Simulation-Optimization Methods for Designing and Assessing Resilient Supply Chain Networks under Uncertainty Scenarios: A Review

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Abstract

The design of supply chain networks (SCNs) aims at determining the number, location, and capacity of production facilities, as well as the allocation of markets (customers) and suppliers to one or more of these facilities. This paper reviews the existing literature on the use of simulation-optimization methods in the design of resilient SCNs. From this review, we classify some of the many works in the topic according to factors such as their methodology, the approach they use to deal with uncertainty and risk, etc. The paper also identifies several research opportunities, such as the inclusion of multiple criteria (e.g., monetary, environmental, and social dimensions) during the design-optimization process and the convenience of considering hybrid approaches combining metaheuristic algorithms, simulation, and machine learning methods to account for uncertainty and dynamic conditions, respectively.

Keywords: Resilient Supply Chain Networks Design; Simulation-Optimization Methods; Uncertainty Scenarios; Metaheuristics

1. Introduction

A supply chain network (SCN) is a typical example of a complex and large-scale system. Bidhandi et al. (2009) define it as a network of suppliers, manufacturing plants, warehouses, and distribution channels organized to acquire raw materials, convert these raw materials into finished products, and distribute

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these products among customers. Many decisions must be made in such a complex system in order to guarantee a good performance. However, the more complex a system is, the more imprecise or inexact is the information available to characterize it and, therefore, the greater the uncertainty level (Booker & Ross, 2011).

Supply chain network design (SCND) is a concept broadly studied during the last decades, both from a qualitative and a quantitative perspective. Authors have referred to it by using the terms *supply chain design* and *supply chain network design*. Carvalho et al. (2012) state that a SCND problem "comprises the decisions regarding the number and location of production facilities, the amount of capacity at each facility, the assignment of each market region to one or more locations, and supplier selection for sub-assemblies, components and materials". These decisions are related to a strategic level, and must be optimized considering a long-term (usually several years) efficient operation of the supply chain as a whole (Altiparmak et al., 2006). One of the more challenging responsibilities in SCND is addressing uncertainty. Anticipating the future is crucial in planning and design processes. However, the future conditions of the business environment is generally difficult to predict. Blackhurst et al. (2004) state that one of the causes of SCNs complexity is their dynamic nature and the uncertainty in variables such as demand, capacities, transportation times, or manufacturing times.

In recent years, a trend in the literature has been the consideration of resilience for designing and assessing SCNs in order to face uncertainty. Christopher & Peck (2004) define *resilience* as "the ability of a system to return to its original state or move to a new, more desirable state after being disturbed". Similar definitions can be found in fields different to SCND, such as ecology, psychology and economy (Ponomarov & Holcomb, 2009), or natural disasters risks mitigation and adaptation in urban systems (Harrison & Williams, 2016). For instance, a concept from earthquake studies is given by Bruneau et al. (2003), who state that "seismic resilience is the ability of both physical and social systems to withstand earthquake-generated forces and demands and to cope with earthquake impacts through situation assessment, rapid response, and effective recovery strategies."

Addressing resilience from the civil infrastructure point of view is very usual in engineering. For instance, in order to design and assess this type of systems, Bocchini et al. (2014) propose a unified framework integrating resilience and sustainability concepts. Biondini et al. (2015) present a probabilistic approach to assess the lifetime of concrete structures seismic resilience. The joint effects of seismic and environmental – e.g., corrosion – hazards are studied. Applications to a concrete frame building and a continuous bridge are considered. Bridges and bridge networks are also considered by Akiyama et al. (2020), who assess the effects of earthquakes and other independent and interacting hazards in the resilience of this type of structures. These authors highlight that the most recent research has focused on studying the civil infrastructure as a connected system instead of individual components. It is relevant to highlight that although the civil infrastructure is a very important part of a supply chain, it is not the only one subject to uncertainty and risks, as we will study in this paper. For instance, after a disruptive event, the recovery of a supply chain takes more time than the infrastructure restoration (Ni et al., 2018), given the multiple and different components of a SCN. Hence, the position of our review is more holistic.

Resilient SCND has been a topic able to attract the attention of researchers, specially when trends such as leanness and globalization have increased the risks that supply chains must face. Regarding leanness, it makes SCNs more vulnerable due to the reduction or even removal of redundancies (Behzadi et al., 2017). Regarding globalization, the increasing complexity of SCNs in a globalized world causes higher uncertainty (Hohenstein et al., 2015). Moreover, globalization increases supply chain vulnerabilities (Dixit et al., 2016). Expanding globally a supply chain raises the likelihood of facing new risks that might not exist in a local range. For instance, a natural disaster such as the 2011 earthquake in Japan, which triggered a tsunami and a nuclear crisis, affected many global companies like those in the silicon wafers industry. Since 60% of silicon wafers world demand were supplied by Japan (Pariazar & Sir, 2018), this product availability decreased considerably. The same disaster affected also all Toyota factories. Although most of them were not directly affected, a two-week shutdown was caused by disruptions in the components supply, given the Toyota's lean production planning (Goldbeck et al., 2020). Human-induced disasters are also a source of disturbances for supply chains, either they are deliberate (e.g., terrorist attacks) or caused by involuntary mistakes or negligence (e.g., the 2010 oil spill in the Gulf of Mexico), as described in Ramezankhani et al. (2018). These examples show the relevance of considering resilience aspects when designing and assessing supply chains, since they need to recover successfully after the occurrence of such disruptive events.

The terms *risk* and *vulnerability* are closely related to resilience. Carvalho et al. (2012) relate supply chain vulnerability to the incapacity of a SCN to react to disturbances. More exactly, Heckmann et al. (2015) define *supply chain vulnerability* as "the extent to which a supply chain is susceptible to a specific or unspecific risk event". Here, the *disturbance* concept is similar to the *risk* concept, being this a primary term previous to vulnerability. Peck (2006) defines *supply chain risk* as "anything that disrupts or impedes the information, material or product flows from original suppliers to the delivery of the final product to the ultimate end-user". Therefore, the more resilient a SCN is, the lower its vulnerability to risks (Rajagopal et al., 2017). A review about the use of quantitative approaches in supply chain risk management is carried out by Oliveira et al. (2019). They perform a Systematic Literature Review (SLR) to analyze and synthesize the contribution of simulation and optimization methods in this field. Moreover, when risks cause a disruption in a few nodes, their effects can easily spread to other parts of the supply chain. This phenomenon is known as *the ripple effect* (Li & Zobel, 2020). According to Dolgui et al. (2018), the ripple effect causes lower revenues, delivery delays, loss of market share and reputation, as well as stock return decreases, hence affecting the global performance of the supply chain.

Epidemic outbreaks are a very special case of SCN risks characterized by a long-term disruption, disruption propagation (i.e., the ripple effect), and high uncertainty due to simultaneous disruptions in supply, demand, and logistics infrastructure (Ivanov, 2020). Particularly in 2020, the global pandemic caused by the COVID-19 disease has largely affected all areas of the economy and society worldwide. Some supply chains have experienced an increase of demand that they are not able to satisfy (facial masks, hand sanitizer, ventilators, etc.), while others are suffering long-time production stops like the ones of non-essential products. These companies are in danger of bankruptcies and needing help from governments. As pointed out by Ivanov & Dolgui (2020), supply availability in global supply chains has been largely decreased and imbalanced with the demands. Thus, this pandemic is an unprecedented and extraordinary situation that clearly shows the need for advancing in research and practices of SCN resilience. In addition, new concepts related to resilience, such as supply chain survivability, are emerging in the literature.

In logistics and supply chain management, quantitative approaches are mainly classified into two groups: optimization and simulation, which are mostly used independently to address uncertainty – e.g., see Govindan et al. (2017) and Stefanovic et al. (2009) for each group, respectively. However, given the growth in computational power, the use of hybrid simulation-optimization (sim-opt) methods has increased in recent years (Juan et al., 2018) in order to combine the most important advantages of both worlds, mainly because of its suitability to address uncertainty (Chiadamrong & Piyathanavong, 2017). Nevertheless, in the more specific topic of SCND, applications of hybrid sim-opt methods are still scarce and, to the best of our knowledge, it is almost nonexistent in SCND resilience. In regard to existing review articles about this topic, most of them still address conceptual papers, which shows the relevance of carrying out a review analyzing papers following a quantitative approach. Accordingly, this work provides a review that synthesizes the main studies related to quantitative SCND resilience, as well as to the sim-opt methods employed for that. Moreover, the paper also highlights some open challenges that need to be addressed by the sim-opt community.

