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Costs of resilience and disruptions in supply chain network design models: A review and future research directions

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ABSTRACT

Supply chain network design (SCND) is a key strategic decision in supply chain management (SCM). One particular area of SCND is concerned with disruption risk modelling. This paper presents a systematic literature review of quantitative models of SCND under disruption risks in industrial SCM and logistics. More specifically, our analysis is focused on different costs induced by the planning of proactive investments in robustness and through parametrical/structural adaptation at the recovery stage. This review can be of value for researchers and decision-makers alike for several reasons. First, we categorise the existing knowledge based on decision-making problems, which can be instructive for a convenient association of a particular SCND problem to a modelling domain according to network-wise, supply-side and demand-side perspectives. Second, our analysis focuses on the costs specifically induced by disruption risks and resilience investments. Third, we offer a dedicated section related to disruption probability formulation methods and their impact on resilience costs. Fourth, the integration of different SCM dimensions (i.e., social impact, environmental impact, responsiveness, and risk-aversion) and the associated multi-objective modelling settings are discussed along with disruption risks in SCND models. Finally, we summarize our findings as insights from a managerial perspective. Drawbacks and missing aspects in the related literature are highlighted, and we lay out several research directions and open questions for future research.

1. Introduction

The design of not only an efficient but a resilient supply chain (SC) capable of operations and demand fulfilment continuity despite disruptions is imperative and has been highlighted in literature and practice alike for the last two decades (Hosseini et al., 2019; Ivanov and Dolgui 2020). However, the COVID-19 pandemic has unveiled the lack of resilience in many SCs, as complex networks failed from disruptions at local nodes and the resulting missing connectivity (Trump and Linkov, 2020). One difficulty in the application of research results on SC resilience to practice is the investment costs which come with building resilience capabilities. Proactive optimisation models for the analysis of SC reactions to disruptions and creating resilient SC network designs (SCND) can contribute to survival of SCs and markets through super disruptions like the COVID-19 pandemic (Ivanov 2021b; Ruel et al., 2021).

In today's global and increasingly turbulent market environments, SCs are exposed to numerous unpredictable events that disrupt their operational activities and worsen the performance entailing lower revenues, delivery delays, loss of market share and reputation, stock return decrease, and so on (Hendricks and Singhal, 2005; Yildiz et al., 2016; Ivanov et al., 2019b). As introduced by Tang (2006), disruption risk is related to a particular type of event that may occur due to natural disaster (earthquakes, floods) or through intentional/unintentional human actions (war, terrorist attack, epidemics/pandemics outbreak, strike). This type of risk is typically marked by a low likelihood of occurrence and a high magnitude of consequence (Kinra et al., 2020; Ivanov 2021c).

SCs rarely perform in a stable steady-state (Haywood and Peck, 2004), and organisations need to carefully plan against uncertain events to overcome the relevant risks (Sabouhi et al., 2018). For example, after the Japanese tsunami and earthquake in 2011, Toyota's parts suppliers were unable to deliver parts at the expected volume and rate. This forced Toyota to halt production for several days (Fortune, 2016). A sudden disruptive event can immediately propagate its effects downstream in the SC, causing a so-called "ripple effect" (Ivanov et al., 2014; Li et al.,

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2021). In March 2012, Ford's key supplier Evonik faced a devastating explosion in its plant in Marl, Germany, which also caused major interruptions in the downstream production facilities of Ford and other major automakers (Simchi-Levi et al., 2014). More recently, the coronavirus outbreak (COVID-19) suspended operations from/to China in many global companies on a larger scale (CNBC, 2020). Further, 94% of the Fortune 1000 companies have been affected by pandemic-driven SC disruptions (Fortune, 2020).

If a facility is disrupted, customers originally designated to that facility have to be reallocated to an active alternative, bearing higher transportation/management costs, or even facing major consequences such as reduction of customer satisfaction, distrust and pessimism toward the company, price inflation, and higher lead time. Without proper planning, the recovery of a disrupted SC would cost major damages (Snyder and Daskin, 2005; Paul and Rahman, 2018; Xie et al., 2019) Therefore, an SC network requires to be designed and planned in a way that can resiliently resist against disruptions (He et al., 2019; Lücker et al., 2019; Blackhurst et al., 2021; Gupta et al., 2020).

Disruption management is drawing significant attention from both academia and industry (Craighead et al., 2007; Tang and Nurmaya Musa, 2011; Snyder et al., 2016; Li et al., 2020; Xu et al., 2020). Within the context of SCM, resilience is playing a significant role in managing and mitigating disruptions. Resilience is commonly understood as the capability of a system to come back to its original state or even a more desirable condition after being disrupted (Shekarian and Parast, 2020). Proactive and reactive mitigation strategies are two basic approaches to hedge against disruption and to increase SC resilience (Tomlin, 2006; Carbonara and Pellegrino, 2017; Elluru et al., 2017; Ivanov, 2018). During the SCND process, the proactive approach builds robustness and accounts for possible perturbations without taking into consideration recovery actions (Klibi et al., 2010; Lin and Wang, 2011; Paul et al., 2019). One of the most common methods is to plan proactive redundancies (e.g. buffer capacities, backup suppliers, pre-positioned inventory, or general facility fortification) at the pre-disruption stage (Ivanov and Dolgui, 2019). On the other hand, the reactive approach aims to adjust SC processes and structures when disruptive events occur (Knemeyer et al., 2009; Paul et al., 2014; Aldrighetti et al., 2019b). This can be through parametrical or structural adaptions, according to the severity of disruption (Dolgui et al., 2020; Li et al., 2021).

This paper presents a systematic literature review of the quantitative models of SCND under disruption risk in the area of industrial SCM and logistics. More specifically, our analysis is focused on different costs induced by the planning of proactive investments in robustness and through parametrical/structural adaption due to disruption risk. The extensive analysis of resilience and disruption costs is the key feature that differentiates our study from and provides a value-added to other literature reviews published on this topic. Snyder et al. (2016) presented a narrative literature review in the field of operations research/management science that categorises SC disruption papers in terms of mitigation strategies: a section was dedicated to facility locations models for mitigating disruption effects. Ivanov et al. (2017a) examined SCND problems that include disruption and recovery consideration in both quantitative and qualitative studies. Rajagopal et al. (2017) presented a systematic literature review of decision-making models for analysing the correlation between SC risk mitigation strategies and modelling techniques. Finally, Hosseini et al. (2019a) analysed both qualitative and quantitative resilience-enhancing features of SCs with a particular focus on the mathematical modelling of SC resilience problems. To the best of the authors' knowledge, however, none of these previous studies focuses on the costs induced by disruption risk and robustness investments (i.e. resilience costs) in SCND optimisation model in the context of industrial SCM and logistics. Whilst there is a great body of literature on quantitative methods for building resilient SCs, the cost terms included in mathematical formulations are highly influenced by the application the model has been adapted for (Govindan et al., 2017). Hence, there is still a great variability among the disruption effects included and quantified in the literature. This survey could, therefore, be particularly helpful for decision-makers and researchers who seek to develop a model with resilience cost formulation for SCND under disruption risk. The strong focus on industrial applications along with an in-depth analysis of mathematical formulations of SCND under disruptions are the distinctive features of our study which permit us to consider our survey as an extension and complement of the existing literature reviews while avoiding overlaps. More specifically, the primary focus and contribution of this study is based on the following four research questions:

RQ1: What SCND problems are most commonly addressed when considering disruption risks?
RQ2: Which are the investments and operational costs terms introduced into mathematical formulations with disruption risks and resilience (i.e., what resilience costs are considered)?
RQ3: Is there any correlation between the uncertainty modelling method and the resilience costs?
RQ4: Which SCM dimensions (social and environmental impact, responsiveness, and risk-aversion) are included into SCND in addition to merely economical and resilience objectives entailing multi-objective formulations?

In order to answer our RQs, papers are first categorised based on the decision-making (DM) problem, which results in some major insights in terms of modelling approaches and network structures (RQ1). Successively, the analysis focuses on the different cost factors specifically induced by the planning of proactive investments in robustness and by the parametrical/structural adaptation at the recovery stage (RQ2). Thirdly, disruption probability formulation methods are discussed in terms of their relation with resilience cost terms (RQ3). Further, as specified by RQ4, the analysis focuses on different SCM dimensions such as such as social impact, environmental impact, responsiveness, and risk-aversion, which are analysed in terms of modelling variables and the changes they cause in objective functions. Lastly, the drawbacks and gaps in the related literature are highlighted, and a list of potential issues is proposed for future research.

The remainder of this paper is organised as follows: Section 2 presents the research procedure following the structured literature review protocol. DM problems are introduced in Section 3 along with an analysis based on the first research question. Successively, Section 4 focuses on the costs specifically introduced by disruption risk and robustness investments. Section 5 investigates different techniques in formulating disruption probability and the possible correlation with cost factors. Successively, social, and environmental impact, responsiveness and risk aversion aspects are analysed in Section 6. Results are discussed in Section 7 along with summarizing managerial implications. Finally, concluding remarks are presented in Section 8 followed by a discussion on future research directions.

2. Scope and review methodology

In this paper, the literature review process is based on the guidelines outlined by Tranfield et al. (2003). As shown in Fig. 1, this systematic literature review was carried out using an iterative process of defining appropriate keywords, filtering the results, analysing the literature, and finalising results in line with other extant literature reviews on similar topics (Hosseini et al., 2020; Queiroz et al., 2020).

It can be observed in Table 1 that we identified two groups of keywords: each row of the table is connected with a Boolean operator “OR”, and the two groups are connected with an “AND”. The first group involves the decision-making (DM) problem we would like to analyse: SCND problems. Some equivalent formulations were included, such as distribution network, logistics network, and resilient network. The second group of keywords is related to the DM environment we would like to investigate. In addition to “disruption” and “resilience”, some

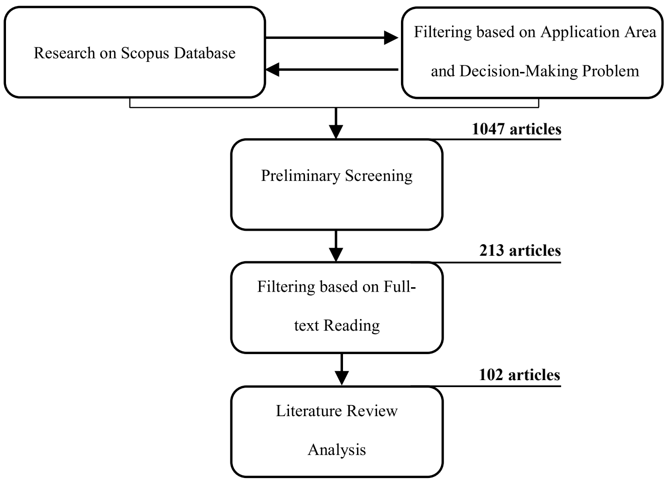

Fig. 1. Flowchart of the literature-review research process.

Table 1
Groups of keywords used for the research.

Group 1	Group 2
"supply chain" AND "design"	disrupt*
"supply network" AND "design"	resilience
"supply chain network" AND "design"	resilient
"distribution network" AND "design"	vulnerability
"logistics network" AND "design"	hazard
"facility location"	catastrophe
"resilient network" AND "design"	

synonymous and correlated terms were included such as "vulnerability" and "hazards". The search was performed on the May 24, 2020. The query was set to "Title, abstract and keyword" in the Scopus database, and the results were limited solely to papers written in English and published in journals until 2019 as publication year.

