Disruption cost evaluation methods in Supply Chain Network Design: state of the art and future steps

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Abstract: Supply Chain Network Design is a crucial area of Supply Chain Management which is responsible for long-term decisions with high monetary impacts. Some of the most important practices included in the SCN Design are the production allocation, supplier selection and in particular the site localization and sizing. In recent years, Supply Chains are becoming more and more complex and companies cannot afford to not reach the customers in time. Disruption risk is a particular kind of threat generated by an event that may occur due to natural disaster (e.g., earthquakes, tsunami, and floods) or through intentional/unintentional human actions (e.g., labour strikes, war, economic crises) that usually have a low likelihood of occurrence against a high magnitude of consequences. Supply Chain Network Design under disruption risks is becoming extremely important with the increase of the occurrence of such these hazards in addition to the complexity and uncertainty of networks. The probability of occurrence of this kind of events and the effect caused by them are still fundamental issues in these research fields that need to be further investigated.
The aim of this paper is to analyze the relevant paper in the field of Supply Chain Network Design under Disruption Risks. More specifically, this study is focused on how researchers quantify the cost triggered by a disruption occurrence. The increase in popularity of this topic led to numerous models published in this field. For this, a review is necessary for understanding the exhaustiveness of the published works and to draw up some future directions.

Keywords: Supply Chain Network Design, Supply Network Design, Facility Location, Disruption cost estimation

1. Introduction

Supply Chain Network (SCN) Design is a crucial planning problem of Supply Chain Management (SCM) that involves strategic decisions on the configuration of Supply Chains (SCs). Some of the most common practices related to SCN Design are to determine the number, location, and capacity of facilities, to select suppliers and to choose the right policy for serving customers. Generally, these decisions involve a significant amount of investments and have long-term effects on the SC's efficacy requiring high efforts to Decision Makers in terms of cost and time. Therefore, since SCNs are designed to last numerous years, alternative plausible futures should be considered to design robust value-creating networks (Klibi and Martel (2012)). When considering future environments, many parameters such as demand, capacity, costs of connections, lead time, etc., can vary in an unexpected manner. Thus, SCN Design problems have inevitably to cope with parameters uncertainty. Klibi et al. (2010) propose a categorization of three level of uncertainties when partial information is available:

- *Randomness:* parameters are considered random variables related to business-as-usual operations with known probability distributions (e.g., demand, prices, raw material cost).
- *Hazard:* low-probability high-impact unusual events. This kind of events are difficult to assess and predict and it may be also difficult to obtain sufficient and quality data to define objective probabilities.
- *Deep uncertainty:* lack of any information to assess the likelihood of plausible future events.

Risk management in SCM has gained considerable attention in both practice and academia recently. It consists of a structured approach to deal with uncertain events through a sequence of human activities (Azad et al. (2013)). The activities and decisions of Supply Chain Risk Management (SCRM) vary from risk assessment, reactive actions preparation (e.g., action plan), proactive robust design (e.g., redundancies, investment in robustness and safety systems, backup supplier) along with others. The aim is to limit the effects of different risks to an accepted level for the company that permits to perform in an efficient as well as robust way.

Organizations can be threatened by numerous types of risk caused by technology, politics, humans, and environment. Tang (2006) categorized SC risks into two different types:

- *Operational risk* usually has no influence on functionality of SCs elements, while it affects the operational factors; based on the previous distinction of uncertainty levels, this risk can be classified as randomness.
- *Disruption risk* is a particular kind of event that may occurs due to natural disaster (earthquakes, floods) or through intentional/unintentional human actions (war, terrorist attack, strike). Usually, they have a low likelihood of occurrence against a high magnitude of consequences; therefore, they can be classified as hazards or deep uncertainty processes.

In a day-to-day basis, companies are used to deal with operational risks; whereas, in recent years, global supply chains are suffering much heavily from major disruptions caused by severe natural and man-made disasters.