The remaining of this document is organized as follows: Section 2 extends the motivation of this paper by explaining the extent of previous literature reviews addressing SCND resilience and sim-opt methods in this field. Section 3 explains the research methodology employed to carry out this review. The findings of this paper are presented in Section 4, where discussions on relevant works are also presented in Subsections 4.1 and 4.2, respectively. Section 5 provides insights and future research directions by analyzing how emerging hybrid methods can be useful for designing resilient SCNs under uncertainty or dynamic conditions, as well as the concept of 'agile' SCND. The paper ends in Section 6 by outlining some concluding remarks.

2. Previous Literature Reviews and Positioning of Our Work

To the best of our knowledge, there are no published literature reviews that combine sim-opt methods with SCN resilience. A review by Pourhejazy & Kwon

(2016) highlights the use of sim-opt frameworks as a growing research area. Integrated problems such as location-routing, inventory-routing, and location-inventory are analyzed, and sim-opt applications are studied. Finally, the authors analyze papers addressing sustainability issues, concluding that this is a relevant trend along with resilience. Therefore, they state that sim-opt frameworks are the main tool to design and manage SCNs. However, despite the relevance these authors give to resilience, they do not analyze papers considering this dimension.

A total of 19 review papers discussing the concept of "supply chain resilience" were found since 2015. Only one review previous to 2015 was found (Ponomarov & Holcomb, 2009). Here, the authors relate the SCN resilience concept to traditional resilience concepts from the ecological, social, psychological, and economic fields. Most of these works are conceptual, i.e., they discuss about resilience and some related concepts. These conceptual papers help to clarify terms in order to have a better understanding on the topic. For instance, Zhao et al. (2017) carry out a systematic review in which risk sources and resilience factors in agri-food supply chains are identified. In addition, particular parameters that can affect this type of SCNs are presented. A systematic review by Stone & Rahimifard (2018) includes 137 articles from different fields such as engineering, operations management, ecology, and social sciences in order to identify definitions, elements, and strategies that can be relevant for resilience in agri-food SCNs. More recently, Gligor et al. (2019) perform also a review from a multidisciplinary point of view (including supply chain management, information systems, psychology, among others) to establish differences and similarities between *agility* and *resilience* concepts.

Tukamuhabwa et al. (2015) reviewed 91 papers related to SCN resilience, showing that most studies (43%) are conceptual or theoretical, and 36% of them adopt modeling approaches. Several definitions of "resilience" are provided, as well as proactive and reactive strategies for building resilient SCNs. Associated concepts like flexibility, redundancy, collaboration, and agility are identified. Little attention is paid by these authors to modeling articles. Such concepts and others related to SCN resilience are also identified by Sawyerr & Harrison (2020), who call them "formative elements". These are compared with characteristics of high reliability organizations. Alternatively, Radhakrishnan et al. (2018) call these concepts as "key capabilities". They identify 4 of them: flexibility, velocity, visibility and collaboration, as well as 13 attributes related to SCN resilience. Shashi et al. (2020) expand such concepts by identifying resilience-related barriers, metrics and strategies. These are presented into a unified framework after analyzing 125 papers. Additional topics are analyzed by Ali & Gölgeci (2019), who combine SLR with VOSviewer Co-occurrence Analysis to identify a set of drivers, barriers, theories, moderators, mediators and research methods in SCN resilience.

A systematic review of 67 papers is carried out by Hohenstein et al. (2015). Here, many SCN resilience definitions are presented. The quantitative approach is only addressed by analyzing some papers regarding how to measure resilient designs. Kochan & Nowicki (2018) establish a typological framework by performing a review of the SCN resilience concept. Few definitions are shown, and the core of the review is to expose such typology. Terms like supply chain disruptions, risk, vulnerabilities, or capabilities form the conceptual taxonomy to classify reviewed papers. This paper highlights that the SCN resilience concept is far from being mature. An SLR methodology is also used in a review by Datta (2017) to synthesize conceptual and empirical studies related to resilience in supply networks. A total of 9 key constructs of SCN resilience are identified and defined: risk, general vulnerability, operational vulnerability, complexity, uncertainty, risk management, agility, supply chain understanding, and collaboration. Kamalahmadi & Parast (2016) review 100 papers, proceedings, and book chapters related to enterprise and supply chain resilience concepts. Only 6 articles that use operations research and management science tools were found. Unlike other review papers, these authors include some resilience-enterprise definitions. Several principles and strategies are also identified.

Elleuch et al. (2016) provide a review focusing on both vulnerability and resilience terms. A total of 40 articles were reviewed, 28 regarding resilience and 12 regarding vulnerability. A few definitions related to these terms are provided. Finally, papers relating resilience, vulnerability, and some performance measures are shown. Ali et al. (2017) also carry out a literature review to analyze the SCN resilience concept based on 103 articles. Many definitions are provided and 5 capabilities are analyzed (ability to anticipate, to adapt, to respond, to recover, and to learn). Nevertheless, its most important contribution is the conceptual synthesis, which is performed via a holistic model. Wang et al. (2016) state the importance of analyzing SCN definitions besides the usual resilience-related ones. Then, a review of studies that apply resilience to supply chain management is provided. The authors conclude that the SCN resilience concept becomes more relevant when considering holistic SCNs, i.e., when a set of SCNs are interdependent.

So far, the 16 shown papers address SCN resilience from a qualitative point of view, i.e., they analyze a set of concepts related to this topic. Common drivers characterizing resilience are identified, such as agility, collaboration or flexibility. Nevertheless, given the relative novelty of the topic, there is not still a unified general framework, and each author shows a different set of concepts. Alternatively, 4 papers addressing quantitative approaches in SCN resilience were found: Ivanov et al. (2017), Dolgui et al. (2018), Ribeiro & Barbosa-Povoa (2018b) and Hosseini et al. (2019). These authors' remarks establish that most of their reviewed papers are conceptual and, therefore, there is a lack regarding the use of quantitative models for addressing SCN resilience. For instance, Ivanov et al. (2017) provide a review about both disruptions and recovery in supply chain design and planning. Their perspective is to show papers that use quantitative tools regarding disruptions risks (natural or human-induced disasters, strikes, etc.), by differentiating these from operational risks (produced by uncertainty in demand, lead-time, or any other business-related variables). The authors dedicate a few paragraphs to papers that address sustainability.

Dolgui et al. (2018) review papers addressing the ripple effect in the supply chain through a quantitative approach. Quantitative tools such as mathematical optimization, simulation, control theory, complexity analysis, and reliability research are identified, although particularities about these models are not analyzed. Ribeiro & Barbosa-Povoa (2018b) offers a review focusing on the use of quantitative methods to support decisions related to SCND resilience. Strategic, tactical, and operational decisions are identified in 39 papers, as well as the modeling approach, definitions, and 48 resilience factors. Hosseini et al. (2019) identify both qualitative and quantitative drivers of SCN resilience. Their work is based on the concept of "resilience capacity", which comprises three lines of defense: absorptive capacity, adaptive capacity and restorative capacity.

Notice that both conceptual and quantitative reviews are quite recent. This shows a growing interest in the SCN resilience topic. Moreover, although the papers by Hosseini et al. (2019), Dolgui et al. (2018) and Ivanov et al. (2017) address the resilience concept along them, the focus is different than the one employed in our review. For instance, the main topic of the review by Dolgui et al. (2018) is not resilience but the ripple effect. Furthermore, we define a taxonomy more exhaustive and explicit than that used by Hosseini et al. (2019) and Ivanov et al. (2017) . For example, the latter shows a clear focus in disruption risks, which we extend by including operational risks in our analysis. Finally, we address some aspects that these authors do not consider explicitly, such as the uncertain parameters analysis or our exposition of papers tackling real-world cases. Regarding the article by Ribeiro & Barbosa-Povoa (2018b), they analyze all decisions levels (strategic, tactical, and operational) from only 39 papers, which shows the need of studying more thoroughly each of these levels. This is an additional contribution of our work.