The search results provided 1047 hits, which were analysed subsequently. The documents identified in the search were analysed and evaluated by reading the abstracts, and then the full text was taken into consideration. Irrelevant papers were discarded based on academic judgment and through an information clustering technique implemented using VOSviewer. In fact, as Fig. 2 shows in the bottom left corner, the high flexibility of keywords led to search results that included a significant amount of work more related to water distribution networks and generally to infrastructure systems design (e.g., electrical systems, telecommunication network). During the evaluation of the search results, the following inclusion and exclusion criteria were applied to the selection:

- Papers should contain a mathematical model of an SCND and the formulation must include strategic (e.g. number and location of facilities) and operational decisions (e.g. allocation of material flows, inventory policies, manufacturing methods) with the inclusion of disruption risks in terms of a facility and/or transportation link failure. More specifically, articles must comprise both decisions (i.e., strategic and operational) otherwise they are excluded from the selection.
- Only optimisation models that include a profit maximization or a cost minimisation objective function were included in the scope of the selection.
- The DM problems were narrowed to applications focused on industrial/commercial SC. Water distribution networks,

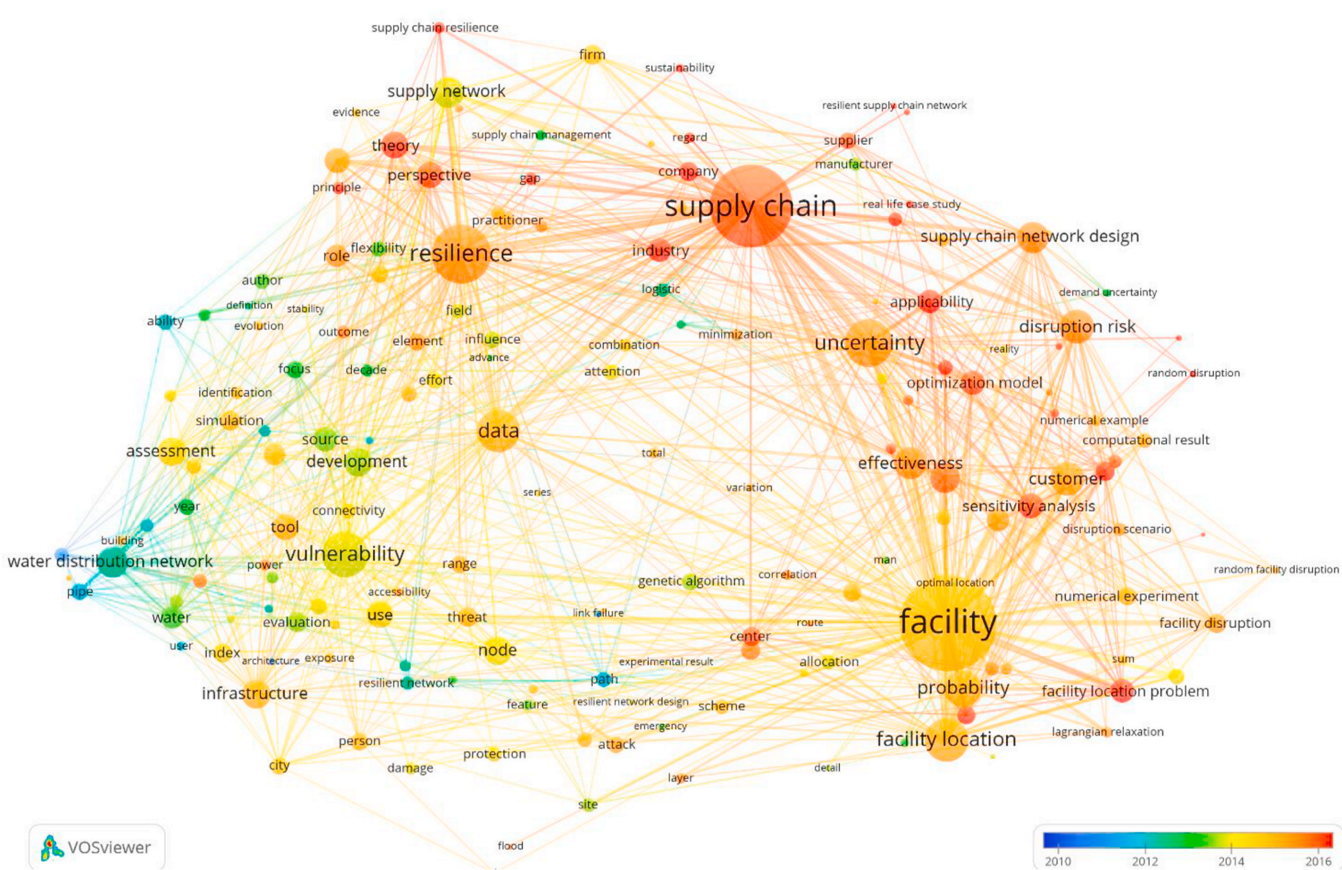

Fig. 2. Keyword Map made with VOSviewer (colours change according to the publication year). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

telecommunication networks and in general survivable communication network design models were therefore omitted due to their focus to always ensure the connectivity of the network in case of failure, which is generally not considered a major objective in SC (Peng et al., 2011). Humanitarian SCs, hazardous material problems, and covering models were excluded since their attention is usually on facility coverage, time management, maximum availability or maximising the lowest service standard (ReVelle et al., 2008; Sheu, 2014; Dubey et al., 2019; Fosso Wamba, 2020). Hub-and-spoke models were considered sector-specific to passengers and air distribution networks and therefore omitted. R-interdiction problem and competitive facility location models were also removed since their objectives are price-related or customer-related, including qualitative methods for representing purchase behaviours, thus losing the focus on logistics issues. Finally, supplier selection problems were furtherly excluded: a supplier is not directly controlled by a company and it has its own strategic and planning decision-makers (Ho et al., 2010; Wetzstein et al., 2016).

To further enrich the search results, a backward and forward snowballing strategy was also applied, based on references and authors of publications that were returned from the search. 102 journal papers were finally identified for the review. We will refer to them as reference papers from now on. Fig. 3 shows the distribution of these reference papers, based on their year of publication. More than 60% of these works were published in the last five years where risk and disruption management have become increasingly important for academia and industry. Fig. 2 presents a map based on the text data, created using VOSviewer with the original search results. The colours delineate the publication years. As shown in Fig. 2, many efforts were focused on disruption and resilience analysis of infrastructure systems (e.g., water distribution networks, telecommunications networks, etc.), especially in the past. However, in recent years, the focus shifted to SC and facility location problems. As a result, resilience and specifically SC resilience is now confirmed as a trending topic. Table 2 shows the number of shared references with a selection of other reviews in the field: the maximum number of shared references is registered less than 20% in Govindan et al. (2017). However, while there are few overlapping areas between other published reviews and ours, to our knowledge, no other review papers have examined the aspects taken into account in this research.

Fig. 4 proposes a classification framework we derived based on the contents and characteristics of the 102 articles selected from the literature search. Frameworks have been widely employed in literature reviews in order to help the reader to understand the main research topic area and to give an overview of the categorization process and the analyses performed (Shekarian and Parast, 2020). The upper part of Fig. 4 aims at delineating the research area of this survey: selected articles come from the intersection between SCND models, disruption risk literature, and papers applied to industrial/commercial SC.

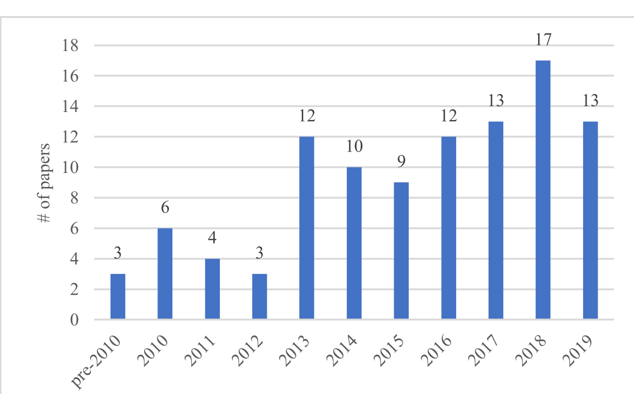

Fig. 3. Annual publications statistics.

Table 2
Scope and overlap of relevant review papers.

Article	Scope and special features	Number of shared papers
Snyder et al. (2016)	Mitigation strategies for SC disruption in the field of Operations Research/Management Science	14 (13.7%)
Ivanov et al. (2017a)	SCND models with disruption and recovery consideration (both quantitative and qualitative models)	12 (11.8%)
Govindan et al. (2017)	SCND under uncertainties with a focus on closed-loop SCs and reverse logistics	20 (19.6%)
Rajagopal et al. (2017)	DM models for SC risk mitigation	13 (12.7%)
Hosseini et al. (2019a)	Quantitative models of SC resilience	9 (8.8%)

Secondly, in terms of classification and analysis, papers have been categorised according to two main categories: problem characteristics and resilience costs. The first group is further detailed into the type of DM problem and the structure of the supply network. In the second group, cost terms have been distinguished between investment costs (i.e., proactive resilience investment) and operational costs (i.e. Expected Disruption Cost) and categorised based on the mitigation strategy employed by the modeller. In the process of analysing and developing strategies and insights about SC resilience, researchers and practitioners generally pass through the identification and management of SC risk, which is furtherly translated into resilience strategies (Christopher and Peck, 2004). When considering SC risk, many authors proposed different categorization of it based on several perspectives, such as internal or external, financial or operational, etc. (Ho et al., 2015; Yiyi and Mark, 2018). The uncertainty circle presented by Mason-Jones and Towill (1998) and successively extended by Christopher and Peck (2004) had four main causes of risk: manufacturing/process, control, supply-side, and demand-side. In our paper, considering our focus on disruption risk, we follow a similar categorization and analyse the resilience based on three main areas: network, supply-side, demand-side perspectives. The network perspective includes the combination of manufacturing/process and control risks and it relates to the focal company characteristics and its internally owned and managed assets in terms of network topology, and whole SCND strategy. Supply-side and demand-side are associated with specific characteristics and consideration of the flow of products and/or information upstream and downstream the SC, respectively. These main categorisations are considered a central angle around which we organise this paper.

3. Problem characteristics

In the process of categorising reference articles, we decided to report the generic DM problems on which the mathematical formulation is based instead of specific problems, to reduce bias in the names of analysed models. In fact, the different ways of introducing disruption effects and resilience investment terms led the authors to give different names for the same formulations (e.g., median problem with unreliable facilities and reliable p-median problem, closed-loop SC design and forward-reverse SC design). Each reference is therefore brought back to the basic DM problem. In the 102 reference papers, 106 models are identified (four papers present two different formulations): we refer to these as reference models. Section 9 in the Appendix lists the reference models and assigns them a number, which is utilised in the analyses of the following sections.

Fig. 5 presents the frequency of reference models according to the DM problems. Two major DM problems were identified for developing SCND with disruption consideration: fixed-charge facility location problem (FLPs) and logistics network design problems (LNDPs) were recognised in 36.8% and 37.7% of models, respectively. FLP is an SCND

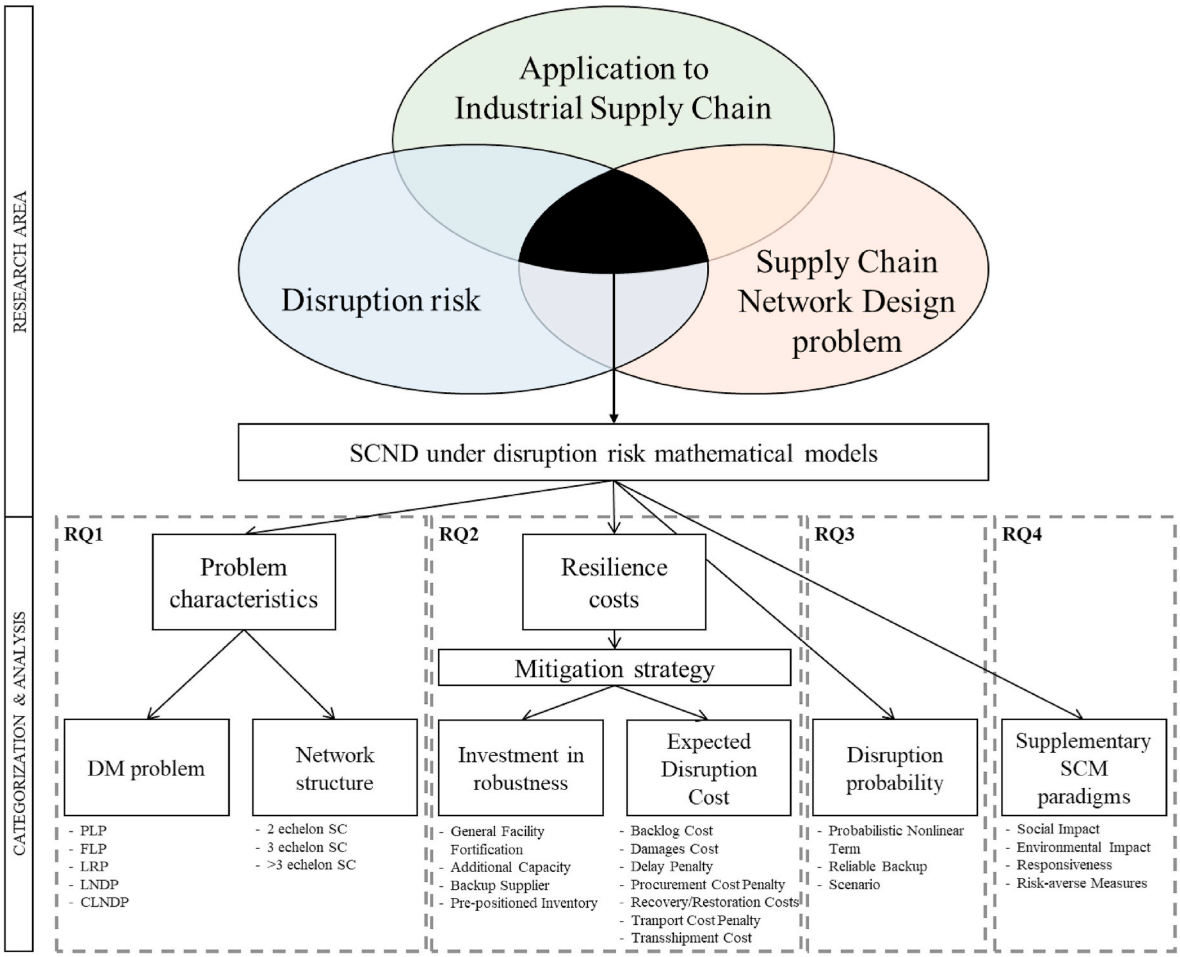

Fig. 4. Classification framework based on the literature search.

