measures for the optimization problem. In RO problems, uncertain parameters may be continuous or specified via some discrete scenarios. For continuous ones, it is often assumed that these uncertain parameters could be varied within a pre-defined interval called interval-uncertainty.

5.6.1. Robust models with discrete scenarios

Different robustness measures with or without probability distributions are defined for the studies in this category. Two common measures for scenario-based RO programs are minimax cost and minimax regret. The *minimax cost measure* obtains a solution minimizing maximum cost over all scenarios. However, in the *minimax regret*, (absolute or relative) regret is determined as the (absolute or percentage) difference between the cost of a solution and the cost of the optimal solution for a scenario. Snyder (2006) reviewed various minimax models in the area of FL problem.

The minimax absolute regret measure is utilized by Realff, Ammons, and Newton (2004) and Ramezani, Bashiri, and Tavakkoli-Moghaddam (2013b) to design a RL and CLSC network, respectively. It should be mentioned that a study minimizing the expected relative regrets for all scenarios in a situation where the probabilities of scenarios are available is presented by De Rosa, Gebhard, Hartmann, and Wollenweber (2013). Further, Ahmadi-Javid and Seddighi (2013) and Govindan and Fattahi (2017) examined a SCND problem with minimax cost measure.

Another approach for obtaining solution robustness is presented by Kouvelis, Kurawarwala, and Gutierrez (1992). By adding some constraints, they made sure that the relative regret is not greater than p, where $p > 0$ is a pre-determined parameter, for each scenario. Snyder and Daskin (2006) called this method as p-robustness in the area of FL. In the related literature, some studies including Hatefi and Jolai (2014), Li, Liu, Zhang, and Hu (2015), Peng, Snyder, Lim, and Liu (2011), Tian and Yue (2014), and Torabi et al. (2016) utilized this approach. This method could lead to infeasibility for some values of p.

Several studies have applied the risk measures for SCND problem and called them as robustness measures. In this regard, variance is used by Jin, Ma, Yao, and Ren (2014) and absolute deviation is applied by Jabbarzadeh et al. (2014), Kara and Onut (2010b), Pan and Nagi (2010), and Sadghiani et al. (2015). It is worth noting that only Aghezzaf (2005), Jin et al. (2014), and Sadghiani et al. (2015) examined model robustness measures for a SCND problem. In Table 9, all studies in the area of scenario-based robust SCND are categorized with respect to their solution approaches, objective functions, and mathematical models.

As demonstrated in Table 9, most studies applied commercial solvers to solve the proposed mathematical models and considering robustness measures usually led to multi-objective optimization problems in several studies.

5.6.2. Robust models with interval-uncertainty

Generally, RO with interval-uncertain parameters has been applied in order to protect optimization problems against infeasibility due to perturbations of uncertain parameters and also to retain computational tractability. The primary step in RO with interval-uncertain parameters was done by Soyster (1973). The general idea was to convert the uncertain optimization problem into a deterministic counterpart program so that each feasible solution should be feasible for all realizations of uncertain parameters within their pre-defined uncertainty sets. However, Soyster's approach mostly achieves over-conservative solutions. In essence, by using this approach, we actually give up optimality for the nominal problem (where uncertain parameters are fixed to their nominal quantities) to ensure robustness. This means to guarantee the robustness, we need to lose optimality.

Then, E.l. Ghaoui, Oustry, and Lebret (1998), El Ghaoui and Lebret (1997), and Ben-Tal and Nemirovski (1998, 1999) addressed the over-conservatism of this robust solution. Their approaches led

Table 9
Solution approach and specifications of the mathematical model for scenario-based robust problems.

Articles	Solution approach				Mathematical model	Objective
	Exact algorithm	Heuristic	Meta-heuristic	Commercial solver		
Realff et al. (2004)				AIMMS	MILP-TSSP	Min(Max(Regret(I-C1-C2-C3-C4-C16)))
Aghezzaf (2005) [1]		LR algorithm			MILP-TSSP	Min M_1+M_2
Pan and Nagi (2010)		A heuristic based on k-shortest path algorithm			MILP-TSSP	Min(C1+C3+C4 +C6+C12 +C14), Min M
Kara and Onut (2010b)				CPLEX	MILP-TSSP	Max(I-C1-C4-C16-C18), Min M
Peng et al. (2011)			GA		MILP-TSSP	Min(C1+C4)
De Rosa et al. (2013)				CPLEX	MILP-TSSP	Min M
Ramezani et al. (2013b)				CPLEX	MILP-TSSP	Min(Max(Regret(I-C1-C4-C5-C6-C7-C16)))
Ahmadi-Javid and Seddighi (2013)			SA		MILP-TSSP	Min(Max(C1 +C17+(production and distribution disruption costs)))
Tian and Yue (2014)	Benders' decomposition				MILP-TSSP	Min(C1+C4+C5+C6+C7 +C8+C10+C14)
Jabbarzadeh et al. (2014)				LINGO	MILP-TSSP	Min(C1+C3+C4+C6), Min M
Jin et al. (2014)			TS		MINLP-TSSP	Min(C1+C4+C5+C6+C8), Min M
Hatefi and Jolai (2014)				CPLEX	MILP	Min(C1+C4+C5+C6+C14+C16)
Li et al. (2015)			artificial fish swarm algorithm		MILP-TSSP	Min(C1+C4+C6+C12+C14)
Torabi et al. (2016)				CPLEX	MILP	Min(C1+C4+C5+C6+C14+C16)
Sadghiani et al. (2015) [2]				CPLEX	MILP	Min(C1+Capital costs of transportation modes), Min M_1, Min M_2
Govindan and Fattahi (2017)				CPLEX	MILP-TSSP	Min(Max(C1+C3+C4+C5 +C6+C7+C14))
Table's summary:	Exact algorithms: **6%**, Heuristic algorithms: **12%**, Meta-heuristics: **18%**, Commercial solvers: **64%**		MILP: **92%**, MINLP: **6%**	Single objective (Minimization: **60%**, Maximization: **0 %**), Multiple objectives: **40%**		

[**1**], [**2**], These papers considered two robustness measures including solution's and model's robustness measures.

to less conservative solutions through allowing the uncertainty sets to be ellipsoids. Nonetheless, their robust formulations resulted in nonlinear but convex models, and thereby being difficult to solve as compared to Soyster's method. Bertsimas and Sim (2003, 2004) presented a different robust approach in which the conservatism level of robust solutions could be controlled and resulted in a linear optimization model. This approach is also applied for discrete optimization models.

However, Ben-Tal, Goryashko, Guslitzer, and Nemirovski (2004) pointed out that in all above conventional RO approaches, all decisions have to be made before uncertainty realization. Nevertheless, most real-world problems, in particular SCND problem, have multi-stage nature, and hence some decisions have to be determined after realization of all or part of existing uncertainties. To this aim, they presented a multi-stage RO approach, called Affinely Adjustable Robust Counterpart (AARC). This idea allows for making adjustable decisions that are affinely contingent on the primitive uncertainties.