An important branch of resilience studies is the metrics used to assess the supply chain performance. Measuring resilience becomes relevant not only to design new supply chains, but also to evaluate an already operational SCN. In this case, resilience metrics are useful for decision-makers to implement strategies that increase resilience at minimal cost. Both quantitative and qualitative indicators can be found. For instance, Cardoso et al. (2015) propose a mixed-integer linear programming model to design a resilient supply chain. The network performance is assessed through 11 quantitative indicators, which are classified into three types: network design, network centralization and operational indicators. A real-world European supply chain is considered as a case study. Sun et al. (2018) perform a review about resilience metrics from the transportation infrastructure point of view. The functionality of these networks is taken as a core to define two types of resilience metrics: functionality-related and socioeconomic metrics.

From a qualitative point of view, Soni et al. (2014) present a study in which 10 resilience enablers are identified to design a unique supply chain resilience index through a graph theory model. Data from both a literature review and surveys answered by Indian firms are used to identify the enablers. Agility, collaboration, supply chain structure, among others, are identified as enablers. Singh et al. (2019) perform an SLR where 17 performance indicators are identified. The supply chain network design is presented as one of these indicators, as well as agility, collaboration and others. Authors divide the SCN resilience into 3 phases: anticipation, resistance, and response and recovery. Notice in all these cited papers that authors highlight the supply chain network design as an important factor to assess resilience, i.e., resilience can not be studied properly without considering design and long-term decisions. This fact shows the relevance of our review.

3. A Systematic Literature Review Methodology

A key requirement in a literature review is that each stage of the process has to be defined in a protocol "intended to guide the whole review, thereby reducing the possible sources of bias which arise from authors making idiosyncratic decisions at different stages of the review process" (Badger et al., 2000). Our review methodology is based on the systematic literature review (SLR) approach introduced by Denyer & Tranfield (2009), which is characterized by "its distinct and exacting principles", its replicability, transparency, and robustness to produce solid and reliable evidence. In addition, reviews related to resilience in SCNs (see Section 2) have been carried out mostly using an SLR methodology.

The SLR steps are: *(i)* question formulation; *(ii)* location of studies; *(iii)* study selection and evaluation; *(iv)* analysis and synthesis; and *(v)* reporting and use of results. Firstly, it is important to formulate suitable questions to delimit the research and avoid to search topics that do not fit into the reviews' objectives. Therefore, a general question was formulated as: *How sim-opt methods have been used to design resilient SCNs?* To answer this general question, the following specific queries were formulated:

1. Which mathematical approaches have been used to design resilient SCNs?
2. Which solving approaches and objective criteria have been used to find solutions to these problems?
3. How uncertainty is addressed when designing resilient SCNs?
4. Which special and real-world cases are addressed by resilient SCND papers?
5. Which challenges remain open when designing resilient SCNs under uncertainty?

Next, papers published in journals and proceedings indexed in *Scopus* and *Web of Science*, as well as papers found in the *ScienceDirect* database, and in the *Google Scholar* search engine were collected. The search was conducted from a more general combination of terms to a more specific one, namely:

- resilien* AND supply AND chain
- resilien* AND supply AND chain AND network AND design
- resilien* AND supply AND chain AND network AND design AND mathematical AND model
- resilien* AND supply AND chain AND network AND design AND optimi?ation

- resilien* AND supply AND chain AND network AND design AND simulation
- resilien* AND supply AND chain AND network AND design AND optimi?ation AND simulation

Notice that the search term "optimi?ation" was employed in order to capture both "optimisation" in British English and "optimization" in American English. The search was carried out in the fields *title, abstract*, and *keywords*. The term *network* was then suppressed to make additional search, since some papers do not use such a word. Mainly qualitative studies were found, even after using the terms *mathematical model, optimi?ation*, and *simulation*. These key terms were mainly used to search for review papers already analyzed in Section 2. In this regard, an additional search was conducted by limiting the document types to *reviews*. In addition, papers previous to the year 2000 were excluded, as well as those studies that do not tackle strategic decisions, according to the definition by Ghiani et al. (2004). However, when using the last combination of terms just a few papers were found. Some of them had already been collected, and others were not coherent with our research questions. For this reason, a sixth research question without including the term *resilien** was formulated, namely: *How sim-opt methods have been used to design SCNs?* Then, a new search was conducted by using the next additional terms:

- supply AND chain AND design AND simulation AND optimi?ation
- supply AND chain AND network AND design AND simulation AND optimi?ation

As a result of this last search, papers not including the combination of optimization and simulation techniques were excluded. In this way, we increased our scope and it was possible to establish a more complete framework. A total of 163 articles were short-listed by considering the aforementioned criteria. From these, 93 papers are related to SCND resilience, 49 to sim-opt methods in SCND, and 21 articles are reviews (all of them already analyzed in Section 2). The short-listed papers were organized in a spreadsheet, where basic information about the papers was registered: title, authors, year, and journal. Also, after an initial review, a taxonomy was built to analyze and synthesize SCND resilience and sim-opt papers, namely:

- *Mathematical approach:* this refers to the method used to model the problem, e.g., robust optimization, stochastic programming, etc.
- *Solving approach:* this refers to the method employed by the authors to solve the proposed model, e.g., exact methods, metaheuristics, etc.
- *Uncertain parameters:* in a model, it is usual to consider some parameters as uncertain and others as known. Common uncertain parameters are: demand, cost, capacity, etc.

- *Uncertainty approach:* this refers to the way the authors model the uncertain parameters, e.g., by means of probability distributions, fuzzy sets, etc.

- *Objective criterion:* variables like cost, income, or profit are usually minimized or maximized in mathematical models when designing SCNs. In addition, it is possible that several conflicting objectives are considered, which leads to adapt the model and its solving approach.

- *Supply chain design special case:* some special cases regarding SCND can be found in the literature. These are conceptual models based on real-world characteristics that influence the design of a supply chain considering criteria that are specific of that model. These criteria can be: objectives, constraints, variables, or parameters. For instance, the sustainable SCND is a special case that not only considers the traditional economic goal but also environmental and social objectives. Other special cases found in the literature are: green SCND, closed-loop SCND, etc.

- *Application to a real-world case:* this refers to the fact that the problem and its solution have been applied to a real-life case; otherwise the paper is classified as a theoretical contribution.

Besides, when analyzing SCND resilience papers, the additional criterion *type of risk* is considered to build the taxonomy, which refers to operational risks, disruption risks, or both (Tang, 2006). Then, a deeper review of the full text of papers was carried out, after which 42 papers (25 related to SCND resilience and 17 to sim-opt methods) were rejected because they do not match our research questions. Hence, 68 SCND papers and 32 sim-opt papers are analyzed in this work. Such analysis consists in: *(i)* identifying basic elements, such as authors, year and journal; *(ii)* identifying how each element of our taxonomy is addressed by every analyzed paper; and *(iii)* classifying extracted information in spreadsheets. Then, the main findings are synthesized in tables and figures for better presentation, and to identify better the characteristics of each paper according to our taxonomy.

4. Main Findings From the SLR Process

A detailed analysis of the short-listed papers is presented in Subsections 4.1 and 4.2. An overview of published works is firstly given here. Notice that the number of papers published in the topic has increased exponentially over time, with about 77% having appeared in the last five years (between 2015 and April 2020). Hence, this research field is under expansion, as shown in Figure 1. Observe that 87% of publications about resilience in SCND appeared during this period. Besides, 66% of the short-listed papers are based on real-life situations, in both SCND resilience and sim-opt SCND topics. The rest of the papers carry out experiments using theoretical data.

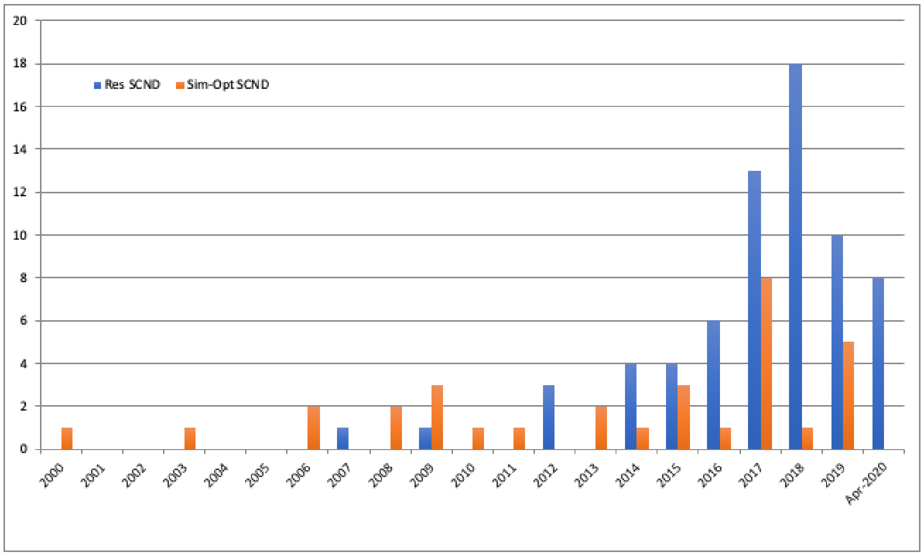

Figure 1: Short-listed papers according to year of publication.