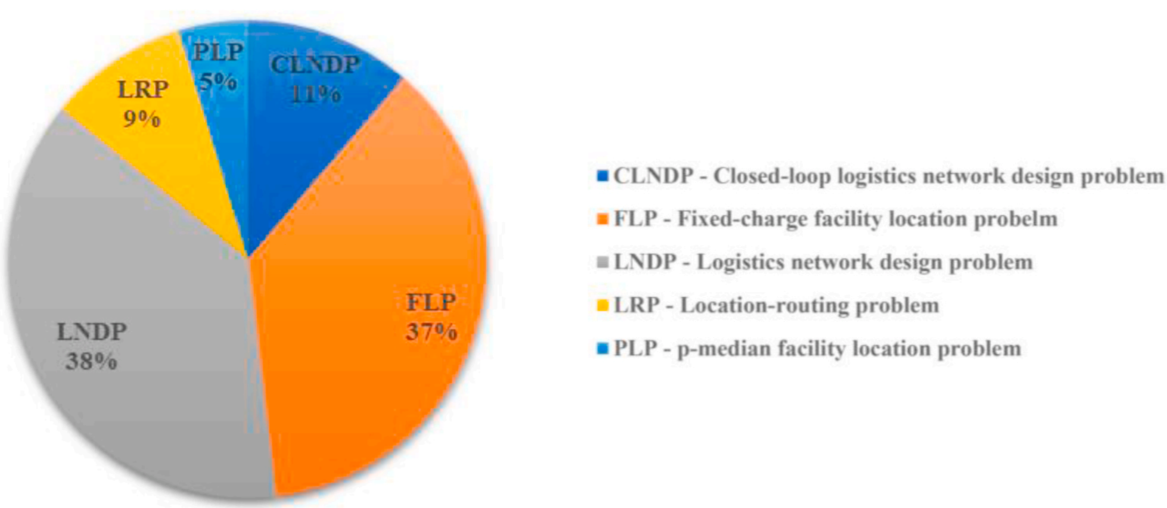

Fig. 5. Frequency of reference papers based on DM problem.

problem distinguished by a finite set of demand nodes and potential locations for the facilities. Two types of decisions must be made: location decisions consist of determining where to establish the facilities; allocation decisions plan the flows that are going to fulfil the demand from established facilities. It is normally assumed that location decisions are strategic, whereas allocation decisions are operational (Fernández and Landete, 2015). On the other hand, LNDP usually combines decisions at three different levels: strategic decisions (e.g., facilities' location and capacity, supplier selection), tactical decisions (e.g., inventory, procurement, and transportation management), and operational decisions (e.g., vehicle routing) (Alumur et al., 2015).

Finally, closed-loop logistics network design problem (CLNDP), location-routing problem (LRP) and p-median facility location problem (PMP) were modelled scarcely. CLNDP registered only 11.3% of works that were all published within the last five years, and it consists of a LNDP where strategic decisions also incorporate the reverse flow of an SC, i.e. all operations involved in a product's return flow from the point of use to the point of disposal or recovery (Alumur et al., 2015). Furthermore, LRP extends the concept of a FLP by including routing decisions and it was modelled by 9% of works. Lastly, PMP was the least commonly addressed DM problem and it consists of locating *p* facilities to minimise the expected sum of the weighted travel distances from demand zones (Hakimi, 1964).

Facilities of the same type usually compose an echelon or tier. Besides, we distinguish between two types of facilities: *selectable facilities* are the set of locations on which decisions are going to be taken; *non-selectable facilities* are already established plants that are not subject to location decisions. A fundamental issue when dealing with SCND problems is the number of echelons included in the network, and in which facilities are selectable or non-selectable (Govindan et al., 2017). The usual SC network structure is composed of suppliers, manufacturing plants, distribution centres, warehouses, and customers. However, modellers usually narrow the problem to the most critical portions of the network, intending to obtain significant results with a model that is easier to solve. In fact, facility location but, more generally, all SCND problems, are known as classic NP-hard problems (Magnanti and Wong, 1981) which require high computational costs. Only small-scale problems are therefore solved directly with commercial solvers like CPLEX or Gurobi. Instead, large-scale datasets are usually combined with heuristics or meta-heuristics in order to obtain results in an acceptable computational time (Xie and Ouyang, 2019).

In Table 3, reference models are categorised based on the forward network structure and the DM problem introduced above. The number of SC echelons in which facilities are selectable is called decision layers. Two and three echelons' SCs were the most modelled SC network structures, with 49% and 33.9% of models, respectively. The vast majority of models consider selectable facilities at only one tier, especially for PLP and FLP. Two decision layers began to be analysed with LNDP and CLNDP since they usually involve a higher number of SC echelons. Finally, only 5.6% of models considered more than two decision layers.

4. Resilience cost

In this section, the analysis focuses on the different cost factors specifically introduced by the planning of proactive investments in robustness and by the parametrical/structural adaption due to disruption risk (i.e., resilience costs). Thus, the focus is posed on the second RQ.

Companies leverage a combination of proactive and reactive strategies in order to hedge against disruptions and increase SC resilience (Elluru et al., 2017; Ivanov, 2018; Parast and Shekarian, 2019). Proactive strategies are considered in an SCND when building robustness to help companies to withstand disruptions.

Considering the network perspective, at the level of the focal facilities, an SC could be reinforced through a G*eneral Facility Fortification* that consists of an investment in robustness that could make facilities partially or fully infallible. This could be seen as specific disruption-resistant features (e.g., water sprinkler against fire, earthquake-resistant racking) or, as recent trends have shown, more flexible systems that can allow switching or adapting the business and operations based on the needs and dynamics that changed during the disruption in order to reduce the disruption magnitude. Furthermore, the robustness of the network can be improved by planning for *Additional Capacity* as an increase in the production, throughput or inventory level at the focal facilities (i.e., network perspective), at distribution centres/retailers (i.e. demand-side), or an expansion in the contract quantities with suppliers (i.e. supply-side).

Focusing on the supply-side, instead of asking for more materials from regular/primary suppliers, the SC could conclude an agreement with a *Backup Supplier* regulated by a contract for emergency supplies. Backup suppliers are considered to be located in safe areas, and thus they are immune to disruptions.

Finally, with *Pre-positioned Inventory*, an SC can proactively plan for additional inventory both on the supply- and demand-side (i.e., upstream and downstream to the network) to be more prepared for disruptions and to deliver parts in case of possible shortages in normal inventories.

On the other hand, reactive resilience strategies consist of post-disruption actions to stabilise and recover the system (Ivanov, 2019; Dolgui et al., 2020; Ivanov and Rozhkov, 2020). Depending on the severity of disruptions, companies could enact a parametrical adaption by fine-tuning critical parameters such as inventory or production rate. Moreover, when facing major interruptions, structure adaption might be necessary through considering a backup supply or contingency transportation plans. Among the analysed models, we identified four major post-disruption mitigation strategies:

- *Backup Supply (BS):* The omissions caused by disruptions are covered by procuring products from external emergency sources or asking for more products than agreed from regular contracted suppliers.
- *Operational Reassignment (OPR):* This strategy relies on changes in structural and operational parameters. Depending on the disruption, it reassigns transportation flows, procurement quantities, production and inventory to other facilities and transportation links based on resource availability.
- *Reliable Backup Assignment (RBA):* When the primary assigned facility is disrupted, the demand is assigned to a secondary reliable facility. It is worth emphasising that the consideration of a proactive investment in robustness is necessary for this mitigation strategy.

Table 3
Classification of decision-making problem and number of echelons of the forward logistics network.

		PLP	FLP	LRP	LNDP	CLNDP
2 echelon SC	*1 decision layer*	[1b, 3, 22, 23a, 29]	[1a, 2, 4a, 4b, 6, 7, 10, 11, 12a. 12b, 17, 18, 23b, 25, 28, 30, 34, 35, 36, 40, 44, 46, 50, 51, 55, 58, 59, 60, 66, 72, 77, 83, 84, 89, 90, 91, 100]	[27, 45, 47, 61, 71, 101]	[9, 67, 88]	[39]
3 echelon SC	*1 decision layer*		[24]	[16, 26, 53]	[8, 13, 15, 20, 21, 31, 32, 68, 69, 70, 73, 75, 82, 85, 102]	[64, 81, 95]
	2 decision layers				[14, 18, 54, 62, 76, 86, 93, 96, 97, 98]	[33, 41, 42, 56]
>3 echelon SC	*1 decision layer*		[43]		[5, 38, 92, 94]	[52]
	2 decision layers			[37]	[78, 87]	[63, 65, 79]
	>2 decision layers				[48, 49, 57, 74, 80, 99]	
Table's Summary:	2 echelons-1 decision layer: **49%**, 3 echelons-1 decision layer: **20.7%**, 3 echelons-2 decision layers: **13.2%**, >3 echelons-1 decision layer: **5.6%,** >3 echelon-2 decision layers: **5.6%,** >3 echelon->2 decision layers: **5.6%,**					

- *Lateral Transshipment (TRS):* This is a strategy of inventory sharing among members of the same group. Specifically, it consists of moving goods horizontally within the same echelon of an inventory system, intending to rebalance the system inventories to improve customer service with a reduced increase in costs (Zhao et al., 2016; Feng et al., 2018). Notably, this mitigation option considers a disrupted facility as it is still able to receive goods. Available facilities thus cover the missing items in production by delivering products to disrupted facilities through lateral transshipment.

Disruptions can affect different parts of an SC. Reactive actions plan different adjustments in operational parameters to maintain the desired service level. Since all models at least involve cost-minimisation or profit-maximization, the effects of disruptions and reactive plans to the SC are analysed in terms of the operational costs that these interruptions introduce into the SCND model: the expected disruption cost (EDC).

Considering the network perspective, three main EDCs have been identified:

- *Damage Costs:* Cost associated with the damage inflicted by the disruption event. They may be damage to the production machines, inventories, or to the buildings' structure.
- *Recovery/Restoration Costs:* Cost for restoring the damage inflicted by disruptions
- *Transshipment Cost:* The transportation cost of lateral transshipment between facilities at the same echelon.

Regarding the supply-side specific EDCs, penalties could be charged due to changes in the predefined supply quantities or to the price of the sourced feedstocks, resulting in a *Procurement Cost Penalty*.

Focusing on the demand-side specific EDCs, we identified three main cost factors as direct consequences of disruption occurrence:

- *Backlog Cost:* Disruptions lead companies to lose a portion of demand and, therefore, the EDC has assumed equals to the opportunity cost of not selling products to customers or to the penalty cost for not satisfying the demand.
- *Delay penalty:* Penalty cost for delivering products late or early. Some models consider products must be shipped within a specified service time window; otherwise, customers apply penalties for late/early deliveries.
- *Transport Cost Penalty:* Penalty applied due to not using optimal routes in transportation. Sometimes, other penalties such as a higher procurement cost or backlog cost are modelled as an increase in transportation cost.