In practice, even though the exact distributions of uncertain parameters are often not known in advance, moment information or uncertainty about the distribution itself is usually known. To deal with this situation, Distributionally Robust Optimization (DRO) was firstly proposed by Scarf, Arrow, and Karlin (1958) and then extended by Delage and Ye (2010), Goh and Sim (2010), and Wiesemann, Kuhn, and Sim (2014). In DRO, an uncertain parameter follows a distribution which is itself subject to uncertainty.

In the area of SCND problem, a few studies proposed robust counterpart formulations where interval-uncertain parameters are taken into account. In Table 10, these studies are listed in which robust problems are solved after proposing their equivalent tractable formulations. The specifications of these equivalent formulations are also highlighted in Table 10.

As illustrated in Table 10, there are a few studies about robust SCND with interval-uncertainty. Most of these reference papers used commercial solvers to solve the equivalent models for their robust counterparts. It is worth noting that in Keyvanshokooh et al. (2016) and Hatefi and Jolai (2014), some uncertain parameters have interval-uncertainty and some others are modeled by using discrete scenarios. This approach is applicable whenever we have different types of uncertainty in the SCND problem.

5.7. Fuzzy mathematical programming in the context of SCND

Fuzzy mathematical programs have been commonly used to design SC networks under uncertainty. In general, the fuzzy mathematical programming can be divided into flexible and possiblistic programming. Consider the classical linear program $Min\ c^T x,\ s.t.\ Ax \geq b,\ x \geq 0$. In accordance with Tanaka, Okuda, and Asai (1973) and Zimmermann (1991), a flexible programming problem can be written as $\widetilde{Min}\ c^T x,\ s.t.\ Ax \tilde{\geq} b,\ x \geq 0$ where fuzzy goals and sets are utilized to characterize the vagueness related to decision maker's aspirations and constraints, respectively. In other words, this approach is applicable to deal with flexible target value of goals and elasticity of soft constraints.

On the other hand, a possiblistic programming problem can be expressed as $\widetilde{Min}\ \tilde{c}^T x,\ s.t.\ \tilde{A}x \geq \tilde{b},\ x \geq 0$ where the imprecise or ambiguous data is modeled through possibility distributions (see Tanaka & Asai, 1984). The application of this approach is to manage deficiency of information for the exact values of a model's parameters. Moreover, in fuzzy mathematical programming, it is possible to take care of ambiguous coefficients and also vague preferences of decision makers.

All studies in this area have two major phases to solve a problem modeled using a fuzzy mathematical programming. Firstly,

Table 10
Solution approach and specifications of the equivalent formulations for robust counterpart of RO problems.

Articles	Solution approach				Equivalent model for robust counterpart of problems	
	Exact algorithm	Heuristic	Meta-heuristic	Commercial solver	Mathematical model	Objective
Pishvaee, Rabbani, and Torabi (2011)				CPLEX	MILP	Min(C1+C4+C14)
Hasani, Zegordi, and Nikbakhsh (2012)				LINGO	MINLP	Max(I-C1-C3-C4-C5-C8-C10-C14-C16)
Vahdani et al. (2012)				GAMS	MILP	Min(C1+C4+C5+C6+C16), Min(Disruption cost)
Zokaee, Jabbarzadeh, Fahimnia, and Sadjadi (2014)				LINGO	MILP	Min(C1+C4+C14)
Hatefi and Jolai (2014)				CPLEX	MILP	Min(C1+C4+C5+C6+C14+C16)
Tong, You, and Rong (2014)		Parametric approach based on Newton's method, Reformulation-linearization method		DICOPT, BARON, SBB	MINLP	Min((C1+C4 +C5+C6+C7+C11-Governmental incentives)/ Sales' amount)
Hasani et al. (2015)			Combined memetic algorithm and adaptive VNS		MINLP	Max(I-C2-C3-C4-C5-C8-C10-C15-C16)
Akbari and Karimi (2015)				CPLEX	MILP	Min(C1+C3+C4 +C5+C6+C7)
Dubey, Gunasekaran, and Childe (2015)				CPLEX	MILP	Min(C1 +C4+C5+C6+C7+C16), Min(Delivery time+Collection time)
Keyvanshokooh et al. (2016)	Benders' decomposition				MILP	Max(I-C1-C3-C4-C5-C7-C14-C16)
Hasani and Khosrojerdi (2016)			Memetic algorithm		MINLP	Max(I-C2-C3-C4-C5-C8-C10-C15)
Table's summary:	Exact algorithms: **9%**, Heuristic algorithms: **9%**, Meta-heuristics: **18%**, Commercial solvers: **64%**		MILP: **72%**, MINLP: **28%**	Single objective (Minimization: **46%**, Maximization: **36%**), Multiple objectives: **18%**		

a fuzzy model is converted into a crisp and usual mathematical model in which the existing uncertainties are handled according to assorted interpretation of the problem. Then in the second phase, this transformed mathematical model is solved by using an optimization approach or tool (Inuiguchi & Ramık, 2000).

SCND problems under a fuzzy environment are categorized in Table 11 based on their fuzzy uncertainties, transformed mathematical models, and solution approaches. It should be noted that in Table 11, we report the optimization tools or techniques for solving the crisp transformed mathematical models as solution approaches. Here, the techniques used for handling multi-objective problems or transforming fuzzy models are not considered. In Table 11**,** in the column for mathematical model, the dashes mean that no crisp transformed model is presented in related studies.

As shown by Table 11, most studies in this area considered ambiguous input data to present a possiblistic programming model and used commercial solvers to solve the transformed equivalent crisp models. Moreover, many studies dealt with multi-objective problems in this area.

5.8. Optimization approaches for SCND with disruptions

As SCND with disruptions has received much attention recently, we discuss different optimization approaches to cope with this problem in this section. Lately, Snyder et al. (2016) provided a review paper regarding the management science and operation research models for handling SC disruptions. Further, Laporte et al. (2015) examined the existing FL models under disaster events.

SCND studies with disruptions can be divided into business and non-business SCs. The goal of a business one is to design a SC such that it can perform well even after disruption occurrence. The non-business SCs such as Liu and Guo (2014), Noyan (2012), and Jeong et al. (2014) are often designed to deliver relief items to the established demand points after disasters and is called humanitarian SC.

While SC disruptions can have substantial influence on key SC parameters such as demand, supply, delivery time of products, and costs, they may also result in reducing capacity of SC facilities and transportation links or even eliminating them. In addition, in humanitarian SCs, the demand for relief supplies has a great deal of uncertainty, depending on the type, magnitude, and location of a disaster.