Regarding the journals where the publications about resilient SCND have appeared (Figure 2), about 60% of works were published in: Computers & Industrial Engineering (12%), International Journal of Production Research (9%), Transportation Research Part E (12%), International Journal of Production Economics (7%), Sustainability (4%), Computer Aided Chemical Engineering (4%), Computers & Chemical Engineering (4%), International Journal of Logistics Systems and Management (3%), and Omega (3%). Also, about 15% of the short-listed works appeared as a conference paper or book chapter. Concerning sim-opt approaches for SCND, 23% of works were published in conference proceedings or book chapters; journal papers are concentrated in the International Journal of Production Research (6%), Computers & Chemical Engineering (9%), Expert Systems with Applications (8%), and Computers & Industrial Engineering (13%).

4.1. Resilient SCND

The taxonomy previously defined has been used to analyze and synthesize 68 short-listed papers. Table 1 shows that most papers use stochastic programming as a modeling tool for the supply chain, followed by mixed-integer linear programming (MILP). Some authors propose hybrid optimization models, such as Fahimnia & Jabbarzadeh (2016) –who propose a model that integrates stochastic, fuzzy, and goal programming–, or Khalili et al. (2017) –who mix stochastic with possibilistic programming. Six papers use both simulation and optimization methods in some way. Four of them use Monte-Carlo simulation to generate test scenarios (Jabbarzadeh et al., 2016; Klibi & Martel, 2012; Li et al., 2017; Mikhail et al., 2019). The other two papers hybridize more deeply simulation

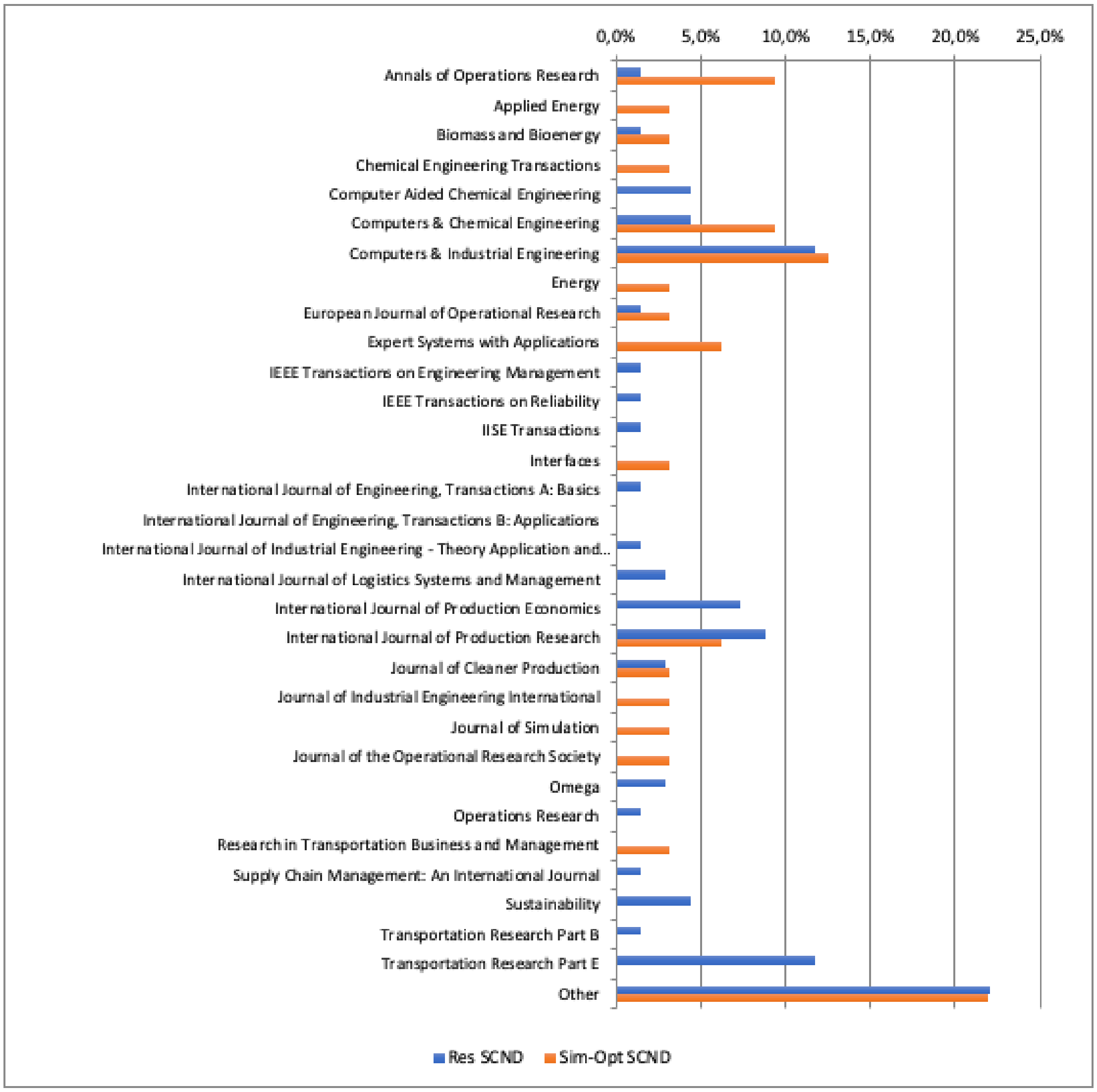

Figure 2: Analyzed papers according to journal of publication.

with optimization methods in a resilience framework. One of them is the paper by Aqlan & Lam (2016), who mix simulation with goal programming to manage supply chain risks in a real-world hybrid sim-opt model. A strategic-tactical multi-objective deterministic linear model that uses goal programming is used in the optimization part. Outputs of this model feed the stochastic simulation part and vice-versa.

Table 1: SCND resilience references according to mathematical approach.

Mathematical approach	**Authors**
Stochastic programming	Behzadi et al. (2017), Fahimnia & Jabbarzadeh (2016), Fattahi et al. (2017), Ghomi-Avili et al. (2019), Haeri et al. (2020), Hosseini-Motlagh et al. (2020), Jabbarzadeh et al. (2016), Jabbarzadeh et al. (2018a), Jabbarzadeh et al. (2018b), Jiang et al. (2009), Khalili et al. (2017), Klibi & Martel (2012), Li & Zhang (2018), Mousavi Ahranjani et al. (2020), Namdar et al. (2018), Ni et al. (2018), Nooraie & Parast (2016), Rezapour et al. (2018), Sabouhi et al. (2018), Tucker et al. (2020), Zahiri et al. (2017), Zahiri et al. (2020)
Mixed integer linear programming	Azad & Hassini (2019), Cardoso et al. (2014a), Cardoso et al. (2014b), Elluru et al. (2017), Ghavamifar et al. (2018), Gong et al. (2014), Maheshwari et al. (2017), Margolis et al. (2018), Mehrjerdi & Lotfi (2019), Mikhail et al. (2019), Mohammed et al. (2018), Mousavi Ahranjani et al. (2020), Prakash et al. (2017), Ribeiro & Barbosa-Povoa (2018a), Sadghiani et al. (2015), Soren & Shastri (2019), Yavari & Zaker (2019)
Robust optimization	Dehghani et al. (2018), Haeri et al. (2020), Hamdan & Diabat (2020), Hamidieh et al. (2018), Hasani & Khosrojerdi (2016), Hosseini-Motlagh et al. (2020), Jabbarzadeh et al. (2016), Jabbarzadeh et al. (2018b), Jabbarzadeh et al. (2019), Mousavi Ahranjani et al. (2020), Sadghiani et al. (2015), Zhao & You (2019)
Fuzzy programming	Fahimnia & Jabbarzadeh (2016), Ghomi-Avili et al. (2018), Hamidieh et al. (2018), Hosseini-Motlagh et al. (2020), Khalili et al. (2017), Mohammed et al. (2019), Mousavi Ahranjani et al. (2020), Sabouhi et al. (2018), Zahiri et al. (2017)
Mixed integer non-linear programming	Bottani et al. (2019), Ghavamifar et al. (2018), Hasani & Khosrojerdi (2016), Rezapour et al. (2017), Taleizadeh et al. (2020), Yavari & Zaker (2020)
Goal programming	Aqlan & Lam (2016), Fahimnia & Jabbarzadeh (2016), Mari et al. (2014)
Linear programming	Li et al. (2017)
Mixed integer quadratic programming	Shrivastava et al. (2017)
Discrete-event simulation	Aqlan & Lam (2016), Carvalho & Machado (2007), Carvalho et al. (2012), Ivanov (2017), Ivanov (2018), Lenort et al. (2016), Lim-Camacho et al. (2017), Macdonald et al. (2018), Wicher et al. (2015)
Monte Carlo simulation	Adenso-Diaz et al. (2012), Jabbarzadeh et al. (2016), Klibi & Martel (2012), Li & Zhang (2018), Li et al. (2017), Mikhail et al. (2019)
Agent-based simulation	Mari et al. (2015a), Mari et al. (2015b)
Graph theory	Chen et al. (2017), Pavlov et al. (2018)
Complex network theory	Mari et al. (2015a), Mari et al. (2015b)
Continuum approximation model	Wang & Wu (2018)