Recently, disruption management has captured so much attention both from academia and industries for different reasons (Snyder et al. (2016), Jabbarzadeh et al. (2016)). First, the occurrence of several events is increasing capturing the public attention: 2017 has been registered as the year with the highest level of economic losses due to natural disaster (Bevere et al. (2018)). Second, the trends of last decades on just-in-time (JIT) philosophy and lean design has led to SC that performs well under standard working conditions, but the systems suffer more vulnerability to major disruptions. Third, companies are less vertical integrated, and suppliers are distributed around the world in regions that sometimes are politically or economically unstable.

These examples underline the importance that Supply Chain Network Design under disruption risks has gained in recent years. The increase in popularity of this topic has led to numerous models published in this field. Hence, a review is needed to understand the exhaustiveness of the published works and to draw up some future directions.

The aim of this paper is to analyze relevant papers in the field of Supply Chain Network Design under Disruption Risks. More specifically, this study is focused on two particular parts of the models: (i) how disruption costs have been inserted in the design models and (ii) which cost factors are considered in the disruption cost quantification. Other literature reviews have been published in the topic of SCN Design with disruption consideration or under uncertainties for example Snyder (2006), Klibi et al. (2010), Snyder et al. (2016) or Hosseini et al. (2019). However, to the best of our knowledge, none of the previous studies have put the focus on the disruption cost quantification.

The reminder of the paper is organized as follow. After a detailed explanation of the research procedures (section 2), section 3 describes the insight obtained from the analysis of the first selection of documents. Further, the focus is shifted on the disruption cost quantification in section 4. Finally, section 5 presents a discussion of the main insights and future directions.

2. Research methodology

The analysis of the literature permits to map and evaluate the current studies for identifying some potential research trends and future development. In this section, the data collection process is presented. The review protocol proposed by Andriolo et al. (2014) has been followed.

The research has been performed in the Scopus database comprising papers until the end of February 2019. Two groups of keywords have been selected as stated in table 1:

- Group1: the first group concerns with the scope of the model. In fact, *"Supply Chain Network Design"* and different synonymous have been inserted in addition to *"Facility location"*.
- Group2: the second group of keywords regards the particular environment of SCN Design that we want to investigate (under uncertainty and, more specifically, under disruption risk).

The query has been performed in "Title, abstract and keyword" and limited to only papers written in English and published (or in press) in Journals or Conference proceedings.

Table 1
Groups of keywords used for the research

Group1	Group2
"Supply Chain Network Design"	*Disruption*
"Supply Network Design"	
"Logistics Network Design"	
"Facility location"	

Results gave 179 hits, which have been considered for this review. Therefore, the documents have been analyzed initially by reading abstract and conclusions; further, the full paper has been taken into consideration. The main criteria for the selection was that the papers should contain one quantitative model which consider at least a facility or transportation link (TL) disruption. Thus, the following analysis is focused on a final selection of 48 documents.

3. Literature analysis comparison and categorisation

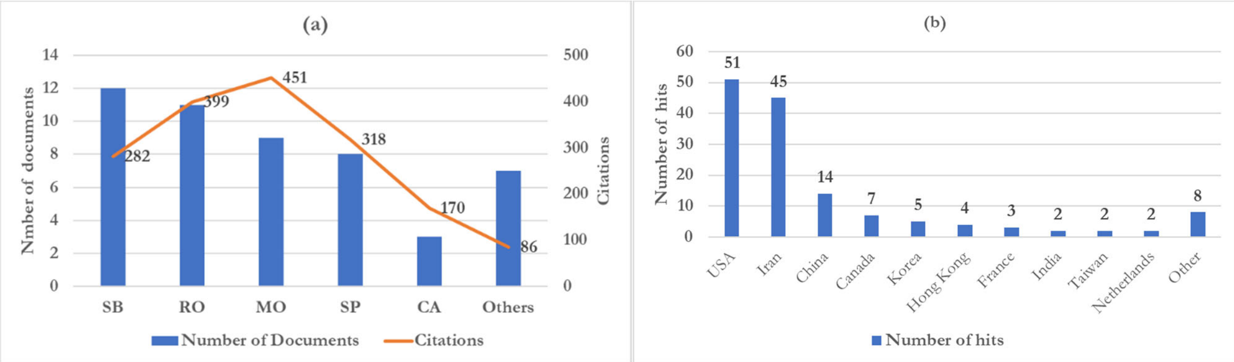
In this section, a summary of the selected papers obtained from the research procedure explained in section 2 is presented. Figure 1(a) shows the number of documents and citations categorized by the design approach.