In this area, most studies assume a failure probability for a facility or transportation link in the face of disruption as a pre-specified parameter. They are also called *reliable SCND models*. These studies include Azad et al. (2014), Azad, Saharidis, Davoudpour, Malekly, and Yektamaram (2013), Cui et al. (2010), Hatefi, Jolai, Torabi, and Tavakkoli-Moghaddam (2015a), Li and Savachkin (2016), Li, Zeng, and Savachkin (2013), Marufuzzaman, Eksioglu, Li, and Wang (2014), Vahdani et al. (2012), Vahdani, Tavakkoli-Moghaddam, Jolai, and Baboli (2013), Vahdani, Tavakkoli-Moghaddam, and Jolai (2013), and Hatefi, Jolai, Torabi, and Tavakkoli-Moghaddam (2015b). In Cui et al. (2010), customers are assigned to more than one facility and hence in the face of disruption, each customer can be served by the nearest operational (non-disrupted) facility. Azad et al. (2014) presumed that if a failure occurs for a facility of SC, then the percentage of its disrupted capacity is a stochastic parameter. They also presented an optimization model by using the CVaR measure.

Sometimes, the uncertainty related to disruptions is modeled as a finite set of discrete scenarios. In this regard, Hatefi and Jolai (2014), Peng et al. (2011), and Li et al. (2015) utilized the *p*-robustness approach. Also, Ahmadi-Javid and Seddighi (2013), Noyan (2012), Sadghiani et al. (2015), and Baghalian, Rezapour, and Farahani (2013) developed some risk-averse scenario-based stochastic models by using well-known risk measures in the stochastic programming context. It is worth noting that most SCND

Table 11
Optimization aspects related to the studies under fuzzy environment.

Articles	Fuzzy mathematical programming				Crisp transformed mathematical model	
	Ambiguous data	Vagueness of constraints	Vagueness of goals	Mathematical model	Solution approach	Objective
Xu, Liu, and Wang (2008)	√			MINLP	Spanning tree based GA	Min(C1+C4+C14), Max R
Selim and Ozkarahan (2008)			√	MILP	CPLEX	Min(C2+C4), Min(C1), Max R
Xu, He, and Gen (2009)	√			MILP	Spanning tree based GA	Min(C1+C4)
Pishvaee and Torabi (2010)	√			MILP	LINGO	Min(C1+C4+C5+C6+C16), Min (Delivery tardiness)
Qin and Ji (2010)[1]	√			-	GA integrated with fuzzy simulation	Min(C1+C4+C16+C18)
Zarandi, Sisakht, and Davari (2011)			√	MILP	CPLEX	Min(C1 +C7+C4), Max R
Pishvaee, Torabi et al. (2012)	√			MILP	LINGO	Min(C1+C4+C5+C7+C11), Min E
Pishvaee and Razmi (2012)	√			MILP	LINGO	Min(C1+C4+C5+C16), Min E
Pishvaee, Razmi, and Torabi (2012)	√			MILP	LINGO	Min(C1 +C4+C5+C11), Max S
Vahdani et al. (2012)			√	MILP	GAMS	Min(C1+C4+C5+C6+C16), Min(Disruption cost)
Bouzembrak, Allaoui, Goncalves, Bouchriha, and Baklouti (2013)	√			MILP	CPLEX	Min(C1+C3+C4+C6)
Vahdani, Tavakkoli-Moghaddam, and Jolai (2013)	√			MILP	GAMS	Min(C1+C4+C5+C6+C16), Min(Disruption cost)
Vahdani, Tavakkoli-Moghaddam, Jolai, and Baboli (2013)	√			MILP	GAMS	Min(C1+C4+C5+C6+C16), Min(Disruption cost)
Jouzdani, Sadjadi, and Fathian (2013)		√		MINLP	LINGO	Min(C1+Traffic congestion cost)
Mirakhorli (2014)		√	√	MILP	GA	Min(C1+C4+C5+C6+C16), Min (Service time)
Balaman and Selim (2014)		√	√	MILP	CPLEX	Min(I-C1-C2-C4-C6-C7-C8), Min (Unused waste)
Jindal and Sangwan (2014)	√			MILP	LINGO	Max(I–C1-C4-C8-C16)
Vahdani, Dehbari, Naderi-Beni, and Kh (2014)	√			MILP	Imperialist competitive algorithm (ICA)	Min(C1+C4), Max(Reliability of facilities)
Ramezani, Kimiagari, Karimi, and Hejazi (2014)	√			MILP	CPLEX	Max(I-C1-C3-C4-C5-C6-C8-C10-C16), Max R
Pishvaee et al. (2014)	√			MILP	Benders' decomposition	Min(C1+C4+C5+C6+C7+C11 +C16-C19), Min E, Max S
Bai and Liu (2016)	√			MILP	LINGO	Min(C1+C4+C5+C8)
Özceylan and Paksoy (2014)	√			MINLP	GAMS	Min(C1), Min(C4), Min(C8), Min(C16)
Subulan, Taşan, and Baykasoğlu (2014)			√	MILP	CPLEX	Min(C1+C4+C5+C8+C16-I), Max (Coverage of return products), Max (flexibility)
Subulan, Baykasoğlu et al. (2014)	√			MILP	CPLEX	Min(C1+C4+C5+C8+C16-I), Max (Coverage of return products)
Tong, Gleeson, Rong, and You (2014)	√			MILP	CPLEX	Min(C1 +C3+C4 +C5+C6+C7+C11-Government incentives)
Sadjadi, Soltani, and Eskandarpour (2014)[2]	√			-	Memetic algorithm	Min(C1+C2+C4), Min (Variance of constrains' deviations)
Mousazadeh et al. (2015)	√			MILP	CPLEX	Min(C1+C3+C4+C5+C7+C11), Min(Max(unsatisfied demand))
Torabi et al. (2016)	√			MILP	CPLEX	Min(C1+C4+C5+C6+C14+C16)
Hatefi et al. (2015a)	√			MILP	CPLEX	Min (C1+C4+C5+C6+C16 +Disruption cost)
Hatefi et al. (2015b)	√			MILP	CPLEX	Min (C1+C4+C5+C6 +C16+Disruption cost)
Fallah, Eskandari, and Pishvaee (2015)	√			MINLP	GAMS	Max(I-C4-C5-C16)
Sadghiani et al. (2015)	√			MILP	CPLEX	Min(C1+Capital costs for transportation modes), Min M_1, Min M_2
Babazadeh et al. (2017)[3]	√			MINLP[1]	CPLEX	Min(C1+C3 +C4 +C5+C6+C7+Importing cost), Min E
Table's summary:	Exact algorithms: **3%**, Heuristic algorithms: **0%**, Meta-heuristics: **18%**, Commercial solvers: **79%**			MILP: **88%**, MINLP: **12%**	Single objective (Minimization: **27%**, Maximization: **6 %**), Multiple objectives: **67%**	

[**1**], [**2**], The crisp transformed model is not presented in these studies. [**3**]In this study, the MINLP model is transferred to an MILP one.

models with disruptions in the literature are single period and only a few papers such as Klibi and Martel (2012a) and Klibi and Martel (2013) can be found which are multi-period.