The other paper that makes use of sim-opt methods is authored by Li & Zhang (2018), who solve the uncapacitated facility location problem with facility disruptions. A two-stage stochastic programming model is presented, as well as a scenario-based model. This problem is solved via the sample average approximation method, which is based on Monte Carlo simulation. Disruptions are modeled in a binary fashion, i.e., a facility may fail completely or not.

In general, the use of simulation methods is not as widespread as optimization. Thus, about 75% of the analyzed papers propose a pure optimization model. Pure simulation methods are used by 16% of the analyzed papers, with discrete-event simulation (DES) as the preferred tool. Finally, only 9% of the papers use a hybrid approach in designing resilient SCNs.

Heuristic and metaheuristic methods are used very scarcely in SCND resilience (Table 2). For instance, only Nooraie & Parast (2016) and Zhao & You (2019) propose heuristics to enhance computational efficiency. Regarding metaheuristics, Bottani et al. (2019) employ an Ant Colony Optimization algorithm (ACO), and Hasani & Khosrojerdi (2016) and Zahiri et al. (2017) propose hybrid metaheuristics as a solution approach: a Taguchi-based memetic algorithm (TMA) for the first case, and a combination among differential evolution algorithm, variable neighborhood search algorithm and game theory (DVG) for the second case. This fact shows the high potential of designing heuristic-based approaches, given that strategic real-world problems might be both *NP-hard* and contain large-sized instances (De Armas et al., 2017; Quintero-Araujo et al., 2017; Aghezzaf, 2005).

Most authors solve their proposed model by using exact methods, although some of them employ a relaxation procedure. For instance, Jabbarzadeh et al. (2016) make use of Lagrangian relaxation. These authors propose a hybrid robust-stochastic optimization model to design an Iranian engine oil SCN. Both supply and demand are uncertain, as well as the occurrence of a fire in any facility. After solving the proposed model, Monte Carlo simulation is used to generate random instances for uncertain parameters and evaluate the solutions yielded by the model. Regardless a hybrid model is used or not, all authors that use any kind of simulation model in Table 1 are referred as they use simulation as solving approach in Table 2. For instance, Carvalho et al. (2012) design a resilient SCN for an automotive sector company in Portugal via a DES model. Redundancy and flexibility strategies are assessed to mitigate the effects of "supply delay" disturbance.

The use of scenarios is the most frequent uncertainty approach (Table 3), either with assigned probabilities or not. Only 7 out of 68 papers do not consider any probability. Thus, for example, Fattahi et al. (2017) propose a stochastic program in which the occurrence probability of each scenario is explicitly defined and introduced in the model.

Employing explicit probability distributions to address uncertainty is not as widespread as employing scenarios with assigned probabilities, although some authors hybridize them (Bottani et al., 2019; Dehghani et al., 2018; Klibi & Martel, 2012; Rezapour et al., 2018). Therefore, the use of probabilities is very frequent in works regarding SCND resilience, due to its easiness of tractability. A total of 21 out of 68 articles include probability distributions in the model, in which 9 papers propose an optimization model, 8 papers propose a simulation model, and 4 papers hybridize both methods. Although only 12 out of 68 papers

Table 2: SCND resilience references according to solving approach.

Authors	Exact method	Heuristic	Metaheuristic	Simulation
Adenso-Diaz et al. (2012)				X
Azad & Hassini (2019)	X			
Aqlan & Lam (2016)	X			X
Behzadi et al. (2017)	X			
Bottani et al. (2019)			ACO[1]	
Cardoso et al. (2014a)	X			
Cardoso et al. (2014b)	X			
Carvalho & Machado (2007)				X
Carvalho et al. (2012)				X
Chen et al. (2017)	X			
Dehghani et al. (2018)	X			
Elluru et al. (2017)	X			
Fahimnia & Jabbarzadeh (2016)	X			
Fattahi et al. (2017)	X			
Ghavamifar et al. (2018)	X			
Ghomi-Avili et al. (2018)	X			
Ghomi-Avili et al. (2019)	X			
Gong et al. (2014)	X			
Haeri et al. (2020)	X			
Hamdan & Diabat (2020)	X			
Hamidieh et al. (2018)	X			
Hasani & Khosrojerdi (2016)			TMA[2]	
Hosseini-Motlagh et al. (2020)	X			
Ivanov (2017)				X
Ivanov (2018)				X
Jabbarzadeh et al. (2016)	X			X
Jabbarzadeh et al. (2018a)	X			
Jabbarzadeh et al. (2018b)	X			
Jabbarzadeh et al. (2019)	X			
Jiang et al. (2009)	X			
Khalili et al. (2017)	X			
Klibi & Martel (2012)	X			X
Lenort et al. (2016)				X
Li & Zhang (2018)	X			X
Li et al. (2017)	X			X
Lim-Camacho et al. (2017)				X
Macdonald et al. (2018)				X
Maheshwari et al. (2017)	X			
Mari et al. (2014)	X			
Mari et al. (2015a)				X
Mari et al. (2015b)				X
Margolis et al. (2018)	X			
Mehrjerdi & Lotfi (2019)	X			
Mikhail et al. (2019)	X			X
Mohammed et al. (2018)	X			
Mohammed et al. (2019)	X			
Mousavi Ahranjani et al. (2020)	X			
Namdar et al. (2018)	X			
Ni et al. (2018)	X			
Nooraie & Parast (2016)		X		
Pavlov et al. (2018)	X			
Prakash et al. (2017)	X			
Rezapour et al. (2017)	X			
Rezapour et al. (2018)	X			
Ribeiro & Barbosa-Povoa (2018a)	X			
Sabouhi et al. (2018)	X			
Sadghiani et al. (2015)	X			
Shrivastava et al. (2017)	X			
Soren & Shastri (2019)	X			
Taleizadeh et al. (2020)	X			
Tucker et al. (2020)	X			
Wang & Wu (2018)	X			
Wicher et al. (2015)				X
Yavari & Zaker (2019)	X			
Yavari & Zaker (2020)	X			
Zahiri et al. (2017)			DVG [3]	
Zahiri et al. (2020)	X			
Zhao & You (2019)	X	X		

Table 3: SCND resilience references according to uncertainty approach and type of risk.