Scenario-Based programming and Robust Optimization result as the most common used practices for modeling the problem in exam, with 12 and 11 documents respectively. However, Multi-objective optimization has obtained the largest amount of citations.

Stochastic Programming (SP) is a well-known approach to mathematical model for involving uncertainties and random parameters. In SP, one or more variables included in the model are governed by a probability distribution; the main stochastic parameters included in SCN Design problems are demand, lead time and prices. Different ways of approaching SP has been used in the literature as Scenario-based programming and Robust Optimization.

Scenario-Based programming (SB) consists in modeling the stochastic parameters as a set of different discrete scenarios with a known probability of occurrence. This technique is largely employed for SCN Design but, as introduced by Snyder (2006), it has two main issues: at first, to associate a probability for each scenario can results in a difficult and awkward task; secondly, for having a representative model, an adequate number of scenarios are required, leading to a large-scale optimization problem. However, SB permits to model statistical dependencies among parameters that it is usually necessary when treating real world, and especially SCN Design problems.

Instead, Robust Optimization (RO) has been introduced by Mulvey and Ruszczyński (1995) and it gained much attention in applications that operate with uncertainty. Since disruptions tend to be rare event, historical data can be difficult to obtain; moreover, the correlated probabilities could be difficult to estimate or not well representative of the event. Thanks to robust optimization, the modeler no more needs to estimate the probability distribution of the random parameters (Peng et al. (2011)): an interval of possible values define the random variables and they are successively modeled as a set of different scenarios. Thus, this approach aims to find solutions that are feasible for all realization of uncertain parameters obtaining results less sensitive to the uncertainties of input data (Hamidieh et al. (2018)).



In Figure 1(a): Robust Optimization (RO); Scenario-Based programming (SB); Multi-objective optimization (MO); Stochastic Programming (SP); Continuum Approximation approach (CA)

Figure 1: Number of documents and citations per design approach (a); Authors affiliation's country (b)

Multi-Objective optimization (MO) is a specific form of mathematical optimization problems that involves two or more objective functions. In addition, there is the possibility to assign different weights to the objective functions based on the priorities of the modeler. This approach is often utilized because it provides greater flexibility (Snyder and Daskin (2005)); furthermore, changing the weights assigned to the objective functions, the modeler can understand more about the impact of different terms and draw up more advanced insights.

Most of the traditional SCN Design problems are NP-hard and therefore require excessive computational efforts for solving it (Li and Ouyang (2010)). To overcome this, in the last years, modelers are adopting the Continuum Approximation approach (CA). This technique consists of converting discrete data (e.g., available locations of facilities, specific information for different locations) into a continuous scale for deriving an analytical model (Lim et al.(2013)). Thus, the CA model is a very good approximation of the exact problem and leads to provide valuable managerial insights in shorter time.

As can be seen in figure 1(b), the vast majority of the documents' authors come from USA and Iran, with the 36% and 32% of the papers respectively. The reason under this can be the high number of disruption events these countries are subject to. USA is every year raided by so many devastating hurricanes and leads the top 10 ranking as the country with the highest economic losses due to natural disaster (Bevere et al. (2018)); Iran is one of most earthquake-exposed country in the world and in the last years, more than 50,000 people passed away because of natural disruption (Jabbarzadeh et al. (2014)).

4. Disruption Cost quantification

In this section disruption cost quantification is analysed. The vast majority of papers modeled the SCN Design problem with Scenario-Based programming and Robust Optimization. Most of these studies are based on defining different set of parameters' values for every scenario. Given that, the following analysis has been limited only on works that present a specific and dedicated quantification of costs triggered by disruptions inside the SCN Design model. More precisely, it has been excluded all models that quantify the disruption effects through changing the values of various cost terms across different scenarios and that no present a precise definition of the costs provoked by disruptions. Thus, this further selection results in a final group of 20 papers. Table 2 illustrate the main characteristics of the selected documents. It is notable that all studies taken into account present an empirical study for testing the model and for achieving more authenticity and trustfulness. Furthermore, eight papers apply the model to a real-life case-study; no trends have been identified regarding the application sector.