Survey papers by Tang (2006a), Tang (2006b), Tang and Tomlin (2008), and Tang and Musa (2011) introduced mitigation strategies which could be utilized to improve SC's resiliency in the face of risks. Moreover, some mitigation strategies expressed by Tang (2006a) and Tang and Tomlin (2008) can be applicable for dealing with operational risks in SCs, which reveals the fact that they are not developed only for disruption risks. However, in SCND, these strategies have been applied to handle a SC under the uncertainty induced by disruptions. Further, a few papers employed mitigation strategies for designing a resilient SC network. Here, we explore the most popular mitigation strategies in the related literature:

Facility fortification: In this strategy, some facilities are chosen for an existing SC network or during the design phase of a SC network in order to fortify them against various disruptions. Hasani and Khosrojerdi (2016), Li and Savachkin (2016), and Qin, Liu, and Tang (2013) utilized this strategy.

Strategic stock: Using this strategy, a SC can hold the inventory for raw materials, semi-finished and finished products in its facilities within different layers of SC. This inventory is often utilized to satisfy the needs of customers and other manufacturing processes. Benyoucef, Xie, and Tanonkou (2013), Hasani and Khosrojerdi (2016), Mak and Shen (2012), Qi and Shen (2007), and Qi, Shen, and Snyder (2010) employed this strategy.

Sourcing strategy: As pointed out by Snyder et al. (2016), this strategy is divided into multiple sourcing and backup sourcing. In the multiple one, sourcing is carried out by using multiple suppliers simultaneously before disruption occurrence. However, the backup sourcing exploits backup suppliers when primary suppliers are disrupted. Cui et al. (2010), Hasani and Khosrojerdi (2016), Klibi and Martel (2012a), Klibi and Martel (2013), Mak and Shen (2012), Qi and Shen (2007), and Li et al. (2013) used one or both strategies.

6. Applications and real-word case studies for SCND

Here, some studies that deal with applications of SCND problem under uncertainty have been reviewed. In this regard, some of them investigated real-life case studies and some others solved randomly generated test instances in an industrial context. One of the essential challenges in designing a SC network based on a specific industrial context is that the design decisions have to be often made according to required processes for producing products (e.g., Schütz et al. (2009) and Govindan and Fattahi (2017) that studied a SC for a meat and glass industry, respectively).

In a survey paper by Barbosa-Povoa (2014), SCs formed for process industries, named as process SCs, are examined. For this aim, the real-life case studies are divided into five major types, including agricultural, biomass/biofuel, gas/hydrogen, pharmaceutical, and oil SCs.

Unlike studies related to business SCs, non-business SC models are often developed based on a specified application. In Table 12, the reference papers developed for specific application or industry and the ones that examined some real-world case studies are listed. In the column for real-life case study, the dashes mean that the related reference paper did not examine a real-life case study and solved some randomly generated test instances for the considered industry or application.

As shown in Table 12, about 24% of reference papers defined their SC networks on the basis of a specific industry or application. It is worthwhile to focus more on designing SC networks for specific industries in business SCs and applications in non-business SCs. Moreover, due to difficulties in collecting, preparation, and aggregation huge data sets, only 20% of reference papers concerned real-life case studies. In this regard, big data analytics tools and techniques would be helpful for future research works.

In terms of the type of logistics networks, about 20% of papers treated the applications of RL or CLSC networks in Table 12. Here, the biomass/biofuel, chemical, gas/hydrogen, and pharmaceutical SCs include 28%, 10%, 10%, and 5% of studies, respectively. Thus, it can be concluded that researchers have paid more attention to biofuel/biomass SCs recently. Furthermore, a review and systematic classification on biomass to energy SC networks is presented by Balaman and Selim (2015).

7. Discussion, conclusions, and future research directions

In this paper, a comprehensive review was presented on the studies in the area of SCND problem under uncertainty. The decision-making environments under uncertainty were divided into three categories in Section 3. In general, the uncertainty sources include (1) the existing uncertainty in parameters such as supply, demand, and costs, which are inherently uncertain, and (2) the uncertainty caused by natural or man-made disruptions. Fewer than 20% of studies considered the second uncertainty source in their problems. Therefore, addressing reliable and resilient SC networks under disruption risks will have high potential as a future research direction. In this paper, we answered the questions mentioned in the introduction section. For this aim, the studies were investigated from two principal perspectives involving (1) SCM aspects, and (2) optimization aspects. In this section, a discussion is presented and several future research directions on the basis of literature's gaps are provided from these two perspectives, separately.

7.1. SCM aspects in SCND under uncertainty

The integration of strategic SC decisions and the other ones related to tactical/operational levels in a comprehensive model under uncertainty will be a future research direction. More specifically, a few reference papers coped with decisions such as routing and price of products. Pricing of products and revenue management issues are addressed by some studies (e.g., Ahmadi-Javid & Hoseinpour, 2015; Fattahi et al., 2015) for deterministic problems, and these studies have the potential to be extended for an uncertain environment. Moreover, a small number of papers have dealt with vehicle routing decisions in a SCND problem under uncertainty, all of which considered routing decisions only for one layer of SC network. Hence, this area requires more attention in the sense that we may make routing decisions for more than one layer of SC or consider the vehicles with different types and capacities. Further, as pointed out in Section 4.2, many studies made inventory and design decisions simultaneously for single or multiple layers of a SC network. However, making such decisions for SCs with highly perishable products such as blood SCs often depends on the products' characteristics and life cycle. There has not been any study that handles this aspect in SCND under uncertainty and hence it promises to be an interesting future research topic.

Only 32% of reference papers took a planning horizon with multiple periods into account. Due to the strategic nature of SCND decisions, defining strategic periods will help a decision maker to have the opportunity of changing strategic decisions in future with respect to the volatile business environment. Additionally, tactical or operational periods can capture changes in the parameters associated with these decision levels. Thus, developing comprehen-

Table 12
Applications and industrial contexts addressed in the related literature.