Authors	**Uncertainty approach**				**Type of risk**	
	Probability distribution	Fuzzy numbers	Scenarios with probabilities	Scenarios without probabilities	Operational	Disruption
Adenso-Diaz et al. (2012)	X					X
Aqlan & Lam (2016)	X				X	
Azad & Hassini (2019)			X			X
Behzadi et al. (2017)	X					X
Bottani et al. (2019)	X		X		X	X
Cardoso et al. (2014a)			X		X	X
Cardoso et al. (2014b)			X		X	X
Carvalho & Machado (2007)	X				X	
Carvalho et al. (2012)	X				X	
Chen et al. (2017)	X					X
Dehghani et al. (2018)	X		X		X	X
Elluru et al. (2017)				X		X
Fahimnia & Jabbarzadeh (2016)	X				X	X
Fattahi et al. (2017)			X		X	X
Ghavamifar et al. (2018)			X		X	X
Ghomi-Avili et al. (2018)		X			X	X
Ghomi-Avili et al. (2019)			X			X
Gong et al. (2014)				X		X
Haeri et al. (2020)			X			X
Hamdan & Diabat (2020)			X			X
Hamidieh et al. (2018)		X			X	X
Hasani & Khosrojerdi (2016)			X		X	X
Hosseini-Motlagh et al. (2020)		X	X		X	X
Ivanov (2017)	X			X	X	X
Ivanov (2018)	X					X
Jabbarzadeh et al. (2016)	X				X	X
Jabbarzadeh et al. (2018a)			X			X
Jabbarzadeh et al. (2018b)			X		X	X
Jabbarzadeh et al. (2019)			X		X	X
Jiang et al. (2009)			X		X	
Khalili et al. (2017)		X	X		X	X
Klibi & Martel (2012)	X		X		X	X
Lenort et al. (2016)	X					X
Li & Zhang (2018)			X			X
Li et al. (2017)	X					X
Lim-Camacho et al. (2017)				X		X
Macdonald et al. (2018)	X				X	X
Maheshwari et al. (2017)			X			X
Mari et al. (2014)			X			X
Mari et al. (2015a)				X		X
Mari et al. (2015b)				X		X
Margolis et al. (2018)			X			X
Mehrjerdi & Lotfi (2019)			X		X	X
Mikhail et al. (2019)	X					X
Mohammed et al. (2018)		X				X
Mohammed et al. (2019)		X			X	
Mousavi Ahranjani et al. (2020)		X	X		X	X
Namdar et al. (2018)			X		X	X
Ni et al. (2018)				X	X	X
Nooraie & Parast (2016)			X		X	X
Pavlov et al. (2018)		X	X			X
Prakash et al. (2017)			X		X	
Rezapour et al. (2017)			X			X
Rezapour et al. (2018)	X		X			X
Ribeiro & Barbosa-Povoa (2018a)			X		X	X
Sabouhi et al. (2018)		X	X		X	X
Sadghiani et al. (2015)		X	X		X	X
Shrivastava et al. (2017)	X				X	X
Soren & Shastri (2019)			X			X
Taleizadeh et al. (2020)			X			X
Tucker et al. (2020)			X			X
Wang & Wu (2018)			X			X
Wicher et al. (2015)	X					X
Yavari & Zaker (2019)			X			X
Yavari & Zaker (2020)			X			X
Zahiri et al. (2017)		X	X		X	X
Zahiri et al. (2020)		X			X	X
Zhao & You (2019)	X				X	X

employ fuzzy numbers, such use shows a recent trend among the recently published papers. Thus, in general 36 out of 68 (53%) papers have been published since 2018, while 9 out of 12 (75%) papers using fuzzy numbers were published in the same period. Only a paper employing fuzzy numbers was published before 2017. This is the paper by Sadghiani et al. (2015), who propose a fuzzy robust optimization model to design a robust and resilient Iranian retail SCN. A multi-step solving methodology is used to reduce the number of scenarios and both operational and disruption risks are considered. They also assign some probabilities to such scenarios.

Table 3 also shows papers classified by type of risk. According to (Tang, 2006), risks can be classified into two types: operational risks and disruption risks. Operational risks are inherent to the supply chain normal operation, such as: uncertain demand, capacity, or costs. Disruption risks are related to serious incidents, such as natural and human-induced disasters (e.g., earthquakes, floods, terrorist attacks, etc.). The fact that 91% of the papers address disruptions indicates that this is a core topic when designing and assessing a resilient SCN, due to the importance of returning to its original state after facing any major incident. Nevertheless, 30 out of 68 papers not only consider disruptions risks but also operational risks. For instance, Klibi & Martel (2012) tackle both by proposing various modeling approaches, which are based in stochastic programming. Scenarios are generated through Monte Carlo simulation and demand and network disruptions are addressed by using a *multi-hazards* approach.

Figure 3 shows the number of papers differentiated by type of risk and mathematical approach. Optimization methods are highly employed whenever disruption risks are considered. The proportion decreases when only operational risks are modeled. This fact shows that using hybrid sim-opt methods is an open challenge when designing and assessing resilient SCNs, especially if both types of risks are considered. Furthermore, the use of hybrid methods becomes relevant to model uncertain scenarios, since it offers a good balance between realism and cost-efficiency.

Table 4 shows the taxonomy regarding the uncertain parameters. *Demand* and *capacity* are the most frequent parameters when considering operational risks. In regard to disruption risks, *node disruption* is modeled by 49% of the papers, which shows the relevance of considering disrupted facilities when designing and assessing resilient SCNs. In our taxonomy, a node disruption occurs when a supplier location or a facility breaks down completely and demand must be met by other facilities. If capacity or supply are only reduced partially, this was not considered in the *node disruption* parameter, but in the *capacity* and *supply* ones, respectively.

Link disruption is also a modeled parameter regarding disruption risk, although not as frequent as *node disruption*. The former one refers to the interruption in the flow, e.g., because an arc in the network is broken or because the means of transport fail. Notice that only Ghavamifar et al. (2018), Shrivastava et al. (2017) and Zahiri et al. (2020) (out of 14 papers) consider link disruptions but not node disruptions. The other 11 articles consider both.

A total of 19 out of 68 papers model only one uncertain parameter, and

Table 4: SCND resilience references according to uncertain parameters.