Models that do not provide any specific term associated with the effects caused by disruption on the SC network adopt a general *Operational Cost Variation* that consists of a variation in several cost factors without distinction between normal and disrupted situation. Due to the focus of this section, these models are considered separately in the following analyses.

Table 4 categorises reference models based on the proactive resilience investment and the expected disruption cost terms through the three analyses lenses introduced in section 3, i.e., network-perspective, supply-side and demand-side (further details of all 106 models based on the cost factors introduced above are available in Table A2 in the Appendix). More than 60% of works did not allow to proactively invest in redundancies or general facilities fortification. Besides, almost 56% of works modelled disruption effects with a simple operational cost variation and without considering any specific term. Finally, Fig. 6 depicts the frequency associated with each post-disruption mitigation strategy. The vast majority of works adopted an operational reassignment strategy; however, this result is affected by the inclusion of only generic operational cost variations in most of the models. In fact, as we can see from the second pie chart on the right, 51% of models adopted an OPR

Table 4
Categorization of reference models based on proactive resilience investments and expected disruption cost.

Expected Disruption Cost		No Proactive Resilience Investment	Proactive Resilience Investment						
			Network-perspective			Supply-side		Demand-side	
			Additional Capacity	General Facility Fortification		Additional Capacity	Backup Supplier	Additional Capacity	Pre-positioned Inventory
				Full	Partial				
Operational Costs Variation		[2, 3, 4a, 4b, 6, 8, 9, 10, 11, 12a, 12b, 15, 17, 18, 22, 24, 31, 33, 34, 36, 38, 39, 40, 42, 43, 44, 45, 46, 47, 53, 56, 57, 58, 59, 66, 68, 69, 71, 72, 73, 75, 84, 92, 94, 100, 101, 102]	[14, 32, 48, 63, 64, 65, 70, 74, 76, 79, 80]	[64]	[49, 74]	[63, 65, 76, 80]		[48, 79, 80]	
Network-perspective	Damage Costs	[88]	[99]			[99]			[99]
	Recovery/ Restoration Costs	[78]	[28, 67, 78, 99]		[62, 96]	[67, 99]	[67]		[99]
	Transshipment Cost	[21, 77, 81, 91, 95]		[41, 83]	[18, 30, 50, 62]				
Supply-side	Procurement Cost Penalty	[5, 77, 88, 91, 93, 97]	[16, 67, 82, 99]		[96]	[67, 99]	[16, 67, 82, 98]		[67, 99]
Demand-side	Backlog Cost	[13, 29, 37, 52, 54, 85]	[61, 99]			[99]			[67, 99]
	Delay Penalty		[61]						[67, 99]
	Transportation Penalty	[29, 77, 78, 86]	[61, 67, 78, 86, 99]	[1a, 1b, 7, 20, 25, 26, 27, 35, 55, 60, 83, 87, 89, 90]	[18, 23a, 23b, 30, 51, 62]	[67, 99]	[67]		

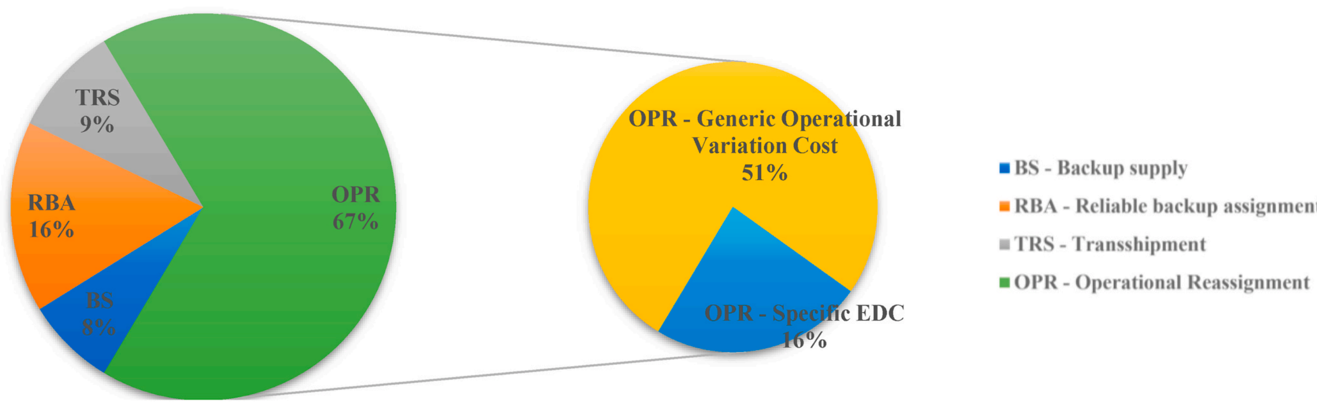

Fig. 6. Frequency of adopted mitigation strategies with a focus on OPR expected disruption cost modelling.

strategy combined with a generic operational cost variation.

4.1. Proactive resilience investment

This analysis is focused on the different cost factors specifically introduced by the planning of proactive resilience investments. This subsection is thus based on a selection of 40 models that presented at least one proactive action to increase SC resilience and hedge against disruption risk. Table 5 categorises the different proactive strategies based on the DM problem and the post-disruption mitigation strategy.

Providing additional capacity to increase robustness and strengthen the SC was the most adopted strategy. From a network-perspective, 19 works included the possibility to invest in additional capacity at focal facilities; furthermore, supply-side and demand-side effects of redundancies were considered scarcely by 6 and 3 works, respectively. Next, general facility fortification was the most adopted strategy. A full fortification was employed by 40% of works, while 37.5% included only partial reliability. Snyder and Daskin (2005) considered the complete reliability of a company's owned facilities and independent distributor warehouses to be subject to disruption. Lim et al. (2010) pointed out that the notion of hardening can be imagined as an actual physical protection for the facility or as outsourcing contracts with exogenous suppliers. Azad et al. (2013) tried to extend full facility fortification by assuming that the capacity of a facility after a disruption depends on the proactive investment in robustness. Considering the nature of the previously introduced fortifications, the cost of this general investment is usually determined through discrete and qualitatively defined levels as an increase from the classic investment in building a facility of 25% (Lim et al., 2010), or 50% (Azad et al., 2013), or 100% (Rusman and Shimizu, 2013). However, Dehghani et al. (2018a) tried to mathematically describe the fortification cost as a function of the protection level that steadily varies as a non-linear function.

Supply-side and demand-side specific investments (i.e., backup supplier and pre-positioned inventory) were scarcely considered in selected works. This result is highly affected by the fact that almost 50% of the reference papers modelled a two-echelon SC (as shown in Table 3 in the previous section). The possibility to establish a contract with backup suppliers were included by only 4 models. Similarly, strategical pre-positioned inventory downstream the SC was considered by two reference works. Finally, the logistics network design problem combined with an operational reassignment strategy is the DM environment that allowed the consideration of more identified resilience strategies. For example, both Khalili et al. (2017) and Snoeck et al. (2019) developed an LNDP that included proactive resilience actions among all three perspectives (i.e., network-wise, supply-side, demand-side).

4.2. Expected disruption cost

This analysis is focused on the expected disruption cost terms, and therefore this subsection is based on a selection of 47 models that include at least one specific EDC term among the seven introduced earlier. Table 6 categorises the presence of specific EDC terms based on

Table 5
Categorization of reference models for proactive resilience investment based on DM problem and post-disruption mitigation strategy.

DM problem	Mitigation Strategy	Proactive Resilience Investments						
		Network-perspective			Supply-side		Demand-side	
		Additional Capacity	General Facility Fortification		Additional Capacity	Backup Supplier	Additional Capacity	Pre-positioned Inventory
			Full	Partial				
PLP	*OPR*		[1b]					
	RBA			[23a]				
FLP	*OPR*	[28]	[1a]					
	RBA		[7, 25, 35, 55, 60, 83, 89, 90]	[18, 23b, 30, 51]				
	TRS			[18, 30, 50, 83]				
LRP	*OPR*			[61]				
	RBA	[16]	[26, 27]			[16]		
LNDP	*BS*	[67, 86]		[96]	[67]	[67, 98]		[67]
	OPR	[14, 32, 48, 67, 70, 74, 76, 78, 80, 82, 99]		[49, 62, 74]	[67, 76, 80, 99]	[67, 82]	[48, 80]	[67, 99]
	RBA	[82]	[20, 87]			[82]		
	TRS			[62]				
CLNDP	*OPR*	[63, 64, 65, 79]	[64]		[63, 65]		[79]	
	TRS		[41]					

Table 6
Categorization of reference models based on expected disruption cost terms based on DM problem and post-disruption mitigation strategy.

DM problem	Mitigation Strategy	Expected Disruption Cost						
		Network-perspective			Supply-side	Demand-side		
		Damage Costs	Recovery/ Restoration Cost	Transshipment Cost	Procurement Cost Penalty	Backlog Cost	Delay Penalty	Transportation Penalty
PLP	OPR					[29]		[1b, 29]
	RBA							[23a]
FLP	BS			[77, 91]	[77]	[91]		[77]
	OPR		[28]	[91]		[91]		[1a]
	RBA			[18, 30, 83]				[7, 18, 23b, 25, 30, 35, 51, 55, 60, 83, 89, 90]
	TRS			[18, 30, 50, 83, 91]		[91]		[18, 30, 83]
LRP	OPR					[37, 61]	[61]	[61]
	RBA				[16]			[26, 27]
LNDP	BS	[88]	[67, 96]		[67, 88, 93, 96, 97, 98]			[67, 86]
	OPR	[99]	[62, 67, 78, 99]	[62]	[5, 67, 82, 97, 99]	[13, 54, 85, 99]		[62, 67, 78, 99]
	RBA				[82]			[20, 87]
	TRS		[62]	[21, 62]				[62]
CLNDP	OPR			[81]		[52]		
	TRS			[41, 81, 95]				

the DM problem and the post-disruption mitigation strategy.

The consideration of EDC as a transportation penalty on the demand-side was the most adopted method, with 57.4% of works included in this analysis. Snyder and Daskin (2005) modelled the allocation process follows a "level-r" assignment. The level-0 assignment is the primary and closest facility; the greater the assignment level that actually serves customers, the higher the transportation cost penalty. In other cases, models included only a primary and a secondary assignment based on distances between the demand point and facilities (Q. Li et al., 2013a, 2013b). Differently, Salimi and Vahdani (2018) modelled a higher transportation cost for being assigned to a customer as a secondary (supportive) facility. Some models included the application of penalties through transportation cost. For example, the development of level-r assignment can result in non-available facilities that lead to backlog cost. Indeed, Poudel et al. (2018) presented a reliable biofuel SCND where the backup supply used as a mitigation strategy was modelled through a penalty in transportation cost weighted by the probability of occurrence.

Considering the network-perspective, recovery/restoration cost and damage costs were included by only 12.7% and 4.3% of models. Turnquist and Vugrin (2013) included the cost of restored capacity at facilities. Fattahi et al. (2017) and Fattahi and Govindan (2018) computed a multi-period LNDP with a recovery cost for the warehouse's disrupted capacity. Shrivastava et al. (2018) assessed damage costs as a penalty for losing a fraction of supply. Finally, Snoeck et al. (2019) modelled the cost associated with shutting down the plant and the associated cleaning and repairs.

Of the 47 models included in this analysis, 13 works (27.6%) proposed the quantification of EDC through a combination of two or more terms. Similar to the previous analysis, the logistics network design problem combined with an operational reassignment strategy allowed modelling most specific EDC terms. For example, Snoeck et al. (2019) developed a formulation including the differences between business-as-usual condition cost and the situation when disruptions are taken into consideration, including backlog costs, damage costs, procurement penalty, restoration cost and transportation penalty.

Finally, it can be seen in Table 6 that post-disruption mitigation strategies had a strong effect on EDC modelling. Operational reassignment and reliable backup assignment were identified as the most adopted reactive strategies, with 19 reference models. The possibility of lateral transshipment was considered as an extension of the transportation penalty by 23.4% of models, and they were mainly focused on transportation variations (only one model included other EDC terms). OPR allowed the inclusion of all different EDC terms, while RBA focused only on transport penalties. Finally, backup supply was modelled by only nine works. This post-disruption strategy is marked by a procurement cost penalty. For example, Fan et al. (2018) modelled a FLP under partial capacity losses and the missing capacity is procured from a perfectly reliable emergency source that costs ten times more than a regular source.