Articles	Non-business supply chain	A specific industry or application	Real-life case study
Realff et al. (2004)		Recovery network for carpet recycling	A case study in USA
Listeş and Dekker (2005)		Recovery network for recycling sand	A case study in Netherlands
Guillen et al. (2006)		A supply chain for chemical industry	–
You and Grossmann (2008a)		A supply chain for polystyrene industry	–
Rappold and Van Roo (2009)		A supply chain for handling reparable items	–
Guillén-Gosálbez and Grossmann (2009)		A supply chain for chemical industry	A case study in Europe
Schütz et al. (2009)		A supply chain for meat industry	A case study in Norway
Guillén-Gosálbez and Grossmann (2010)		A supply chain for chemical industry	A case study in Europe
Lee et al. (2010)		A supply chain for an international electrical company	A case study in Asia Pasific region
Sabio et al. (2010)		Hydrogen supply chain	A case study in Spain
Kim et al. (2011)		Biofuel supply chain	A case study in southern part of USA
Giarola et al. (2012)		Ethanol supply chain	–
Noyan (2012)	√	A supply chain network for distributing relieif supplies after occurrence of a disaster	–
Chen and Fan (2012)		Bioethanol supply chain	A case study in the state of California (USA)
Almansoori and Shah (2012)		Hydrogen supply chain	A case study in Great Britain
Gebreslassie et al. (2012)		Hydrocarbon biorefinery supply chain	A case study in the state of Illinois (USA)
Kazemzadeh and Hu (2013)		Biofuel supply chain	A case study in the state of Iowa (USA)
Baghalian et al. (2013)		A supply chain for an agri-food industry	The rice industry of a country in the Middle East
Jouzdani et al. (2013)		Milk and dairy supply chain	A case study in Iran
Tong et al. (2013)		Hydro carbon biofuel and petroleum supply chain	–
Balaman and Selim (2014)		Bioenergy supply chain	A case study in Turkey
Jeong et al. (2014)	√	A supply chain network for distributing relieif supplies after occurrence of a disaster	A case study in the state of South Carolina (USA) based on historical disasters
Marufuzzaman et al. (2014)		Biofuel supply chain	A case study in the southeast region of USA
Jabbarzadeh et al. (2014)	√	A supply chain network for blood distribution after occurrence of a disaster	A case study for Tehran's earthquake
Zokaee et al. (2014)		Bread supply chain	A case study in Iran
Tong, You et al. (2014) and Tong, Gleeson et al. (2014)		Hydro carbon biofuel supply chain	A case study in the state of Illinois (USA)
Madadi et al. (2014)		Pharmaceutical supply chain	–
Li and Hu (2014)		Biofuel supply chain	A case study in the state of Iowa (USA)
Liu and Guo (2014)	√	A supply chain network for distributing relieif supplies after occurrence of a disaster	A case study based on Great Wenchuan earthquake in China
Pishvaee et al. (2014)		A CLSC for medical needle and syringe industry	A case study for an industry in Iran
Subulan, Taşan et al. (2014) and Subulan, Baykasoğlu et al. (2014)		A CLSC for lead/acid battery industry	A case study for an industry in Turkey
Dayhim et al. (2014)		Hydrogen supply chain	A case study in the state of New Jersey (USA)
Ayvaz et al. (2015)		RL for waste management of electrical and electronic equipments	A case study in Turkey
Hasani et al. (2015) and Hasani and Khosrojerdi (2016)		A CLSC for medical devices industry	A case study in Iran
Mousazadeh et al. (2015)		Pharmaceutical supply chain	A case study in Iran
Babazadeh et al. (2017)		Biodiesel supply chain	A case study in Iran
Govindan and Fattahi (2017)		A supply chain for glass industry	A case study in Iran

sive models under uncertainty with multiple periods requires more attention. In particular, deterministic multi-period SCND problems in which there exists the possibility of changing the location and capacity of facilities over different strategic periods, have been widely addressed (e.g., Melo et al., 2006; Thanh, Bostel, & Péton, 2008). These studies also have potential to be extended for an uncertain decision-making environment. Moreover, we could not find any SCND study under uncertainty that deals with a planning horizon where strategic and tactical periods are integrated.

As shown by Fig. 9, a few papers addressed social responsibility or environmental aspects in designing SC networks under uncertainty. Nevertheless, government legislation and customers' awareness have caused most corporations and organizations to pay more attention to these issues. Evidently, more research is still required on these aspects, whose significances have been emphasized and raised by social and environmental concerns. Further, dealing with financial factors and different types of competitions in SCND problems under uncertainty are another two potential research areas. Farahani et al. (2014) surveyed competitive SCND and represented the existing research gaps in this area.

Designing humanitarian SC networks needs more investigations, and indeed many studies in this area can be done with respect to different disaster types and desired applications. Sometimes, it may not be possible to satisfy all demands in humanitarian SC networks, so there is a need to develop models considering fairness for shortages that may occur at different demand points. Moreover, demand points in this type of network often need different commodities, but their priority varies. This aspect has been rarely regarded in humanitarian SC networks. In general, two aspects that should be considered by researchers in this area are: (1) planning decisions, network structure and performance measures depend on the considered application and can be quite different from business SCs; and (2) modeling uncertain parameters is contingent upon the type and magnitude of disasters.

Designing responsive SC networks has been examined by only 12% of reference papers. In these studies, the fill rate of customers' demands and their service time are often used as performance measures for evaluating the responsiveness of SC. In all of these studies, customers' demand is not dependent on the responsiveness of SC. Nonetheless, in today's competitive business environment, designing a SC network in which customers' demand is sensitive to SC's responsiveness is a valuable future research. Moreover, defining other criteria for the SC's responsiveness based on business goals of companies is of importance in different applications.

Finally, there were a few papers to cope with real-world situations. The reason is twofold: (1) the necessity for collecting a large data set to model comprehensive SCND problems, and (2) the difficulties in obtaining correct estimates for uncertain parameters. Thus, it would be worthwhile to carry out studies based on a SC network defined for real-life case studies.

7.2. Optimization aspects in SCND under uncertainty

In this paper, assorted modeling frameworks that have been applied for SCND problems under uncertainty were introduced and thus the studies were investigated in terms of their developed solution methodologies and mathematical models. In this section, research gaps and potential future research guidelines in terms of optimization aspects are discussed.

More than 50% of reference papers made use of commercial solvers to solve their optimization problems. This fact demonstrates two practical issues. Firstly, commercial solvers have had significant progress over recent years such that they have suitable performance in solving optimization problems in this area. Second, many industries would prefer to exploit a proven commercial solver for solving smaller problem instances instead of using a custom designed solution approach, which results in an approximate solution.

A few studies applied meta-heuristics approaches. Due to the NP-hardness nature of SCND problem under uncertainty, developing this type of solution approaches still remains a future research direction. It is worth noting that meta-heuristics cannot guarantee the optimal solution for an optimization problem. However, these approaches can solve large-scale problems within appropriate time. Therefore, developing this kind of solution approaches is worthwhile. Further, presenting solution algorithms, which are based on the combination of exact methods with heuristics or meta-heuristics is another future area of research.

In scenario-based stochastic programs for SCND, Benders' decomposition or L-shaped method, as exact approaches, were widely applied due to the problem's special structure. However, exact solution approaches for problems with minimax or weighted mean-risk objectives are still scarce and will be welcomed by researchers and practitioners. In addition, developing multi-stage stochastic programs and presenting efficient solution approaches for them is another challenging issue, and it needs greater consideration. In this regard, the progressive hedging algorithm, an applicable method for solving two and multi-stage stochastic programs, has been used scarcely in the related literature.

Another significant aspect for scenario-based stochastic programs is to generate an efficient set of scenarios to model underlying stochasticity in SCND. More importantly, evaluating scenario generation methods in terms of stability and quality criteria should be examined in SCND problem as well. There are different approaches to deal with scenario generation and reduction in the Stochastic Programming community (e.g., Dupačová et al., 2003; Heitsch & Römisch, 2003; Høyland & Wallace, 2001) that can be applied in this research area.