Uncertain parameter	**Authors**
Demand	Azad & Hassini (2019), Bottani et al. (2019), Cardoso et al. (2014a), Cardoso et al. (2014b), Dehghani et al. (2018), Fahimnia & Jabbarzadeh (2016), Fattahi et al. (2017), Ghavamifar et al. (2018), Haeri et al. (2020), Hamdan & Diabat (2020), Hamidieh et al. (2018), Hasani & Khosrojerdi (2016), Hosseini-Motlagh et al. (2020), Ivanov (2017), Jabbarzadeh et al. (2016), Jabbarzadeh et al. (2018b), Jabbarzadeh et al. (2019), Jiang et al. (2009), Khalili et al. (2017), Klibi & Martel (2012), Macdonald et al. (2018), Mehrjerdi & Lotfi (2019), Mohammed et al. (2019), Mousavi Ahranjani et al. (2020), Ni et al. (2018), Nooraie & Parast (2016), Ribeiro & Barbosa-Povoa (2018a), Sadghiani et al. (2015), Shrivastava et al. (2017), Zahiri et al. (2020), Zhao & You (2019)
Capacity	Azad & Hassini (2019), Fattahi et al. (2017), Ghavamifar et al. (2018), Hasani & Khosrojerdi (2016), Hamidieh et al. (2018), Ivanov (2017), Jabbarzadeh et al. (2016), Jabbarzadeh et al. (2018a), Jabbarzadeh et al. (2018b), Jabbarzadeh et al. (2019), Khalili et al. (2017), Klibi & Martel (2012), Lenort et al. (2016), Li et al. (2017), Mehrjerdi & Lotfi (2019), Mikhail et al. (2019), Mohammed et al. (2019), Namdar et al. (2018), Ni et al. (2018), Nooraie & Parast (2016), Sadghiani et al. (2015), Taleizadeh et al. (2020), Wicher et al. (2015), Zhao & You (2019)
Costs	Dehghani et al. (2018), Fattahi et al. (2017), Hamidieh et al. (2018), Hasani & Khosrojerdi (2016), Hosseini-Motlagh et al. (2020), Jabbarzadeh et al. (2018b), Mehrjerdi & Lotfi (2019), Mohammed et al. (2019), Mousavi Ahranjani et al. (2020), Ni et al. (2018), Nooraie & Parast (2016), Zahiri et al. (2017)
Supply	Bottani et al. (2019), Haeri et al. (2020), Hamdan & Diabat (2020), Hasani & Khosrojerdi (2016), Hosseini-Motlagh et al. (2020), Maheshwari et al. (2017), Nooraie & Parast (2016), Sabouhi et al. (2018), Shrivastava et al. (2017), Soren & Shastri (2019)
Lead time	Ivanov (2017), Ni et al. (2018), Prakash et al. (2017)
Processing time	Carvalho et al. (2012), Carvalho & Machado (2007)
Transport time	Carvalho et al. (2012), Carvalho & Machado (2007)
Node disruption	Adenso-Diaz et al. (2012), Cardoso et al. (2014a), Cardoso et al. (2014b), Chen et al. (2017), Elluru et al. (2017), Fahimnia & Jabbarzadeh (2016), Ghomi-Avili et al. (2018), Ghomi-Avili et al. (2019), Gong et al. (2014), Hamdan & Diabat (2020), Ivanov (2018), Jabbarzadeh et al. (2016), Jabbarzadeh et al. (2018a), Jabbarzadeh et al. (2019), Li & Zhang (2018), Lim-Camacho et al. (2017), Macdonald et al. (2018), Margolis et al. (2018), Mari et al. (2014), Mari et al. (2015b), Mari et al. (2015a), Mehrjerdi & Lotfi (2019), Mohammed et al. (2018), Namdar et al. (2018), Pavlov et al. (2018), Rezapour et al. (2017), Rezapour et al. (2018), Ribeiro & Barbosa-Povoa (2018a), Taleizadeh et al. (2020), Tucker et al. (2020), Wang & Wu (2018), Yavari & Zaker (2019), Yavari & Zaker (2020)
Link disruption	Adenso-Diaz et al. (2012), Cardoso et al. (2014a), Cardoso et al. (2014b), Elluru et al. (2017), Ghavamifar et al. (2018), Gong et al. (2014), Hamdan & Diabat (2020), Jabbarzadeh et al. (2019), Rezapour et al. (2017), Ribeiro & Barbosa-Povoa (2018a), Shrivastava et al. (2017), Yavari & Zaker (2019), Yavari & Zaker (2020), Zahiri et al. (2020)
Disruption time	Lenort et al. (2016), Li et al. (2017), Wicher et al. (2015)
Product price	Ghomi-Avili et al. (2018), Ghomi-Avili et al. (2019), Mousavi Ahranjani et al. (2020)
Yield	Behzadi et al. (2017), Mousavi Ahranjani et al. (2020)
Quantity of returned product	Jabbarzadeh et al. (2018b), Mehrjerdi & Lotfi (2019)
CO_2 emissions	Mehrjerdi & Lotfi (2019), Mohammed et al. (2019)
Spot market price	Namdar et al. (2018)
Lost sale penalty	Namdar et al. (2018)
Harvest time	Behzadi et al. (2017)
Quantity of disposed product	Jabbarzadeh et al. (2018b)
Recovery time	Li et al. (2017)
Emergency inventory	Khalili et al. (2017)
Revenues	Nooraie & Parast (2016)
Quality in materials	Prakash et al. (2017)
Purchasing quantities	Mohammed et al. (2019)
Contract price	Ni et al. (2018)
Lost safety stock	Ni et al. (2018)
Cycle time	Aqlan & Lam (2016)
Consumed energy	Mehrjerdi & Lotfi (2019)
Generated employment	Mehrjerdi & Lotfi (2019)

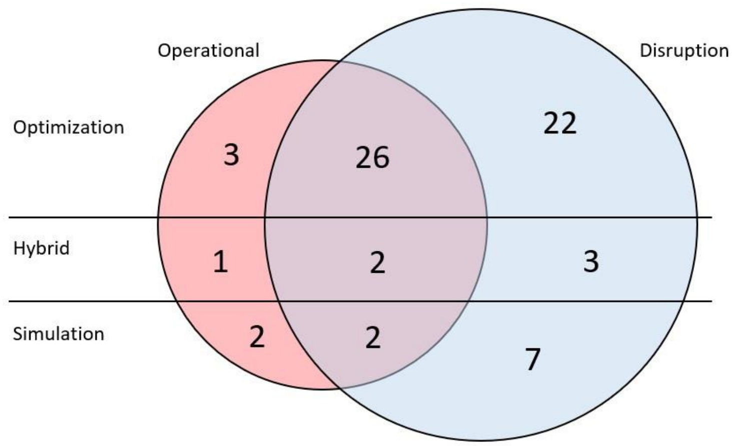

Figure 3: Number of analyzed SCND resilience papers according to type of risk and mathematical approach.

the rest considers at least two of them. For instance, Mohammed et al. (2019) consider that demand, capacity, costs, and CO_2 emissions are uncertain. They show a fuzzy multi-objective programming model to design and assess a green and resilient SCN. Four resilience pillars are proposed to be maximized: robustness, agility, leanness, and flexibility. Also, they consider minimization of cost and environmental impact.

Some authors use particular uncertain parameters that are not considered in other papers. For example, Namdar et al. (2018) consider that *spot market price*, *lost sale penalty*, *capacity*, and *node disruption* (in the supplier) are uncertain. They propose a scenario-based two-stage stochastic programming model to design a resilient supply chain considering risk aversion and both operational and disruption risks. Both proactive and reactive strategies are analyzed to achieve resilience. Visibility and collaboration are among the proactive strategies, while spot purchasing and multiple sourcing are among the reactive strategies. Finally, some numerical examples are used to test the approach.

Table 5 shows the model objective criterion. Both optimization (minimization and maximization) and non-optimization criteria are considered. The latter one refers especially to simulation models in which the objectives are the model output variables. In this case, measuring resilience is the most used objective. In general, the most utilized criterion is *cost minimization* (53% of papers), either in a single-objective model or a multi-objective model. For instance, Dehghani et al. (2018) propose only a cost minimization objective, considering both business-as-usual and disruption uncertainties to design a resilient solar photo-voltaic cells manufacturing SCN. Robust optimization is used to model this strategic-tactical problem in which 30 parameters are uncertain. Most of them are different types of fixed and variable costs. *Profit* and *net present value* maximization are also relevant objectives considered in some papers. For instance, Behzadi et al. (2017) propose a strategic-tactical stochastic programming model to help agri-food supply chain decision-makers to choose robust and resilient strategies versus disruption risk. The model is applied to a kiwifruit global SCN. Nevertheless, *profit*, *net present value* and the other objective variables considered by a few authors are not as used as *cost minimization*. *Resilience*, the core concept of interest in our work, is maximized only in 5 out of 68 papers, although alternatively 3 works minimize *de-resiliency* or *non-resiliency*. Some researchers also address environmental aspects, such as *CO_2 emissions* or *environmental impact*, as well as *social impact*.

Also, 25 out of 68 references optimize multiple objectives, which are identified with an asterisk in Table 5. Notice that neither *resilience* nor *de-resiliency* are never a unique objective, i.e., they are always optimized along with *cost*. This shows that, despite resilience may have a relative relevance in an explicit objective, it should not be considered alone due to the high cost that a resilient design may lead to. Papers that employ multiple objectives must use some procedure in order to address such multiplicity. Khalili et al. (2017) are the only authors who employ the *Reservation Level-driven Tchebycheff Procedure* (RLTP), and explain why both the weighted sum method and the ε-constraint method are not appropriate. However, evidence shows that these methods are preferred when considering multiple objectives, as well as the use of the LP-metric method or Compromise programming (Table 6). For example, Jabbarzadeh et al. (2018a) propose a bi-objective model that seeks to minimize expected total cost and to maximize expected sustainability performance. A set of scenarios with a probability of occurrence is defined and the model is applied to a plastic pipe industry. In addition, authors never consider more than 4 objectives. Besides, there is not a clear relation between the number of objectives and the solving method, which shows that apparently such number does not have any influence in the chosen method. Anyway, since 2018 there is a clear trend in employing either the ε-constraint or the LP-metric method instead of weighted sums. Deeper research is necessary to establish pros and cons of using one or another method to solve multi-objective models oriented to design and assess resilient SCNs.

SCND special cases are also studied. They imply to consider particular variables, objectives or constraints, which are additional to traditional parameters such as costs, demand, or capacity. Green SCND is the special case that addresses environmental aspects. The closed-loop SCND special case also usually considers green aspects (Jabbarzadeh et al., 2018b). Likewise, the sustainable SCND must include them by definition (Zahiri et al., 2017), as well as social topics. Some authors have mixed these special cases with SCND resilience (Table 7). Notice that sustainability and green practices may impact negatively on the supply chain resilience (Ivanov, 2018). For instance, a paper by Fahimnia & Jabbarzadeh (2016) couples the sustainability concept with the resilience concept. This is achieved by designing a SCN through stochastic fuzzy goal programming. The sustainability approach implies that the model is multi-objective. These authors define SCND resilience as "the capacity of a supply chain to absorb disturbances and retain its basic function and structure in the face of disruptions". This definition is similar to the *robust supply chain* defini-

Table 5: SCND resilience references according to objective criterion.