In the following analysis, the words disruption, interruption and failure are considered interchangeable. In addition, we will refer to a reliable facility as a facility that is completely immune to failures; further, reliable, indefectible and nonfailable are considered synonymous.

Every model is briefly introduced in terms of modeling technique and disruption modeling. Finally, the focus is placed on the Expected Disruption Cost (EDC) quantification.

Snyder and Daskin (2005) introduced a new method for the customers assignment in the facility location problem called "level-r" assignment. They assume that every customer can be assigned to a maximum number *r* of facilities: the level-0 facility is the primary assignment that will serve it under standard operating conditions; from level-1 to level-r, the customer is assigned at backup facilities. In other words, if the primary facility fails, a second backup facility (r=1) is already planned, and so on.

In the multi-objective model developed by Snyder and Daskin (2005), the level-r assignment is extended by considering reliable and unreliable facilities. Thus, each customer has a level-r assignment for each r=0, …, r, unless it is assigned to a level-s facility that is reliable (i.e., nonfailable), where s<r. Therefore, the expected disruption cost consists of the penalty transportation cost of not serving the customer through the level-0 facility.

Instead, Deleris et al. (2004) analyzed the impact of fire risk into a large U.S. manufacturing supply network through a simulation study. The paper does not present in detail the terms used for the cost quantification, but the EDC is qualitatively defined as the sum of lost production cost and the property damage cost caused by hazards. As explained in the section 2, the CA model is a good alternative for solving large-scale problems to overcome some issues of the discrete model. Li and Ouyang (2010) presented a continuous location problem with spatial correlated disruptions consideration. This application assumes customers have complete information about the facility

Table 2
Disruption cost's term considered by the documents included in the analysis

	Modeling method	TP	TS	BC	PD	I	LP	S	RF	Model application
Anand and Kumar (2017)	SP	✓	✓						✓	NE
Azad et al. (2013)	SP	✓	✓						✓	NE
Azad et al. (2014)	SP	✓	✓						✓	NE
Bozorgi Atoei et al. (2013)	MO		✓							NE
Deleris et al. (2004)	SIM				✓		✓			CS
Fattahi et al. (2017)	SB				✓				✓	CS
Hatefi et al. (2015)	SP		✓						✓	NE
Jabbarzadeh et al. (2016)	RO		✓						✓	CS
Jabbarzadeh et al. (2018)	RO		✓							CS
Lee et al. (2014)	MO			✓						CS
Li and Ouyang (2010)	CA	✓							✓	NE
Lim et al. (2013)	CA	✓							✓	NE
Mari et al. (2016)	MO			✓						NE
Marufuzzaman et al. (2014)	SB	✓								NE
Salimi and Vahdani (2018)	SP	✓							✓	CS
Shukla et al. (2011)	SB			✓						CS
Snoeck et al. (2019)	SB	✓		✓	✓			✓		CS
Snyder and Daskin (2005)	MO	✓							✓	NE
Yun et al. (2015)	SP	✓		✓						NE
Zhang et al. (2016)	SP	✓				✓				NE
Table's summary:	Transportation penalty: 60%, Transshipment cost: 35%, Backlog cost: 20%, Property Damage cost: 15%, Inventory variation cost: 5%, Lost Production: 5%, Sourcing Variation cost: 5%;									

In this table: Transportation Penalty (TP), Transshipment cost (TS), Backlog cost (BC), Property Damage cost (PD), Inventory variation cost (I), Lost Production (LP), Sourcing Variation cost (S); Reliable Facilities consideration (RF); Stochastic Programming (SP); Scenario-Based programming (SB); Multi-objective optimization (MO); Robust Optimization (RO); Continuum Approximation approach (CA); Simulation-based optimization (SIM); Numerical Example (NE); Real-life Case-Study (CS).

state, i.e. they are aware if the facility is disrupted and therefore able to choose another site (this assumption can be considered reasonable giving the modern information technology devices). A customer shall only be served if a facility lies inside a distance limit otherwise the model registers a penalty cost for not fulfilling the demand. Thus, the expected disruption cost is quantified as the excessive transportation cost of not being served by the closest facility.