As mentioned before, there exist two types of risks including operational and disruption risks in a SC, for which risk management plays an indispensable role in reducing these existing risks. Because only a few papers addressed this issue, risk management in SCND problem is a potential future research direction. By exploring the papers in Section 5.5, it can also be highlighted that most ones utilized the well-known risk measures for alleviating the risks based on their economic objectives such as SC's cost or profit. However, studying the SC's risk based on other strategic goals of SC such as responsiveness is still a challenge. It is worth noting that Heckmann et al. (2015) discussed this research gap in the area of supply chain risk management with more details. Moreover, most SCND models with disruption risks are single period in the related literature. However, disruptions can affect the SC's performance for a long time. Thus, developing SCND models under a planning horizon with multiple periods and modeling uncertain effects of disruptions over this planning horizon is another concern. Further, a number of papers employed some mitigation strategies for managing SC's disruption risks, as discussed in Section 5.8. However, as pointed out by Tang (2006a) and Tang and Tomlin (2008), there are other mitigation strategies such as flexible manufacturing process, responsive pricing, supply contracts, and so on that can be used for designing resilient SCs. Hence, future research works may develop SCND models based on these other strategies and assess their effectiveness. It is worth mentioning that using mitigation and contingency strategies simultaneously is another interesting future research for designing resilient SC networks.

Robust SCND has gained less attention in comparison with fuzzy and stochastic programs. However, it must be noted that in many real-world applications, enough historical data are not present to estimate parameters' distributions, but robust optimization is a suitable tool for handling such a situation. Using AARC and DRO approaches in the area of SCND problems is another research direction for which there has not been any paper in the related literature. Additionally, developing modeling approaches in the context of SCND problem that fill out the gap between stochastic programming and RO could be an interesting research idea. In addition to these aspects, exploring new applicable robustness measures to address solution or model robustness will be another promising research direction.

Simulation is a powerful tool to validate obtained policies in uncertain decision-making environments and unfortunately, such a methodology has been rarely examined in the related SCND literature. In addition, to the best of our knowledge, there has not been any research to compare different modeling philosophies such as stochastic programming, RO, and fuzzy programming to design a SC network under uncertainty. Therefore, a systematic comparison between these modeling approaches will be required.

The last conclusion that can be drawn from this survey paper is while there are many research studies for SCND problem under uncertainty, this research area still needs more studies presenting realism models based on real-world applications and handling computational aspects to solve large-sized problems.

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Appendix A. Features and structure of logistics networks in the related literature

Table A.1
Features and structure of supply chain networks and forward networks in closed-loop supply chains in the related literature. (F and TL are abbreviations of facilities and transportation links, respectively).

Articles	Paper's number	RLN	# of location layers	Multiple commodities	Flows		Uncertain parameters in forward network	Disruption in forward network		Decision-making environment group
					Intra-layer flows	Direct flows to customers from upper layers		F	TL	
Sabri and Beamon (2000)	[1]		2	√			D, ST, PT			G1
Tsiakis et al. (2001)	[2]		2	√			D			G1
Daskin et al. (2002)	[3]		1				D			G1
Hwang (2002)	[4]		1				AF	√		G1
Shen et al. (2003)	[5]		1				D			G1
Alonso-Ayuso et al. (2003)	[6]		1	√	√		D, C, P, PR			G1
Guillén et al. (2003)	[7]		2	√			D			G1
Miranda and Garrido (2004)	[8]		1				D			G1
Shen (2005)	[9]		1				D			G1
Shen and Daskin (2005)	[10]		1				D			G1
Avittathur et al. (2005)	[11]		1				D			G1
Guillén et al. (2005)	[12]		2	√			D			G1
Aghezzaf (2005)	[13]		1		√		D			G1
Santoso et al. (2005)	[14]		3	√	√	√	D, S, C, CA			G1
Shu et al. (2005)	[15]		1				D			G1
Guillen et al. (2006)	[16]		3	√			D			G1
Vila et al. (2007)	[17]		1	√		√	D (Agreements/ contracts with customers)			G1
Romeijn et al. (2007)	[18]		1				D			G1
Qi and Shen (2007)	[19]		1				D, AF	√		G1
Shen and Qi (2007)	[20]		1				D			G1
Snyder et al. (2007)	[21]		1				DP			G1
Goh et al. (2007)	[22]		1				D, FP			G1
Listeş (2007)	[23]	√	1				D			G1
Shen (2007a)	[24]		1				D			G1
Lee et al. (2007)	[25]	√	1	√			D			G1
Salema et al. (2007)	[26]	√	2	√			D			G1
Xu et al. (2008)	[27]		2				D,C			G3
Chouinard et al. (2008)	[28]	√	1	√			D			G1
Miranda and Garrido (2008)	[29]		1				D			G1
Poojari et al. (2008)	[30]		3	√			D			G1
Selim and Ozkarahan (2008)	[31]		2	√			FG			G3
You and Grossmann (2008a)	[32]		2	√	√		D			G1
You and Grossmann (2008b)	[33]		1				D			G1
Tanonkou et al. (2008)	[34]		1				D, ST			G1
Azaron et al. (2008)	[35]		1	√			D, C, S			G1
Rappold and Van Roo (2009)	[36]		2				D, PT			G1
Guillén-Gosálbez and Grossmann (2009)	[37]		2	√			EP			G1
Lee and Dong (2009)	[38]	√	1	√			D			G1
Schütz et al. (2009)	[39]		3	√	√	√	D, S, C, CA			G1
Pishvaee et al. (2009)	[40]	√	2				D, C			G1
Xu et al. (2009)	[41]		3				D, S, C			G3
You and Grossmann (2009)	[42]		1				D			G1
Franca et al. (2010)	[43]		2	√			D			G1
Javid and Azad (2010)	[44]		1				D			G1
Qi et al. (2010)	[45]		1				D, AF	√		G1
Park et al. (2010)	[46]		2				D			G1
Lee et al. (2010)	[47]	√	2	√			D, C, CA			G1
Guillén-Gosálbez and Grossmann (2010)	[48]		2	√			EP			G1
Pan and Nagi (2010)	[49]		>3				D			G1
You and Grossmann (2010)	[50]		1				D			G1
Nasiri et al. (2010)	[51]		1	√			D			G1
Sabio et al. (2010)	[52]		2	√			C			G1
Pishvaee and Torabi (2010)	[53]	√	1				D, C, CA			G3
Cui et al. (2010)	[54]		1				AF	√		G1
Shu et al. (2010)	[55]		1				D			G1
Mo et al. (2010)	[56]		2	√			D			G1
You and Grossmann (2011)	[57]		1				D			G1
Bidhandi and Yusuff (2011)	[58]		2	√			D, C, CA			G1
Longinidis and Georgiadis (2011)	[59]		2	√			D, P, CA, SS			G1

(continued on next page)

Table A.1 (*continued*)