5. Disruption probability formulation

This analysis aims to answer the third research question (RQ3) "Is there any correlation between the disruption probability formulation method and the resilience costs?".

Disruptions tend to be rare events and they, therefore, are difficult to predict (Klibi et al., 2010; Peng et al., 2011; Chopra and Sodhi, 2014; Snyder et al., 2016). The literature regarding the probability estimation of disruptions describes some fundamental issues: sufficient and valuable historical data might be difficult to obtain, and subjective probabilities must often be used (Klibi et al., 2010). As we can see in Table A1 in the Appendix, only 37% of models were related to a real-life case study. Additionally, new types of disruptions are also constantly emerging. As a result, it can be very difficult to estimate parameters such as the disruption and recovery probabilities/rates (Snyder et al., 2016).

Table 7 categorises the reference papers based on the disruption probability formulation and the different cost factors specifically introduced by the planning of proactive investments in robustness and by the parametrical/structural adaption due to disruption risk. The most implemented method for defining disruption probability was the scenario approach, where the stochastic parameters are modelled as a set of different plausible discrete scenarios with an associated probability of occurrence. Successively, Probabilistic Nonlinear Term (PNT) and Reliable Backup (RB) were employed by 23.5% and 19.8% of works, respectively. PNT formulation is based on level-r customer reassignment policy where the model includes a nonlinear term for the probability of each customer to be served by the assigned facilities at different backup levels. Furthermore, RB is a suitable formulation for models with primary and secondary (reliable) facility assignment.

First, the probabilistic nonlinear term formulation was typically associated with less complex DM problems, such as PLP and FLP, and was therefore employed for mathematical models that did not include any resilience' enhancing proactive plan with a compact operational

Table 7
Categorization of reference models based on Disruption Probability formulation and Resilience Cost terms.

Resilience Cost		Disruption Probability Formulation			
		Reliable Backup	Probabilistic Nonlinear Term	Scenario	Others
Proactive Resilience Investment	No Proactive Resilience Investments	[52, 77]	[3, 4b, 6, 9, 10, 12a, 17, 22, 24, 39, 40, 44, 46, 47, 58, 59, 66, 68, 72, 101]	[2, 4a, 5, 8 11, 12b, 13, 15, 18, 21, 29, 31, 33, 36, 42, 43, 45, 53, 54, 56, 57, 69, 71, 73, 75, 81, 84, 85, 91, 92, 93, 94, 95, 97]	[34, 37, 38, 88, 100, 102]
	Network-perspective	[7, 18, 20, 23a, 23b, 25, 26, 27, 30, 35, 41, 51, 55, 60, 61, 83, 89, 90]	[1a, 1b, 70, 86]	[14, 32, 48, 49, 50, 63, 64, 65, 74, 76, 79]	[16, 62, 78, 80, 87, 96, 99]
	Supply-side	[98]		[28, 63, 65, 67, 76, 82]	[16, 80, 99]
	Demand-side			[67, 79]	[80, 99]
Expected Disruption Cost	Operational Cost Variations		[3, 4b, 6, 9, 10, 12a, 17, 22, 24, 39, 40, 44, 46, 47, 58, 59, 66, 68, 70, 72, 101]	[2, 4a, 8, 11, 12b, 14, 15, 18, 28, 31, 32, 33, 36, 42, 43, 45, 48, 49, 53, 56, 57, 63, 64, 65, 69, 71, 73, 74, 75, 76, 79, 81, 82, 84, 92, 94, 97]	[34, 38, 80, 100, 102]
	Network-perspective	[18, 30, 41, 83]		[21, 28, 50, 67, 81, 91, 95]	[62, 78, 88, 96, 99]
	Supply-side	[98]		[5, 67, 82, 91, 93, 97]	[16, 88, 96, 99]
	Demand-side	[7, 18, 20, 23a, 23b, 25, 26, 27, 30, 35, 51, 52, 55, 60, 61, 77, 83, 85, 89, 90]	[1a, 1b, 86]	[13, 29, 54, 67, 91]	[37, 62, 78, 87, 99]

costs formulation without any expected disruption cost. Moreover, focusing on proactive resilience investments, reliable backup was adopted in most of the models that consider resilience only at the network-perspective level. On the other hand, a scenario-based formulation led to a more complete inclusion of proactive investments such as additional capacity, backup supplier, and pre-positioned inventory. Successively, in terms of EDC, reliable backup was mainly employed when disruption effects were modelled through cost factors associated with the demand-side of the SC (i.e., backlog cost, delay penalty, transportation penalty). Furthermore, a scenario-based formulation resulted as more flexible to adapt to different EDC at the three perspectives. In fact, this modelling method was largely preferred for LNDP and CLNDP (for more information about probabilities and DM problems, the reader is referred to Table A1 in the Appendix).

With the increase in the complexity of the DM problem, other methods of formulating the disruption probability were employed. For example, Klibi and Martel (2012) and Snoeck et al. (2019) modelled disruption into meta-events with generic impacts called multi-hazards. Facilities have different incident profiles in terms of impact and time to recovery. To map potential threats, the geographic territory in which the SC operates is partitioned into a set of hazard zones with an associated exposure level. Finally, multihazards occur independently, and distributions are generated based on historical data, expert opinion, and the literature. This probability modelling formulation permitted a wide variety of EDC terms to be included: backlog costs, damage costs, procurement cost penalties, recovery/restoration costs, and transportation cost penalties. Fattahi et al. (2017), Fattahi and Govindan (2018) and Hamidieh et al. (2018a) assumed that the disruption probability in each period follows a Bernoulli distribution. Salimi and Vahdani (2018) used a spatial statistic model for approximating failure probabilities. In geo-statistics, variability depends on two parts: the first part is random, while the second part is a function of distance and direction. Thus, the failure probability was modelled through the average probability of a disaster event (based on historical data) and a spatial dependence. When no historical data is available, the spatial variable was used for the estimation of probability.

6. Multi-objective formulations with consideration of different SCM dimensions

Modern SC should no longer optimise only economic goals, such as meeting customer demand, minimising costs and maximising profits (Andriolo et al., 2015; Mari et al., 2014). Governments are always asking more from companies in terms of conforming to environmental and sustainable standards, pollution regulations, products disposal, and so on (Chen and Sheu, 2009; Pavlov et al., 2019). Furthermore, today's markets change rapidly and require responsive operations to satisfy customer needs (Hamidieh and Fazli-Khalaf, 2017).

The business goals of companies affect their SCND problem and objectives. A suitably designed SC network enhances the attainment of competitive advantages (Govindan et al., 2017). Different paradigms have therefore been proposed in recent years. To answer our RQ4, this section provides an analysis of how two different sustainability factors (i.e., social impact, and environmental sustainability) are employed in SCND under disruption. Finally, two sub-sections are dedicated to SC responsiveness and risk/robustness measures.

6.1. Social impact in SCND

Social responsibility is one of the three pillars of sustainability (Elkington, 1998), and it has been less explored in the literature about SCND (Seuring and Müller, 2008). It includes various aspects related to human rights (e.g. child and forced labour), work conditions (e.g. exposure to dangerous materials), social commitment (e.g. enhancement of a population's health, education and culture, equal access to healthcare services), and business practice (e.g. fight against corruption) (Jabbarzadeh et al., 2018a).

Disruptions could heavily impact sustainability and social responsibility development (Zahiri et al., 2017), and therefore some efforts have been focused on managing these issues together. Usually, social impacts are integrated into SCND through an indicator called the social performance score (SPS). SPSs comprise several metrics with different weights, and the performance for each metric can be estimated by a panel of experts with an assessment score on a scale of 1–10, with 10 being the best practice. For example, Fahimnia and Jabbarzadeh (2016) organised the score with four equally weighted categories of metrics: labour practices and decent work (e.g. fair wages, working condition, occupational health and safety, and training and education), human rights (including child and forced labour, and discrimination incidents), society (including local community investment and public policy involvement), and product responsibility (including product labelling and customer privacy). Jabbarzadeh et al. (2018a) applied the fuzzy c-means clustering method to combine different sustainability metrics and split suppliers into different clusters with corresponding sustainability scores. The SCND problem was solved using the sustainability scores as input for the mathematical model. The SPS focused on human rights, labour working conditions, society contributions and product responsibility issues. Zahiri et al. (2017) included two social measures, the creation of job opportunities and the establishment of new facilities with respect to unemployment, and they include them as an objective function in their multi-objective optimisation model.

6.2. Green SCND

SC sustainability is predominantly directed at reducing the environmental impact of an SC (Fahimnia et al., 2015). According to Rose (2011) and Ivanov (2020a), disruption events could badly affect the environment: uncertainty correlated to disruptions leads firms to look for alternate solutions, incurring a loss in sustainability (Mari et al., 2014).

A step towards environmental sustainability has been made with the consideration of both forward and reverse logistics resulting in managing closed-loop SC (Battini et al., 2017; Özçelik et al., 2020). Reverse logistics activities are responsible for collecting end-of-life products from the customer zone and recycling their raw materials. These actions prevent hazardous wastes from entering ecological systems and maintain natural resources for future generations (Vahdani et al., 2012). Among our reference papers, 12 out of 106 models concerned closed-loop SC, and only two included environmental impact quantification in the mathematical model. Mari et al. (2016) presented a fuzzy goal programming model where environmental impacts were estimated through embodied carbon footprints and carbon emission in transportation, production, and reverse logistics processes (including emissions due to recycling). Indeed, Fazli-Khalaf et al. (2017) developed a multi-objective robust fuzzy stochastic programming model where the second objective function focused on minimising the environmental metrics. The latter was measured as the total harmful CO_2 gas emissions emanated by production activities, truck transportation, and plant recycling and recovery centres establishment.

The consideration of environmental sustainability is also possible in forward logistics networks. Mari et al. (2014) developed a weighted goal programming for a four-echelons' SC where sustainability goals were measured through the embodied carbon footprint of the materials procured from different suppliers and the total carbon emissions due to transportation and manufacturing. Fahimnia and Jabbarzadeh (2016) proposed an environmental performance score (EPS) evaluated by a panel of industry experts and composed of three metrics: alternative energy sources, water consumption, and supplier's greenhouse gas emissions. Zahiri et al. (2017) included the minimisation of CO_2 emissions which were considered a function of both the number of products and time, allowing to buy and sell carbon credits. In another work by Fahimnia et al. (2018), EPSs were determined for each manufacturing plant based on the production technology adopted, green initiatives undertaken, and sustainability performance of the raw material supplier. Finally, Jabbarzadeh et al. (2018a) composed a sustainability index where the environmental impact was included through the safe treatment and disposal of hazardous materials (such as hydrogen peroxide), waste collection, the emission of pollutants, and renewable and non-renewable energy consumption.

6.3. Responsive SCND

In recent years, the responsiveness of logistics networks has gained increasing attention as an additional goal towards accomplishing competitive advantage (Yu et al., 2018). Among the various definitions, SC responsiveness could be assumed as the ability to react quickly and cost-effectively to changes in market needs (Gunasekaran et al., 2008). Responsiveness could increase customer loyalty and satisfaction. This might result in the increasing market share of enterprises and their long-term planned benefit (Hamidieh and Fazli-Khalaf, 2017).

Disruptions can directly affect the SC responsiveness by causing delays and losing demand (Roh et al., 2014). Among our reference papers, some studies included both disruption risk and responsiveness issues in SCND. Rienkhemaniyom and Ravindran (2014) presented a four echelons LNDP where customer responsiveness was modelled through the lead-time from plant to customer zone. Similarly, Asl-Najafi et al. (2015) defined the time to ship different vehicle types as the second objective function, with the aim of minimising the total travelling time. Alternatively, Hamidieh and Fazli-Khalaf (2017) considered that products should arrive on time: early as well as late deliveries lead to customer dissatisfaction because they cause delays or product holding costs at customer zones. Each DC had a predefined preferred delivery time and responsiveness was measured as the total earliness or tardiness of product deliveries. Recently, Hamidieh et al. (2018b) presented a scenario-based stochastic optimisation model where the second objective function aimed to maximise the processing speed at different echelons of the network and transportation speed between facilities. Finally, although all of the studies presented above include responsiveness through an objective function, Fattahi et al. (2017) found that demand directly depends on lead-time. The responsiveness of an SC was thus modelled as a percentage of the potential demands of customer zones. The responsiveness level was also controlled through a measure of semi-deviation from the target.