An extension of the previous model is introduced by Lim et al. (2013). The authors add the possibility to differentiate the facilities between reliable and unreliable. A customer has assigned at least one unreliable and one reliable site by a distance point-of-view. If the closest facility is unreliable and fails, the demand is served by the closest reliable facility. Thus, the EDC is modeled as the additional transportation cost for going to the farther reliable facility.

Shukla et al. (2011) developed a mixed-integer linear program using a scenario planning approach where the objective function aims to maximize the trade-off between efficiency and robustness. The former is defined as the total operation cost i.e. the sum of infrastructure, material handling and transportation costs. On the other hand, the robustness metric is equivalent to the expected disruption cost defined as the backlog the supply network can incur during disruption.

Another interesting contribution to the literature has been introduced by Azad et al. (2013) and Azad et al. (2014). The authors presented a capacitated SCN Design model for the Distribution Centers (DCs) location-allocation with random disruption at facilities and transportation links. Both for DCs and TLs, there is the possibility to build reliable/unreliable and safe/unsafe items respectively and disruptions cannot affect reliable facilities and safe TLs. Furthermore, the authors introduce the *soft-hardening strategy:* when a disruption occurs, an unreliable DC undergoes only a capacity reduction based on its investment level in robustness. In addition, when dealing with an interruption, the model considers the *good sharing strategy* where customers of a disrupted DC are not assigned to other DCs necessarily, since the capacity lost in the disrupted DC will be amended from a non-disrupted DC (lateral transshipment). The expected disruption cost is modeled as a combination of an increment in cost due to the secondary transport assignment after a TL disruption and a penalty cost for moving goods from reliable DCs to unreliable ones.

Bozorgi Atoei et al. (2013) presented a multi-objective programming model for SCN Design considering random disruption at distribution centers and suppliers. The objective function aims to minimize the total cost and maximize the reliability. As in Azad et al. (2013), disruptions can partially disable a percent of capacity at the facilities which can compensate this lack of availability asking goods to other non-disrupted facilities. Hence, the expected disruption cost is directly defined as the transportation costs of lateral transshipment.

Then, Lee et al. (2014) proposed a Weighted Goal Programming (WGP) model for a network optimization with sustainability consideration in terms of carbon emissions and embodied carbon footprints. All the 3 lever facilities (supplier, manufacturing, and warehouse) can fail. The EDC is specifically quantified as the quantity of goods

transported to the disrupted facility (directly related to the disruption probability) multiplied by the profit margin of the goods *(backlog cost)*.
Successively, Mari et al. (2016) proposed an extension of the previous work with a multi-objective mixed integer linear model, considering economics, sustainability, and resilience targets in a Closed-Loop SCN design. The expected disruption cost considers only the forward supply chain and consists in the backlog cost quantified as the transported quantity influenced by the disruptions multiplied by the product price.
Before, Hatefi et al. (2015) presented a stochastic mixed-integer linear programming model for a forward-reverse logistics network with hybrid distribution-collection facilities (HDC) that can be subject to random disruption. The study allows two types of HDC, reliable and unreliable, and when an interruption occurs, the unreliable facility can suffer a partially reduction both in distribution and collection capacity. Additionally, a good sharing strategy is also possible between facilities. The expected disruption cost consists in the cost of lateral transshipment from reliable HDC centres to unreliable one.
Moreover, Jabbarzadeh et al. (2018) developed a stochastic robust optimization model for a Closed-Loop SCN Design where disruptions can affect multiple actors of a supply chain (suppliers, production centers and collection centers). Lateral transhipment between production centers has been included as a possibility to mitigate the effect of an interruption. Thus, the EDC consists of the transportation costs for sending goods from a non-disrupted facility to a disrupted one.