Articles	Paper's number	RLN	# of location layers	Multiple commodities	Flows		Uncertain parameters in forward network	Disruption in forward network		Decision-making environment group
					Intra-layer flows	Direct flows to customers from upper layers		F	TL	
Georgiadis et al. (2011)	[60]		2	√			D, CA, SS, lower and upper bounds of supply chain's flows			G1
Shukla et al. (2011)	[61]		1				AF, AT	√	√	G1
Cardona-Valdés et al. (2011)	[62]		1				D			G1
Shimizu et al. (2011)	[63]		1				D, C, P			G1
Kim et al. (2011)	[64]		2	√			D, S, P, CP			G1
Zarandi et al. (2011)	[65]	√	2	√			FG			G3
Peng et al. (2011)	[66]		1				AF	√		G2
Rajgopal et al. (2011)	[67]		1				D, C, S, Salvage value of products			G1
Giarola et al. (2012)	[68]		1	√			C, P			G1
Kiya and Davoudpour (2012)	[69]		1	√			D, C			G1
Abdallah et al. (2012)	[70]	√	1				D			G1
Noyan (2012)	[71]		1	√			D, C, CA, DC	√	√	G1
Jabbarzadeh et al. (2012))	[72]		1				DC	√		G1
Mak and Shen (2012)	[73]		1				D, AF	√		G1
Chen and Fan (2012)	[74]		2				D, S			G1
Klibi and Martel (2012a)	[75]		1				D, CA	√	√	G1
Almansoori and Shah (2012)	[76]		3	√		√	D			G1
Pishvaee, Torabi et al. (2012)	[77]		2				D, C, CA, EP			G3
Gebreslassie et al. (2012)	[78]		1	√			D, S			G1
Hasani et al. (2012)	[79]	√	1	√			D, PR			G2
Nickel et al. (2012)	[80]		1	√			D, FP			G1
Pishvaee and Razmi (2012)	[81]	√	1				D, C, CA			G3
Pishvaee, Razmi et al. (2012)	[82]		2				D,C, CA, PS			G3
Vahdani et al. (2012)	[83]	√	-				FG, C, CA, CP			G1&G2&G3
Amin and Zhang (2013)	[84]	√	1	√			D			G1
De Rosa et al. (2013)	[85]	√	2				D			G1
Benyoucef et al. (2013)	[86]		1				D, ST			G1
Albareda-Sambola et al. (2013)	[87]		1				D, C, Minimum number of facilities and customers to be opened and serviced, respectively			G1
Kazemzadeh and Hu (2013)	[88]		1				C, P, S			G1
Pimentel et al. (2013)	[89]		1	√			D			G1
Qin et al. (2013)	[90]		1				AF	√		G1
Ramezani et al. (2013a)	[91]	√	2	√			D, C, P			G1
Ramezani et al. (2013b)	[92]	√	2	√			D			G2
Longinidis and Georgiadis (2013)	[93]		2	√			D, P, FP, SS			G1
Bouzembrak et al. (2013)	[94]		2		√	√	D, S, C			G3
Kumar and Tiwari (2013)	[95]		2	√			D			G1
Azad and Davoudpour (2013)	[96]		1				D			G1
Cardoso et al. (2013)	[97]	√	3	√	√	√	D			G1
Baghalian et al. (2013)	[98]		2	√			D, AF, AT	√	√	G1[1]
Vahdani, Tavakkoli-Moghaddam, and Jolai (2013)	[99]	√	1	√			D, C, CA, CP, AF, CS	√		G1&G3
Ahmadi-Javid and Seddighi (2013)	[100]		1				CA, Annual number of vehicles' visits	√		G1
Singh et al. (2013)	[101]		1				D			G1
Vahdani, Tavakkoli-Moghaddam, Jolai, and Baboli (2013)	[102]	√	-	√			D, C, CP, CS			G1&G3
Jouzdani et al. (2013)	[103]		3				D			G3
Li et al. (2013)	[104]		1				AF	√		G1
Azad et al. (2013)	[105]		1				CA, AT	√	√	G1
Tong et al. (2013)	[106]		3				D, S, C, Governmental incentives			G1

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Table A.1 (*continued*)

Articles	Paper's number	RLN	# of location layers	Multiple commodities	Flows		Uncertain parameters in forward network	Disruption in forward network		Decision-making environment group
					Intra-layer flows	Direct flows to customers from upper layers		F	TL	
Klibi and Martel, (2013) [2]	[107]		1				D, CA	√		G1
Nasiri et al. (2014)	[108]		1	√			D			G1
Tian and Yue (2014)	[109]		2	√			D, C, CS			G1
Mirakhorli (2014)	[110]	√	2				D, FG			G3
Meisel and Bierwirth (2014)	[111]		3	√			Arrivals of customers' orders, PT, TT			G1
Jabbarzadeh et al. (2014)	[112]		1				D, C, S, CA			G1
Madadi et al. (2014)	[113]		1				S (the fraction of tainted production at facilities)			G1
Mari et al. (2014)	[114]		2				AF	√		G1
Jeong et al. (2014)	[115]		2				AF	√		G1
Balaman and Selim (2014)	[116]		2	√			FG			G3
Jindal and Sangwan (2014)	[117]	√	-	√			D, C, CA			G3
Marufuzzaman et al. (2014)	[118]		2				AF	√		G1
Vahdani et al. (2014)	[119]	√	-				C			G3
Li and Hu (2014)	[120]		2				PR, CP, S			G1
Cardona-Valdés et al. (2014)	[121]		1				D			G1
Azad et al. (2014)	[122]		1				CA, AT	√	√	G1
Ramezani et al. (2014)	[123]	√	2	√			D, C, CA, P			G3
Liu and Guo (2014)	[124]		1	√			D, Amount of critical populations			G1
Jin et al. (2014)	[125]		2	√			D, C			G1
Rodriguez et al. (2014)	[126]		2				D			G1
Yongheng et al. (2014)	[127]		2				D			G1
Pishvaee et al. (2014)	[128]	√	1				D, C, CA, EP, PS			G3
Soleimani et al. (2014)	[129]	√	>3	√			D, P			G1
Li and Savachkin (2016)	[130]		1				AF	√		G1
Bai and Liu (2016)	[131]		2	√			D, C			G3
Huang and Goetschalckx (2014)	[132]		3	√			D, C, CA, P			G1
Zokaee et al. (2014)	[133]		2				D, C, S			G2
Zeballos et al. (2014)	[134]	√	3	√	√		D, S			G1
Özceylan and Paksoy (2014)	[135]	√	-				D, C, CA			G3
Dayhim et al. (2014)	[136]		2	√			D			G1
Hatefi and Jolai (2014)	[137]	√	2				D, AF	√		G1&G2
Subulan, Taşan et al. (2014)	[138]	√	1	√			FG			G3
Subulan, Baykasoğlu et al. (2014)	[139]	√	1	√			D, C, maximum allowable distance between SC entities			G1&G3
Tong, Gleeson et al. (2014)	[140]		3	√		√	D, S, CP			G3
Tong, You et al. (2014)	[141]		3	√		√	D, S			G2
Mousazadeh et al. (2015)	[142]		3	√	√		D, C, SS			G3
Li et al. (2015)	[143]		1				AT		√	G1
Pasandideh et al. (2015)	[144]		1	√			D, C, PT			G1
Kılıç and Tuzkaya (2015)	[145]		1	√			D, P			G1
Torabi et al. (2016)	[146]	√	2				D, C, CA	√		G2&G3
Khatami et al. (2015)	[147]	√	-	√			D			G1
Hasani et al. (2015)	[148]	√	3	√			D, C			G2
Hatefi et al. (2015a)	[149]	√	2				D, C, CA	√		G1&G3
Hatefi et al. (2015b)	[150]	√	2				D, C, CA	√		G1&G3
Fallah et al. (2015)	[151]	√	2				D, C, CA			G3
Akbari and Karimi (2015)	[152]		1	√			CR			G2
Sadghiani et al. (2015)	[153]		1	√			D, C, CA, TT, S	√		G1&G3
Dubey et al. (2015)	[154]	√	1	√			D			G2
Govindan et al. (2015)	[155]		3			√	D			G1
Keyvanshokooh et al. (2016)	[156]	√	2				D, C			G1&G2
Hasani and Khosrojerdi (2016)	[157]		3	√			D, C, CA, S	√		G1&G2
Babazadeh et al. (2017)	[158]		>3	√			D, C, S, EP			G3
Govindan and Fattahi (2017)	[159]		2	√			D			G1 - G2