6.4. Risk-averse measures in SCND

More than 50% of papers analysed in this survey dealt with uncertainty through stochastic programming (SP). SP is a mathematical modelling approach where random variables are usually characterized by probability distributions which depend on the values of decision variables. The problem consists of optimising a function characterising the distribution of random variables with their expected values. However, the optimisation's results can be subject to a significant variability incurring in higher costs (Govindan et al., 2017). In addition, despite the numerous advantages of this approach, this modelling method is risk-neutral since the remaining parameters characterising the distribution associated with random variables are not taken into consideration by the optimisation (Oliveira et al., 2013).

To quantify, control and limit the risk preference of a decision-maker, researchers usually include a term that represents the measure of risk associated with profit distribution. Within the context of SCND with disruption consideration, many measures firstly developed in the area of finance and insurance have been applied. Fig. 7 details the presence of these measures among our reference papers. The most widely applicable ones are variance, standard deviation, semi-deviations, and conditional value-at-risk (CVaR). Conditional value-at-risk is one of the most applied risk measures in SC risk management literature (Snoeck et al., 2019). It can be incorporated in the model's constraints (Azad et al., 2014) or objective function (Madadi et al., 2014; Khalili et al., 2017; Yu et al., 2017; Snoeck et al., 2019). CVaR is a measure that derives from value-at-risk (VaR). VaR represents the maximum cost associated with a specified confidence level $\alpha \varepsilon (0,1)$ of outcomes (i.e., the likelihood that costs will not exceed the amount defined as VaR). Consequently, CVaR indicates the conditional mean value of the expected cost of the worst $(1-\alpha)$ risk scenarios. Another approach to risk consideration is based on the dispersion from predefined target/goals. Some studies include risk measures as a semi-deviation of SC outcomes from this target. For example, Fattahi et al. (2017) modelled semi-deviation from targeted SC responsiveness.

An alternative to developing a risk-averse model is including the *p*-robustness criterion to control the reliability level of the network. This

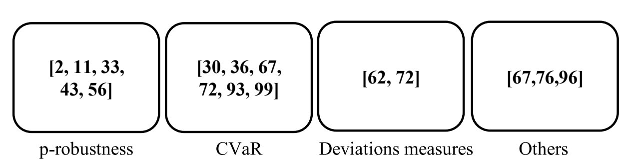

Fig. 7. Risk-averse measures included in the reference papers.

method was first introduced for a facility layout problem by Kouvelis et al. (1992). Successively, Snyder and Daskin (2006) adapted it for a facility location problem. The *p*-robustness criterion involves adding a constraint to the mathematical model to restrict the relative regret in each scenario to be no more than *p*. The regret is defined as the difference between the cost of the solution in that scenario and the cost of the optimal solution for that scenario. In other words, the cost under each scenario must be within $100(1 + p\%)$ of the optimal cost for that scenario. It is worth underlining that if $p = \infty$, the constraint become inactive and the formulation is equivalent to the risk-neutral one. One concern with the *p*-robustness approach is that the feasible region of solutions is highly restricted by the constraint, and it becomes difficult to find feasible solutions at smaller *p* values. Fahimnia et al. (2018) therefore developed an extension of the p-robustness measure, called "*elastic p-robustness*" with the aim of overcoming this issue. Lastly, reliability/resilience measures can also be included in objective functions. For example, Khalili et al. (2017) assessed the resilience of the whole chain as the available capacities in all echelons of the SC.

6.5. Supplementary SCM dimensions and resilience costs

As we can see from Table 8, the integration of sustainability factors (social and environmental impact) or responsiveness terms in the resilient SCND problem induces an increase in complexity of the mathematical formulation leading authors to mainly consider only operational variation and no proactive mitigation strategies in terms of EDC and resilience investment, respectively. Nevertheless, Hatefi et al. (2015) and Kumar and Anand (2018) developed a complete multi-objective formulation considering both sustainability factors and resilience actions at the three analyses perspective and considering specific EDC. Finally, risk-averse measures are cogent with the scope of the application, and authors were able to model complex combinations of expected disruption costs and proactive resilience investment as in Hatefi et al. (2019) and Snoeck et al. (2019).

7. Discussion and future research directions

In this section, we discuss and identify potential future research directions following, the classification framework and guidelines proposed in Section 2. In the first part of the analysis, we focus on the modelling characteristics and develop future research directions based on the four streams of the framework associated with each RQ: problem characteristics, resilience costs, disruption probability formulation, and multi-objective issues by combining different SCM paradigms. Finally, to highlight the practical areas that require further investigation, the last section summarises the managerial insights proposed by the reference papers in terms of SC configuration, network topology, and the effectiveness of proactive and reactive resilience strategies.

7.1. Problem characteristics

The two most applied DM problems were the FLP and LNDP. Similarly, two echelons SCs is the most modelled network structure. The combination of FLP and two echelons SC allowed considering disruptions in the supply networks by maintaining relatively low computational and modelling complexity. However, FLPs were frequently published around 2013 and 2014. In fact, in recent years, thanks to the advent of more advanced process models and computational power, researchers have focused on more complex and integrated SC networks, shifting the attention towards the LNDP. It is also notable that the increase in the complexity of DM problems has led to an increase in the considered SC echelons and decision layers. However, only 16.8% of works considered more than three echelons. Because SCs have become increasingly global, focusing on only a part of the network might lead to suboptimal designs that omit important disruption management phenomena such as risk propagation and risk pooling. Disruption events cause structural dynamics in SCs and the ripple effect, which refers to disruption propagations and the disruption-based scope of changes in the SCND structures (Liberatore et al., 2012; Ivanov et al., 2014; Ivanov, 2020b). Thus, the inclusion of a more complex network with multiple DM layers in future research could enrich the literature with additional analyses of disruptions propagation (i.e., the ripple effect). The inclusion of systematic performance management techniques to quantify and manage the ripple effect in SCND mathematical models is a promising research idea (Dolgui et al., 2018; Bier et al., 2019; Ivanov et al., 2019a; Ivanov and Dolgui, 2020a). Furthermore, as Ivanov (2020c) showed, the effects of disruption on SC profitability could be highly diverse, depending on the characteristics of the interruption. It might be interesting, therefore, to analyse different configurations of disruption propagation among all elements of an SC network, such as simultaneous or sequential disruption, short- or long-term duration, propagation direction (i.e., upstream or downstream), and propagation speed. By understanding the relationships between these elements, managers could better decide how to address specific investments to enhance SC resilience.

Finally, the location-routing problem and closed-loop logistics network were developed only a few times. Although these two additional SC characteristics, that is vehicle-routing and reverse logistics flows, are marginal categories in the field of SC disruption and lead to more complex management problems, they have a significant influence on SC performance (Wilson, 2007; Xu et al., 2020). In terms of managerial implications, the optimisation of numerous sub-problems in different applications could lead to several suboptimal designs that could be vulnerable to infrequent disruptions (Snyder and Daskin, 2005; Cui et al., 2010; Paul and Rahman, 2018; Xie and Ouyang, 2019). By integrating more features into optimal problems, managers could gain excellent insights and obtain more advanced solutions to their DM problems. Including vehicle-routing decisions could allow considering transportation links disruptions. Consequently, reverse flows might help mitigate the disruption impact due to interruptions in the upstream part of the SC, and they could enhance resilience and flexibility in case of major changes.

7.2. Resilience costs

Generally, when considering disruptions in the SCND process, DM

Table 8
Categorization of reference papers based on supplementary SCM Paradigms and resilience cost terms.

Resilience Cost		SCM Paradigms			
		Social Impact	Environmental Impact	Responsiveness	Risk/Robustness Measure
Proactive Resilience Investment	No Resilience Investment		[37, 53]	[38, 39, 92, 94, 95]	[2, 11, 21, 33, 36, 38, 43, 56, 72, 93]
	Network-perspective	[48, 82]	[48, 64, 82, 76]	[65,79]	[30, 63, 67, 76, 96, 99]
	Supply-side	[82]	[76, 82]	[65]	[63, 67, 76]
	Demand-side	[48]	[48]	[79]	[67, 99]
Expected Disruption Cost	Operational Cost Variations	[48]	[48, 53, 64, 76]	[38, 39, 65, 79, 92, 94]	[2, 11, 33, 36, 38, 43, 56, 63, 72, 76]
	Network-perspective			[95]	[21, 30, 67, 96, 99]
	Supply-side	[82]	[82]		[67, 93, 96, 99]
	Demand-side		[37]		[30, 67, 99]

should consider the possibility to invest in robustness to better mitigate the disruption effects. However, only 40 models (38% of the reference models) allowed for proactive resilience strategies.

The more complex the DM problem, the greater the consideration of specific resilience investments. One exception is closed-loop logistics network design problems, whereby the high complexity in the network structures has led to the consideration of only general fortification. Including specific proactive resilience investment (e.g., backup suppliers and pre-positioned inventories) in the CLNDP and specifically in the reverse flows of an SC could thus be an interesting research idea.

Additional capacity was the most considered method for increasing robustness and therefore being more ready to adapt and satisfy market changes due to uncertain events. However, this proactive resilience action was mostly considered only from a network-perspective, i.e., at focal facilities. Another widely employed proactive investment was facility fortification; however, a significant number of applications include the possibility of setting fully reliable facilities. Nevertheless, this modelling characteristic is unrepresentative of reality because it is almost impossible to build a disruption-immune site (Ivanov, 2018; Aldrighetti et al., 2019a). No techniques can completely eliminate a loss by reducing the disruption magnitude or the failure probability to zero. Therefore, future research needs to address the concept of facility fortification/protection through a more feasible and closer to reality model, such as associating disruption magnitude reduction based on protection's investment level with no possibility of completely infallible sites. Specifically, among the selected works, only Dehghani et al. (2018a) attempted to mathematically describe fortification cost as a function of protection level. Thus, it would be useful to quantitatively analyse the correlation between resilience investment and disruption probabilities reduction with the aim of including this in SCND models. Besides, both additional capacity and general facility fortification were analysed mainly from the network perspective, i.e., at focal facilities. Generally, future efforts should try to understand in which part of the SC redundancies are more effective, expanding the analyses to multi-echelon SC to comprise proactive resilience actions over the three perspectives, i.e., network-wise, supply-side specific and demand-side specific. Additional capacity and other specific resilience measures on the demand-side of the SC were addressed really scarcely. Similarly, some lacks have been identified in analysing how to increase resilience in the upstream and downstream part of a SC. When dealing with the supply side of an SC, complex multi-criteria DM methods are often employed, especially for supplier selection problems (SSPs), that elevate the computational and modelling complexity of the application (Chai and Ngai, 2015; Wetzstein et al., 2016). Exploring the SSP literature, it is notable that more efforts have been made to include proactive resilience investment as in Ruiz-Torres and Mahmoodi (2006), Ravindran et al. (2010), Meena and Sarmah (2013), Sawik (2013), Torabi et al. (2015), Kamalahmadi and Parast (2017), Namdar et al. (2018), Ni et al. (2018), Hosseini et al. (2019b), and Gupta et al. (2020). Future research could, therefore, aim to match the objective of logistics network design and supplier selection problems by moving towards the inclusion of different proactive resilience investments on the supply-side in multi-echelon SCND models.

Focusing on EDC, specific expected disruption costs were included in 44.3% of the works. The vast majority of models included only transportation penalties. This is because transportation activities are mandatory in any DM problem related to SCND. In fact, as the complexity of the DM problem increases, a wider variety of EDCs is considered. However, only 12 models included EDCs among two of the three perspectives included in the analyses. Focusing on the supply-side specific EDC, procurement cost penalties was modelled by only 12 works. On the other hand, in terms of a network-perspective, damage costs and recovery/restoration costs were rarely addressed. Especially for long-term interruptions with a significant impact on the operations, recovery actions allow for better representation of real-life evolutions and a quick return to the previous capacity level (Hosseini et al., 2019b).

In addition, when a disruption occurs, there may be damage to facility buildings, production resources, or warehouse goods, especially when dealing with natural disasters, such as earthquakes, floods, or hurricanes. When the value of machinery or products is high, the impact of the damage in terms of costs might be serious. Evaluating the damage after the disruption is still an open key issue: while this topic has been debated in regard to humanitarian SCs (Wagner and Thakur-Weigold, 2018; Ioanna and Tina, 2019), a set of performance measures is needed for industrial/commercial SC (Duong and Chong, 2020).