Jabbarzadeh et al. (2016) designed a robust stochastic optimization model with random supply/demand and facility disruptions. The facilities can be reliable or unreliable and the interruptions occurrence and magnitude on unreliable facilities depends from a fortification level. Disruptions have a direct impact in the objective function as a transportation penalty cost for moving products from non-disrupted DC to disrupted DC during the interruption period.
Successively, Fattahi et al. (2017) proposed a multi-stage stochastic program for a multi-period SCN Design composed by production plants, warehouses, and customer zones. The model considers random stochastic demand and only warehouses can be threatened by disruptions that cause variations in the capacity based on the fortification level. The expected disruption cost has been estimated as the cost of recovering a failed warehouse after a hazard occurrence. Considering that the disruption magnitude follows the soft-hardening strategy introduced by Azad et al. (2013), even the EDC is directly correlated to the fortification level.
Moreover, Anand and Kumar (2017) developed a distribution network design model considering unexpected disruption at DCs and transportation links. The facilities can be protected from interruptions or their capacity can be partially unavailable based on three level of investment in robustness. The supply network reacts to a disruption occurrence with the good sharing strategy proposed by Azad et al. (2013). Therefore, the EDC is defined as an increment in transportation costs due to secondary assignment of transportation mode and the penalty costs of lateral transshipment between DCs.

Marufuzzaman et al. (2014) design a Scenario-Based SCN Design of a bio-fuel network consisting of biomass suppliers, intermodal hubs, and bio-refineries. The model considers intermodal hubs can be subject to site-dependent probabilistic disruption that completely shut down the center. When an intermodal hub fails, the route supplier-hub-refinery is no longer available; thus, the traffic is rerouted to an emergency direct line supplier-refinery. Since extraordinary services usually cost more than a scheduled one, the EDC is modeled as a penalty transportation cost quantified as β times higher than the regular cost.
Then, Yun et al. (2015) proposed a mixed-integer non-linear programming where customers do not know the real-time state of the facilities. Each customer is assigned to a number *r* of facilities and it always tries them sequentially according to its level-r pre-specified assignment. Hence, the expected disruption cost is quantified as the additional transportation cost of not finding available the primary assignment facility; additionally, the authors added the possibility of not finding any available facility incurring in a shortage cost for non-fulfilling the demand.
Another interesting work is the one of Zhang et al. (2016). The authors developed a stochastic mixed-integer non-linear programming considering all failable facilities but adding the influence of disruption in the inventory cost. If a DC is disrupted, it is completely unavailable, and the services are reassigned to other surviving DCs to a higher level. In addition, when facility fails, the inventory system is not able to operate optimally because they do not yet reflect the new customer assignments. Thus, the EDC consists of the higher costs in the inventory system and in the transportation when customers are served with a level-r assigned facilities instead of the primary assignment.
Successively, Salimi and Vahdani (2018) designed mixed-integer non-linear stochastic model for the location-allocation of bio-refineries in a bio-fuel SCN. Facilities can also be set up perishable or indefectible to interruption, but disruptions can completely disable only bio-refineries and transportation links. When a facility fails, the risk pooling effect is considered: customers assigned to a failed bio-refinery are re-assigned to another operating facility. Thus, the EDC is quantified as a penalty in transportation costs due to a secondary facility assignment.

Finally, Snoeck et al. (2019) has recently proposed a scenario-based stochastic model considering operational and disruption risk (randomness and hazard uncertainties). The expected disruption cost is expressed as function of the deviation between the standard operational conditions of the network and the conditions during the disruption period. The main affected variable costs are four. Firstly, the SC difficulty is able to sell the same quantity of products as in the standard operational conditions leading to (i) lost sales. Consequently, the changes in the production influence the required quantity of supply causing variation in the feedstock price ((ii) resourcing costs). Hence, a change in sourcing influences also the (iii) transportation costs. Finally, if the in-out flow of a facility is lower than a predefined minimum, the process should be shutdown incurring in a (iv) shutdown costs. For some specific production process, it could be possible to enter in stand-by mode to avoid the high cost of a shutdown.