[**1**] In this study, both scenario based and continuous stochastic parameters are considered.
[**2**] This study proposed a generic mathematical model; however, the Table's information is based on the location-transportation case studies that were solved by the study.

Table A.2
Features and structure of reverse logistics networks and reverse network in closed-loop supply chains in the related literature.

Articles	Paper's number	FLN	# of location layers	Multiple commodities	Uncertain parameters in reverse network	Disruption in reverse network		Decision-making environment group
						Facilities	Transportation links	
Realff et al. (2004)	[160]		1	√	R, SP			G2
Listeş and Dekker (2005)	[161]		2		R, DS			G1
Listeş (2007)	[23]	√	1		R			G1
Lee et al. (2007)	[25]	√	1	√	R, PA			G1
Lieckens and Vandaele (2007)	[162]		1		Inter-arrival time of returns, PT			G1
Salema et al. (2007)	[26]	√	2	√	R			G1
Chouinard et al. (2008)	[28]	√	2	√	R, DS, DR, PA			G1
Lee and Dong (2009)	[38]	√	1	√	R			G1
Pishvaee et al. (2009)	[40]	√	3		R, C, DR			G1
Lee et al. (2010)	[47]	√	2	√	R, C, CA			G1
Pishvaee and Torabi (2010)	[53]	√	3		R, C, CA, DS, DR			G3
Qin and Ji (2010)	[163]		1		R, C			G3
Kara and Onut (2010a)	[164]		1		R, DS			G1
Kara and Onut (2010b)	[165]		2		R, DS			G1
Pishvaee et al. (2011)	[166]	√	3		C, CA, DS, R			G2
Zarandi et al. (2011)	[65]	√	1	√	FG			G3
Abdallah et al. (2012)	[70]	√	1		R			G1
Hasani et al. (2012)	[79]	√	1	√	-			G2
Pishvaee and Razmi (2012)	[81]	√	1		R, C, CA			G3
Vahdani et al. (2012)	[83]	√	1	√	FG, C, AF	√		G1&G2&G3
Amin and Zhang (2013)	[84]	√	2	√	R			G1
De Rosa et al. (2013)	[85]	√	2		R			G1
Ramezani et al. (2013a)	[91]	√	2	√	R, C			G1
Ramezani et al. (2013b)	[92]	√	2	√	R			G2
Cardoso et al. (2013)	[97]	√	3	√	-			G1
Vahdani, Tavakkoli-Moghaddam, and Jolai (2013)	[99]	√	2	√	R, C, CA, PA, AF, CS	√		G1&G3
Vahdani, Tavakkoli-Moghaddam, Jolai, and Baboli (2013)	[102]	√	2	√	R, C, CA, PA, AF, CS	√		G1&G3
Mirakhorli (2014)	[110]	√	2		R, FG			G3
Jindal and Sangwan (2014)	[117]	√	3	√	R, C, CA, PA, PP			G3
Vahdani et al. (2014)	[119]	√	3		R, C, CA, DS, AF	√		G3
Ramezani et al. (2014)	[123]	√	2	√	R, C, CA, DR, PA			G3
Pishvaee et al. (2014)	[128]	√	1		R, C, CA, EP, PS			G3
Soleimani et al. (2014)	[129]	√	>3	√	R, DS, SP, BP			G1
Zeballos et al. (2014)	[134]	√	>3	√	R			G1
Özceylan and Paksoy (2014)	[135]	√	1		R, C, CA			G3
Hatefi and Jolai (2014)	[137]	√	3		R, DR, AF	√		G1&G2
Subulan, Taşan et al. (2014)	[138]	√	2	√	FG			G3
Subulan, Baykasoğlu et al. (2014)	[139]	√	2	√	R, C, DR, BP, PA, SP, maximum number of opened facilities, maximum allowable distance for collecting return products			G1&G3
Sadjadi et al. (2014)	[167]		1	√	R			G3
Kaya et al. (2014)	[168]		2	√	R, DS			G1
Soleimani and Govindan (2014)	[169]		3	√	DS, BP, SP			G1
Torabi et al. (2016)	[146]	√	3		R, C, CA	√		G2&G3
Khatami et al. (2015)	[147]	√	2	√	R			G1
Hasani et al. (2015)	[148]	√	1	√	DS			G2
Hatefi et al. (2015a)	[149]	√	3		R, C, CA	√		G1&G3
Hatefi et al. (2015b)	[150]	√	3		R, C, CA	√		G1&G3
Fallah et al. (2015)	[151]	√	3		R, C, CA			G3
Dubey et al. (2015)	[154]	√	2	√	R			G2
Ayvaz et al. (2015)	[170]		3	√	R, C, PA			G1
Keyvanshokooh et al. (2016)	[156]	√	2		R, C			G1&G2

Appendix B. Mathematical definition of well-known risk measures in the related literature

Table B.1
Definition of well-known risk measures for loss/cost distributions.

Risk measure	Definition
Variance	$\rho(Y) = \mathrm{E}[(Y - \mathrm{E}(Y))^2]$
Absolute deviation	$\rho(Y) = \mathrm{E}[\lvert Y - \mathrm{E}(Y)\rvert]$
Standard deviation	$\rho(Y) = \sqrt{\mathrm{E}[(Y - \mathrm{E}(Y))^2]}$
Conditional value at risk	$\rho(Y) = CVaR_\alpha(Y) = \inf_{z\in\mathbb{R}}\{z + \frac{1}{1-\alpha}\mathrm{E}[(Y-z)_+]\}$
pth central semideviation	$\rho(Y) = (\mathrm{E}[(Y - \mathrm{E}(Y))_+^p])^{1/p}$
pth semideviation from target T	$\rho(Y) = (\mathrm{E}[(Y - T)_+^p])^{1/p}$

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