In conclusion, researchers in this area should consider developing common practices to help modellers and practitioners understand which EDC to include to obtain a complete and relevant cost characterisation over the three-level of analysis (i.e., network-perspective, supply-side, demand-side), thereby enabling them to analyse more realistic disruption effects.

7.3. Uncertainty modelling

Uncertainty modelling is a complex aspect of SCND under disruption risks, and the literature regarding the probability estimations of disruptions still has some fundamental issues. This is for two reasons. First, data related to rare events are difficult to obtain. Second, even when available, such data can hardly be considered representative of reality. In fact, only 37% of the reference works were based on real-life case studies. Less than 15% of works formulated the disruption probability based on historical data (further details on model applications and data are available in Table A1 in the Appendix). Using real-life case study data in probability estimation for SCND could thus be worthwhile for future research.

The probability formulation technique reveals to be closely correlated to the resilience investment and EDC terms considered by the reference models. The scenario approach, whereby probabilities were mainly estimated through expert knowledge or were randomly generated, was the most commonly implemented method. Applications to other DM problems in SCM successfully adopted more advanced techniques for formulating probabilities, such as decision-tree and probabilistic graphical models. For example, Kamalahmadi and Parast (2017) developed a scenario-based mathematical program whereby the likelihood of all scenarios depended on supplier failures and regional disruptions, and each probability was therefore defined using a decision-tree analysis. In another work, Hosseini et al. (2019b) used the Bayesian network theory to compute the supplier disruption probability caused by a variety of random disruption risks such as floods, earthquakes, hurricanes, and labour strikes. The Bayesian network allowed for consideration of the dependency between the suppliers and the disruptive event; was the most commonly implemented method. Despite an increase in computation complexity, these probability formulation methods led to greater flexibility to better characterise disruption effects in terms of EDC terms and the consideration of proactive investments in robustness (Hosseini et al., 2020). Therefore, using probabilistic graphical models or spatial statistics probability formulation could be an interesting research idea for achieving a complete formulation of resilience cost.

7.4. Multi-objective formulations with consideration of different SCM paradigms

As observed in Section 6, a few papers integrated supplementary paradigms in addition to cost and reliability factors. Adding extra objectives results in multi-objective optimisation problems, which are more complex in terms of data collection and solution.

Responsive SCND models with disruption risk are scarce. In all of these studies, customer demand is not dependent on the responsiveness of SC, which is measured by lead time. SC responsiveness could be highly correlated with disruption management and the concept of SC resilience (Shekarian et al., 2020). Responsiveness has been widely recognised as a major capability to mitigate disruptions of supply and demand in SCs (Babazadeh and Razmi, 2012; Nooraie and Mellat Parast, 2015). Modelling demand that is sensitive to SC responsiveness and disruption risk thus remains a research stream that requires further analysis.

Social impact is the least addressed issue, although environmental sustainability attracted more attention. However, sustainable factors should be considered together, as in Andriolo et al. (2015), Dubey et al. (2015), Jabbarzadeh et al. (2018) and Pavlov et al. (2019). Moreover, there is minimal awareness of the broader impacts of sustainable actions on the ability of SCs to tolerate disruptions. While sustainable practices usually require for great efficiency in the use of resources, this may inadvertently cause the SC to become more vulnerable to interruption (Fahimnia and Jabbarzadeh, 2016). Because both the economic and non-economic sustainability performance of an SC can be significantly affected by disruptive events (Zahiri et al., 2017), more research is required in these areas. Studies on SC sustainability differ across methodologies but commonly argue that the adoption of sustainable SCs

Table 9
Summary of managerial insights obtained by reference papers.

	Network perspective	Supply-side specific	Demand-side specific
Decision-making problem	• PLP, FLP, LRP, LNDP, CLNDP	• LNDP, CLNDP	• PLP, FLP, LRP
Disruption consideration	*Major managerial implications*		
	• Increase in resilience investments costs could result in reductions in failure costs and operational costs when disruptions occur • Diversification of facility locations in low-risk areas • Network decentralisation	• Supply-side disruptions affect the whole network structure and may entail the ripple effect	• Disruption correlation with demand fulfilment should be analysed to design more resilient SCs
	Mitigation Strategy		
	• Reassign the material flows based on actually available capacities and still-operating suppliers • Apply lateral transshipment for providing additional inventories to partially disrupted facilities	• Asking backup supply to primary or backup suppliers	• Leverage on previously set up reliable facilities for satisfying customer demand and cover disrupted capacity
Proactive resilience actions	*Major managerial implications*		
	• Proactive resilience strategy helps maintain available sites at high risk and strategic locations • Fortify/protect facilities to maintain a strategic location next to major demand points	• Backup supplier contracting • Criticalities of suppliers located in risky areas • Differentiate sourcing strategy • Multiple sourcing • Supply base segmentation	• Capacity expansion at downstream facilities, i.e. DCs • Prepositioning extra-inventory to strategic downstream locations
	Costs of proactive investments		
	• Investments costs increase due to a more segmented network • Investment costs in protection and more flexible systems	• Cost of contract with backup suppliers • Investments costs increase due to more robust supply base	• Cost of capacity expansions at downstream facilities • Additional holding costs due to pre-positioned inventory
Reactive resilience actions	*Major managerial implications*		
	• Clustering facilities to enhance and facilitate supply and demand reallocation • Operational reallocation of demand and supply • Production re-purposing	• Multiple sourcing to face suppliers' interruptions/partial supplies • Re-allocation of materials flows to available suppliers	• Demand substitution • Multiple sourcing in distribution to customer zones • Transshipment between facilities
	Costs of reactive strategies		
	• General operational costs variation • Damage costs in terms of capacity/production and/or inventory losses • Cost of recovery disrupted features to restore operations • Transportation cost of lateral transshipment for providing additional inventories to partially disrupted facilities	• Procurement penalty applied for emergency supply • Transportation penalty for not using optimal transportation routes or source	• Backlog costs for not satisfying demand • Delay penalty due to lateness/earliness of products • Transportation penalty for not using optimal transportation routes or source

Acronyms: PMP: p-median facility location problem; FLP: fixed-charge facility location problem; LRP: location-routing problem; LNDP: logistics network design problem; CLNDP: closed-loop logistics network design problem.

preserves business continuity to reduce long-term business risks. At the same time, business continuity is one of the fundamental characteristics of SC resilience (Ivanov et al., 2017b). Managing the sustainability-reliability paradigm through the use of quantitative methods and mathematical models is still an emerging field. Future works might investigate the effect that sustainability enhancement has on SC resilience and robustness. Specifically, the inclusion of social impacts as sudden workforce shortage due to new governmental policies in terms of work retirement or changes in ageing workforce involvement (Bogataj et al., 2019) are good potential research directions for the future.

Adding a risk-averse measure to the model allows the risk to be quantified, controlled, and limited, based on the decision-maker's preferences; however, these measures were included in only 15% of the reference models. CVaR was the most popular risk measure, despite the drawback of increasing the problem complexity (Oliveira et al., 2013). Indeed, deviation measures were less employed because they ask decision-makers to set targets for SC outcomes (Qiu and Wang, 2016). Considering its non-complex formulation, *p*-robustness gained considerably more attention than other robustness measures. From an SC manager's perspective, it is difficult to justify the investment made in disruption recovery management. This is because today's SCs are cost-oriented, and benefits can be reaped only when a disruption occurs, which is a low-probability event (Sawik, 2016; Rajagopal et al., 2017; Dubey et al., 2021). Therefore, including risk-averse measures in SCND under disruption risk could be worthwhile. More specifically, the inclusion of resilience metrics (e.g. node complexity, node density, and geographic dispersion) as KPIs in optimisation models could help researchers and practitioners with measures in addition to cost/profit to better evaluate possible SC design alternatives (Zahiri et al., 2017; Betti and Ni, 2020; Fattahi et al., 2020; Hosseini et al., 2020).

7.5. Managerial insights

The aim of this section is to summarize the main theoretical and practical insights developed by the analysed SCND models in terms of disruption risk consideration, network topology, and the effectiveness of proactive and reactive resilience actions (Table 9). Table 9 classifies our findings in terms of managerial implications related to four major areas, i.e., why to use SCND models with disruptions, how to increase resilience at the network level, and what proactive and reactive measures should be taken. Table 9 shows that the results of the existing studies can help to design SCs to mitigate disruptions. Since many factors are involved with a resilient SCND, Table 9 provides a framework on how to utilize the SCND models with disruptions to make investment decisions. Moreover, Table 9 accounts for the type of SC disruption (i.e., network-wise, supply-centric, and demand-oriented) since there are significant differences in designing an SC with respect to different types of SC disruption drivers (Wagner and Bode, 2008; Chen et al., 2013). These contingencies should be considered in the design and development of SCND.

It has been widely recognised that considering uncertain disruptions in the design phase can help in reducing their negative effects and render immense cost reductions compared to evaluating only business-as-usual scenarios (Diabat et al., 2019). Generally, the consideration of disruption risks tends to increase network robustness and resilience, which means increasing investment and operational costs. While decision-makers may be reluctant to undertake large increases in SC costs, they may be aware that substantial improvements in resilience and efficiency can be attained with minimal increases in SC cost (Snyder and Daskin, 2005; Shukla et al., 2011; Yan and Ji, 2019). In addition, these results are confirmed both for forward SC and closed-loop SC networks (Torabi et al., 2016). Realistically, company managers may not accept an SC with high investment and operational costs just to hedge against very rare disruptions risk. However, considering a good trade-off could is achievable with only minimal efforts, the inclusion of possible disruptions could give companies a significant competitive advantage, especially in these times, which are dominated by high and inherent uncertainty.

In terms of network topology, most of the modellers seem to support that for an SC to be reliable and resilient, there is a need to avoid building facilities in high-risk areas and to generally reduce the workload and flow ratios of these most probable disrupted locations on both the supply and demand sides (Azadeh et al., 2014; Mari et al., 2016). However, this construct is based on disruption probability which, as shown in Section 5, is most often based on subjective evaluation and cannot be easily and correctly predicted or measured through historical data. To reduce operational costs, decision-makers usually tend to centralise the network and set up facilities next to big demand points. When considering disruption risks, this configuration could generate higher costs for two main reasons: (1) big demand points could be associated with higher-risk regions (An et al., 2014), and (2) in case of disruption, the cost of serving these points would be higher. Therefore, it seems reasonable to design the global SC structure with the aim of sharing the risk by delocalising and setting up facilities at widely spaced locations (e.g. to diversify facility location) (Hasani and Khosrojerdi, 2016).

The first and most common action for building robustness and being ready to sustain disrupted periods is to plan to open more facilities (X. Li et al., 2013a, 2013b; Jalali et al., 2017). Additional sites can provide better redundancy for reliable service quality against facility failure, especially when transportation cost has a greater impact than inventory/holding cost (Chen et al., 2011; Zhang et al., 2016). More available capacity could overcome possible facility shortages and make an SC more flexible to adapt to market variations (Garcia-Herreros et al., 2014; Azad and Hassini, 2019) even if this could increase management complexity. An alternative to increasing the number of facilities is to invest in protection/fortification systems, which would reduce the facility's vulnerability against disruption risk and its effects. As shown in Bahri and Rusman (2013), Tang et al. (2016), and Kumar and Anand (2018), protection systems allow an SC to reduce the number of opened facilities and to obtain substantial benefits in terms of total cost minimisation (Turnquist and Vugrin, 2013; Khalili et al., 2017; Jabbarzadeh et al., 2018a). As a contingency strategy, the higher the disruption probability and magnitude, the more facilities tend to be strengthened. Facility fortification allows SCs to keep opening sites in highly strategic and demand areas even if they are considered high-risk location (Tang et al., 2016; Fattahi et al., 2017). Conversely, facility fortification is expensive; therefore, only a few more important facilities would be protected. As the fortification/protection becomes more expensive, a general risk-neutral model would open more unreliable facilities and accept more disruption costs. However, considering a risk-averse attitude, the decision-maker could test different risk-awareness situations and analyse scenarios with the aim of maintaining a high service level and creating a more reliable SC (Madadi et al., 2014; Yu et al., 2017).