5. Discussion and Future Research steps

This paper provides a literature review in the topic of Supply Chain Network Design with disruption risk consideration. Despite their rare occurrence, disruptions have often disastrous consequences on the business continuity of firms making this area really interesting both for academics and practitioners.
At first, some initial and generic considerations are taken on a selection of 48 papers analysing the most frequent modeling technique and the origin of the documents. Successively, the examination has been focused on the quantification of the expected disruption cost on a narrower selection of 20 papers.

Disruption consideration in SCN Design, but generally in all risk management practices, are processes marked by uncertainties. Therefore, it is reasonable that the most used modeling techniques are Stochastic Programming organised in Scenario-Based programming and Robust Optimization. Although these approaches are employed for reducing the complexity of these problems, the data collection process for applying the proposed models can require excessive efforts resulting in models that are difficult to apply by companies and practitioners.
An important point of reflection regards how to model the disruption impact and the reaction phase of the supply chain actors. Some papers treat disruptions as they completely shut down a site (Lim et al. (2013), Li and Ouyang (2010), Marufuzzaman et al. (2014), Salimi and Vahdani (2018), Shukla et al. (2011), Snyder and Daskin (2005), Yun et al. (2015), Zhang et al. (2016)); otherwise, others consider only a partial reduction in capacity (Bozorgi Atoei et al. (2013), Hatefi et al. (2015), Snoeck et al. (2019)), sometimes based on the investment in robustness (Anand and Kumar (2017), Azad et al. (2013), Azad et al. (2014), Fattahi et al. (2017), Jabbarzadeh et al. (2016)). Thus, this topic requires further investigation.
Another outstanding issue is related to the activities a disrupted site can perform: some models permit the disrupted facilities to be able to serve customers and, during the interruption, goods are provided by other non-disrupted sites through lateral transshipments (Anand and Kumar (2017), Azad et al. (2013), Azad et al. (2014), Bozorgi Atoei et al. (2013), Hatefi et al. (2015), Jabbarzadeh et al. (2016), Jabbarzadeh et al. (2018)); differently, other works impose the reassignment of the customers served by failed facilities to other non-failed ones (Lim et al. (2013), Li and Ouyang (2010), Salimi and Vahdani (2018), Snyder and Daskin (2005), Yun et al. (2015) Zhang et al. (2016)). Therefore, this ambiguity should be additionally analyzed.
Furthermore, disruption cost quantification seems still to be an issue in SCN Design. As it can be seen from table 2, there are no common practice in modeling them. Most of the studies consider a penalty in the transportation costs (60% of the analyzed works) but they omit some important factors such as property damage cost (comprised only by Deleris et al. (2004), Fattahi et al. (2017), and Snoeck et al. (2019)). However, the work published by Snoeck et al. (2019) seems to be the most complete with regards to the different cost factors included in the model. Furthermore, as a limitation of the study, by extending the analysis to a wider selection of papers, the distribution of disruption cost's terms inserted in the model with regard to the percentages presented in table 2 can be subject to variations.

Finally, future efforts in this context should consider the following guidelines directly derived by the literature analysis before described:

- As figure 1(b) shows, there is a lack of documents that come from Italy although the risk of disruption in this country is reasonably high, especially from natural hazards.
- A significant number of models (50% in the specific analysis in section 4) consider the possibility of setting up reliable facilities that are non failable. Nevertheless, this modeling characteristic is highly not representative of the reality because it is fairly impossible to build disruption immune sites (Ivanov (2018)).
- The possibility of varying the disruption occurrence probability and magnitude based on the investment level in setting up facilities represents a good direction for including robustness and proactive risk-mitigation strategy in SCN Design problems. However, disruptions are all different and, additionally, some mitigation strategy can impact only on some kind of risks and not on others. Therefore, future studies should try to quantitatively examine the correlation between investment in robustness and disruption probabilities reduction.
- As stated before, we highlight different ways in establishing the activities affected by an interruption and the others still available (e.g., disruptions pause only the in-bound processes; production is stopped; complete shutdown of the facility). Thus, a common practice is required regarding the tasks that facilities can perform under disruption.
- Regarding disruption cost quantifications, a common practice is needed for integrating in the SCN Design models all the impact a disruption can have in terms of both operational and investment costs.

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