Multiple sourcing has been widely recognised as a successful strategy for coping with disruption risk (Klibi and Martel, 2012; Fahimnia and Jabbarzadeh, 2016; Jabbarzadeh et al., 2018a). On one hand, on the demand side, it consists of the consideration of a primary assignment and then multiple secondary assignments from focal facilities/DCs to customer zones that will be responsible for the material flow only if the primary facility is disrupted. This sort of reallocation strategy allows substantial reductions in operational costs in disrupted periods (Cui et al., 2010; X. Li et al., 2013a, 2013b; Liu et al., 2017). In addition, multi-sourcing can be enhanced and facilitated by lateral transshipment, which has been recognised as an effective strategy for sustaining fluctuations and facility shortages (Hatefi and Jolai, 2015; Jabbarzadeh et al., 2018b) even if it is more desirable for short-term/small-scale disruption (Aldrighetti et al., 2019b). When the backup reassignment of material flows is adopted as the main resilience strategy, SC networks tend to set up facilities in clusters as the aggregated average distance between customer zones and primary and secondary assignments is minimised (Chen et al., 2011; Yun et al., 2015). However, this network topology tends to present some issues: the risk-pooling effect starts to decrease, and in the case of correlated disruption, nearby facilities are more likely to fail simultaneously (X. Li et al., 2013a, 2013b; Lu et al., 2015). Consequently, network decentralisation and diversification of facility locations are generally preferred.

On the other hand, multiple sourcing on the supply side consists of developing contracts and relationships with more suppliers or with primary suppliers and backup ones. Supply disruption or, more generally, disruption on the left side of an SC has been identified as the most critical and impactful event in terms of SC cost performance and network structure (Qi et al., 2010; Jabbarzadeh et al., 2018a). For example, if a manufacturing plant/supplier is often disrupted, there is no convenience to be gained by building other facilities (i.e., distribution centres) in the nearby area. The engagement of more raw material suppliers in a resilient SC allows for the unaffected suppliers to compensate for the supply shortage in disruptions, i.e. switching material requisition amongst the suppliers (Fahimnia and Jabbarzadeh, 2016). Besides, it reduces the dependency on a single source that could be highly efficient but more vulnerable to disruption (Hasani and Khosrojerdi, 2016).

Other resilience strategies that have not been thoroughly analysed are postponement and prepositioning extra-inventory. The former results in an effective action to produce semi-manufactured goods and make the SC more flexible and agile in response to uncertainty due to disruption risk. Conversely, the extra-inventory strategy increases operational costs and provides resilience against only short-term/small-scale disruption (Hasani and Khosrojerdi, 2016; Aldrighetti et al., 2019b).

Finally, in terms of supplementary SCM paradigms, sustainability objectives seem to contrast with reliability and resilient ones. Mari et al. (2014) found that a strictly green SC has the greatest overall uncertainty regarding potential facility disruption. To hedge against disruption risks, firms try to switch their operations by producing and transporting smaller quantities, which reduces the impact of disruption but increases cost and environment inefficiencies. However, other researchers found that the socio-environment performance of the SC remains almost unaffected in the face of disruption (Fahimnia et al., 2018). Furthermore, Jabbarzadeh et al. (2018a) identified some degree of synergy between environmental sustainability and resilience and found that greening a robust SC is considerably less costly than greening a frail SC.

8. Concluding remarks

This paper presented a comprehensive and structured review of the studies of SCND under disruption risks in the area of industrial SCM and logistics, following four main research questions. The main objective was to analyse disruption effects in terms of different cost factors that are specifically introduced through the planning of proactive investments in robustness and parametrical/structural adaption due to disruption risk.

Proactive investments in robustness were rarely included among our reference works. The most commonly modelled characteristic was “general facility fortification”, which allows for a reduction in disruption occurrences and impacts based on discrete qualitative definitions. Conversely, great variability was identified in the modelling of expected disruption costs. Many works considered only transportation penalties or transshipment costs, avoiding the consideration of other relevant EDC terms such as damage or recovery/restoration costs. In terms of managerial insights, the literature seems to support the position that locations diversification and network decentralisation are important characteristics of a resilient SC, along with avoiding high-risk areas. However, in cases in which critical locations could be strategic to the company, SCs could maintain efficient and reliable operability by locating their plants in more vulnerable areas and planning for investment in protection systems. In general, proactive resilience investments have been recognised as successful actions with respect to providing robustness to the system and improving readiness to hedge against uncertain and high-impact events. Facility fortification/protection might need more contextualisation in the practical context: most of the papers considered completely reliable facilities that are infallible which might not be very representative of practical situations. On the supply side, in terms of contracting with backup suppliers, the possibility to procure the material from different sources increases the flexibility and ability to adapt to several disruption scenarios such as unexpected capacity reduction or immediate demand increase. For example, a good resilient supply strategy could be to differentiate sourcing among the components of our products: all irreplaceable parts could be supplied through two different sources, while replaceable parts are supplied by a single source. Finally, proactive resilience actions could provide high capabilities of adaption and mitigation, although the effectiveness is sometimes limited to short-term/small-scale disruption. In general, the evaluation of combinations of proactive and reactive resilience strategies together could be worthwhile, as it could allow managers to understand the real efficacy of the different actions and provide a more integrated plan to hedge against disruption risk.

With regards to research gaps and open questions, we identified four main promising directions: (1) integrating different proactive and reactive resilience strategies that consider disruption in more SC echelons and evaluating the real effectiveness of resilience and its practical implication for efficiency; (2) analysing the effects of disruptions on closed-loop SCs in greater detail; (3) developing DM problem integrating sustainability, responsiveness and resilience metrics to evaluate their effects on SC reliability and robustness, and (4) presenting realism models that are based on real-world data and applications.

As for future research directions, the recent coronavirus (COVID-19) outbreak has imposed a new disruption context unlike any seen before (Ivanov and Dolgui, 2021; Queiroz et al., 2020). Indeed, SC resilience theory has been developed to manage disruptions which are considered events. With the COVID-19 pandemic, some novel context has been unveiled which goes beyond an instantaneous event-driven understanding and can be described as an *SC crisis* characterized by long and severe uncertainty of current and future conditions and entailing extensions toward SC *viability* (Ivanov, 2020a). First, a pandemic is characterized by a very long existence of disruption and its unpredictable scaling (Ivanov, 2020c). Second, the recovery begins in the presence of the disruption, and its unpredictable scaling. This is different to “instantaneous” disruptions such as an earthquake which hit the supply chain once, and the recovery begins when the disruption is over. Third, in the pandemic, we have simultaneous disruptions in demand, supply, and logistics infrastructure. This is different to classical disruption risks which usually impose shocks on either supply or demand. Fourth, the pandemic is challenging by the timing of disruption propagation driven by simultaneous disruption and epidemic outbreak propagations with simultaneous and/or sequential openings and closures of suppliers, facilities and markets. Different SC echelons are bit by disruptions (i.e., due to lockdowns and quarantines entailing workforce shortages and surges in demand) at different times (Queiroz et al., 2020). Future research on disruption management in SCs might be highly influenced by analyses and investigations of the effects and consequences of the COVID-19 pandemic. Therefore, this review could be particularly helpful in understanding the modelling characteristics and approaches of SCND models with disruption risk considerations in the pre-COVID-19 era. Through the pandemic times, we have seen a number of novel contexts such as re-purposing, substitution, and SC intertwining (Ivanov and Dolgui, 2020c) which can motivate new research in SC resilience. Another interesting research direction is stemming from the observation that SC resilience capabilities are usually considered in light of some anticipated events and are as passive assets, which are “waiting” for use in case of an emergency. This, however, can be costly. Moreover, the current COVID-19 pandemic has revealed difficulties in the timely deployments of resilience capabilities. With that in mind, it seems to be important to develop research exploring utilization of resilience capabilities for value creation as posed by the AURA (active usage of resilience assets) framework (Ivanov, 2021a) to consider resilience as an inherent, active, and value-creating component of operations management decisions, rather than as a passive "shield" to protect against rare, severe events.

Appendix

9. *List and enumeration of the 106 models considered in the analysis*

All the below references have been cited in tables and figures.

[1a]	Snyder & Daskin (2005)	[50]	Jabbarzadeh et al. (2016)
[1b]	Snyder & Daskin (2005)	[51]	Li & Savachkin (2016)
[2]	Snyder & Daskin (2006)	[52]	Mari et al. (2016)
[3]	Berman et al. (2007)	[53]	Qiu & Wang (2016)
[4a]	Cui et al. (2010)	[54]	Shu et al. (2016)
[4b]	Cui et al. (2010)	[55]	Tang et al. (2016)
[5]	Kumar et al. (2010)	[56]	Torabi et al. (2016)
[6]	Li & Ouyang (2010)	[57]	Vahid Nooraie & Parast (2016)
[7]	Lim et al. (2010)	[58]	Xie et al. (2016)
[8]	Mete & Zabinsky (2010)	[59]	Zhang et al. (2016)
[9]	Qi et al. (2010)	[60]	Anand & Kumar (2017)
[10]	Chen et al. (2011)	[61]	Elluru et al. (2017)
[11]	Peng et al. (2011)	[62]	Fattahi et al. (2017)
[12a]	Shen et al. (2011)	[63]	Fazli-Khalaf et al. (2017)
[12b]	Shen et al. (2011)	[64]	Fazli-Khalaf et al. (2017)
[13]	Shukla et al. (2011)	[65]	Hamidieh & Fazli-Khalaf (2017)
[14]	Babazadeh & Razmi (2012)	[66]	Jalali et al. (2017)
[15]	Jabbarzadeh et al. (2012)	[67]	Khalili et al. (2017)
[16]	Klibi & Martel (2012)	[68]	Liu et al. (2017)
[17]	Aboolian et al. (2013)	[69]	Pariazar et al. (2017)
[18]	Azad et al. (2013)	[70]	Rayat et al. (2017)
[18]	Baghalian et al. (2013)	[71]	Shishebori et al. (2017)
[20]	Bahri & Rusman (2013)	[72]	Yu et al. (2017)
[21]	Bozorgi Atoei et al. (2013)	[73]	Cheng et al. (2018)
[22]	Lei & Tong (2013)	[74]	Dehghani et al. (2018b)
[23a]	(Q. Li et al., 2013a, 2013b)	[75]	Dehghani et al. (2018a)
[23b]	(Q. Li et al., 2013a, 2013b)	[76]	Fahimnia et al. (2018)
[24]	(X. Li et al., 2013a, 2013b)	[77]	Fan et al. (2018)
[25]	Lim et al. (2013)	[78]	Fattahi & Govindan (2018)
[26]	Rusman & Shimizu (2013)	[79]	Hamidieh et al. (2018a)
[27]	Shishebori & Jabalameli (2013)	[80]	Hamidieh et al. (2018b)
[28]	Turnquist & Vugrin (2013)	[81]	Jabbarzadeh et al. (2018a)
[29]	An et al. (2014)	[82]	Jabbarzadeh et al. (2018b)
[30]	Azad et al. (2014)	[83]	Kumar & Anand (2018)
[31]	Azadeh et al. (2014)	[84]	Li & Zhang (2018)
[32]	Garcia-Herreros et al. (2014)	[85]	Pariazar & Sir (2018)
[33]	Hatefi & Jolai (2014)	[86]	Poudel et al. (2018)
[34]	Hernandez et al. (2014)	[87]	Salimi & Vahdani (2018)
[35]	Li & Ru (2014)	[88]	Shrivastava et al. (2018)
[36]	Madadi et al. (2014)	[89]	Wang & Wu (2018)
[37]	Mari et al. (2014)	[90]	Afify et al. (2019)
[38]	Rienkhemaniyom & Ravindran (2014)	[91]	Azad & Hassini (2019)
[39]	Asl-Najafi et al. (2015)	[92]	Diabat et al. (2019)
[40]	Bai et al. (2015)	[93]	Dutta and Shrivastava (2020)
[41]	Hatefi et al. (2015)	[94]	Gholami et al. (2019)
[42]	Hatefi et al. (2015)	[95]	Ghomi-Avili et al. (2019)
[43]	Li et al. (2015)	[96]	Hatefi et al. (2019)
[44]	Lu et al. (2015)	[97]	Hu & Dong (2019)
[45]	Shishebori & Yousefi Babadi (2015)	[98]	Ramshani et al. (2019)
[46]	Yun et al. (2015)	[99]	Snoeck et al. (2019)
[47]	Zhang et al. (2015)	[100]	Xie et al. (2019)
[48]	Fahimnia & Jabbarzadeh (2016)	[101]	Xie et al. (2019)
[49]	Hasani & Khosrojerdi (2016)	[102]	Yan & Ji (2019)

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijpe.2021.108103.

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