Objective criterion		Authors
Minimize	Cost	Azad & Hassini (2019), Dehghani et al. (2018), Elluru et al. (2017), Fahimnia & Jabbarzadeh (2016)*, Fattahi et al. (2017), Gong et al. (2014)*, Haeri et al. (2020)*, Hamdan & Diabat (2020)*, Hamidieh et al. (2018), Hosseini-Motlagh et al. (2020)*, Jabbarzadeh et al. (2016), Jabbarzadeh et al. (2018a)*, Jabbarzadeh et al. (2018b), Jiang et al. (2009), Khalili et al. (2017)*, Li & Zhang (2018), Maheshwari et al. (2017), Margolis et al. (2018)*, Mari et al. (2014)*, Mehrjerdi & Lotfi (2019)*, Mohammed et al. (2018)*, Mohammed et al. (2019)*, Mousavi Ahranjani et al. (2020), Namdar et al. (2018), Nooraie & Parast (2016)*, Prakash et al. (2017), Sabouhi et al. (2018), Sadghiani et al. (2015), Shrivastava et al. (2017), Soren & Shastri (2019), Wang & Wu (2018), Yavari & Zaker (2019)*, Yavari & Zaker (2020)*, Zahiri et al. (2017)*, Zahiri et al. (2020)*, Zhao & You (2019)*
	CO_2 emissions	Ghomi-Avili et al. (2018)*, Jabbarzadeh et al. (2019)*, Mari et al. (2014)*, Mehrjerdi & Lotfi (2019)*, Mohammed et al. (2018)*, Yavari & Zaker (2019)*, Yavari & Zaker (2020)*,
	Environmental impact	Fahimnia & Jabbarzadeh (2016)*, Mohammed et al. (2019)*, Zahiri et al. (2017)*
	De-resiliency	Haeri et al. (2020)*, Hosseini-Motlagh et al. (2020)*, Zahiri et al. (2017)*
	Lead time	Aqlan & Lam (2016)*, Bottani et al. (2019)*
	Delivery time	Ghomi-Avili et al. (2019)*, Hamdan & Diabat (2020)*
	Risk	Aqlan & Lam (2016)*, Zahiri et al. (2020)*
	Customer's dissatisfaction	Ghomi-Avili et al. (2019)*
	Inefficiency	Haeri et al. (2020)*
	Disruption cost	Mari et al. (2014)*
	Embodied carbon footprint	Mari et al. (2014)*
	Energy consumption	Mehrjerdi & Lotfi (2019)*
	Failure probability	Pavlov et al. (2018)
	Lost sales cost	Ghavamifar et al. (2018)*
	Mitigation and restoration costs	Ni et al. (2018)
	Restoration time	Gong et al. (2014)*
	Inclination level of resellers to order from the unknown suppliers	Ghavamifar et al. (2018)*
Maximize	Profit	Aqlan & Lam (2016)*, Behzadi et al. (2017), Bottani et al. (2019)*, Ghavamifar et al. (2018)*, Ghomi-Avili et al. (2018)*, Ghomi-Avili et al. (2019)*, Jabbarzadeh et al. (2019)*, Klibi & Martel (2012), Mikhail et al. (2019), Rezapour et al. (2017), Rezapour et al. (2018), Taleizadeh et al. (2020), Tucker et al. (2020)
	Resilience	Jabbarzadeh et al. (2019)*, Khalili et al. (2017)*, Mohammed et al. (2018)*, Mohammed et al. (2019)*, Zhao & You (2019)*
	Net present value	Cardoso et al. (2014b), Cardoso et al. (2014a), Hasani & Khosrojerdi (2016), Ribeiro & Barbosa-Povoa (2018a)*
	Social impact	Fahimnia & Jabbarzadeh (2016)*, Hosseini-Motlagh et al. (2020)*, Mehrjerdi & Lotfi (2019)*, Zahiri et al. (2017)*
	Network flow complexity	Ribeiro & Barbosa-Povoa (2018a)*
	Revenue	Nooraie & Parast (2016)*
	Overall connectivity	Margolis et al. (2018)*
	Expected sustainability performance	Jabbarzadeh et al. (2018a)*
Non-optimization	Resilience	Chen et al. (2017), Li et al. (2017), Lim-Camacho et al. (2017), Macdonald et al. (2018), Mari et al. (2015a), Mari et al. (2015b)
	Cost	Carvalho & Machado (2007), Carvalho et al. (2012), Ivanov (2017)
	Unsold units	Ivanov (2017), Lenort et al. (2016), Wicher et al. (2015)
	Lead time	Carvalho et al. (2012), Ivanov (2018)
	Climate resilience	Lim-Camacho et al. (2017)
	Continuity of supply	Lim-Camacho et al. (2017)
	Evenness	Lim-Camacho et al. (2017)
	Negative change in inventory	Macdonald et al. (2018)
	Number of orders delivered to customers	Carvalho & Machado (2007)
	Profit	Ivanov (2018)
	Reliability of each product	Adenso-Diaz et al. (2012)
	Revenues	Ivanov (2017)
	Sales	Ivanov (2018)
	Service levels	Ivanov (2018)

Table 6: SCND resilience references according to the solving method for multiple objectives.

Method	**Number of objectives**		
	2	3	4
ε-constraint	Ghomi-Avili et al. (2018) Hamdan & Diabat (2020) Jabbarzadeh et al. (2018a) Margolis et al. (2018) Zahiri et al. (2020) Zhao & You (2019)	Jabbarzadeh et al. (2019) Mohammed et al. (2018) Mohammed et al. (2019)	Zahiri et al. (2017)
Weighted sum	Bottani et al. (2019) Gong et al. (2014) Nooraie & Parast (2016)	Aqlan & Lam (2016) Fahimnia & Jabbarzadeh (2016)	Mari et al. (2014)
LP-metric	Yavari & Zaker (2019) Yavari & Zaker (2020)	Ghavamifar et al. (2018) Ghomi-Avili et al. (2019) Hosseini-Motlagh et al. (2020)	Mehrjerdi & Lotfi (2019)
Other	Khalili et al. (2017) Ribeiro & Barbosa-Povoa (2018a)	Haeri et al. (2020)	

tion given by Behzadi et al. (2017).

Agricultural SCN is also a studied special case in our taxonomy. We classify a paper as *agricultural* if at least one modeled uncertain parameter is directly related to agricultural aspects, e.g., *harvest time* and *yield* affected by diseases in crops (Behzadi et al., 2017), or *supply* impacted by floods or droughts (Maheshwari et al., 2017). Other specific characteristics that increase vulnerability of agricultural SCNs are seasonality in supply and demand (Vlajic et al., 2012), as well as perishability of products (Tordecilla-Madera et al., 2018).

Competitive supply chain is another identified special case in SCND. In this context, "competitive" means that competition among rivals is explicitly considered when designing a SCN. Rivals' competitive actions may lead to lose market-share because, for example, clients buy the product to other suppliers (Ghavamifar et al., 2018; Rezapour et al., 2017). Therefore, quantities supplied by rivals are variables in the proposed model. Finally, Ghomi-Avili et al. (2018) do not only design a competitive supply chain, but they take into account green and closed-loop characteristics in a bi-objective fuzzy model that considers both operational and disruption risks.

Table 7 also shows that most papers (45 out of 68) apply their model to a real-world case. This fact shows the high importance of considering resilience to solve problems of real-life SCNs, and demonstrates the relevance that companies give to the negative consequences of operational and disruption risks, such as loss of customers and money, or even loss of lives due to the occurrence of natural or human-induced disasters. Besides, most papers that address some supply chain special case apply the model in a real-world case, which shows that theoretical models usually address generic SCNs. Finally, notice that some papers considering real-world cases from the agricultural sector are not classified as belonging to agricultural special case. This is because these papers do not address any uncertain parameter specific of an agricultural supply chain.

Table 7: SCND resilience references according to the supply chain special case and real-world case.

Authors	**Supply chain special case**	**Real-world case**
Aqlan & Lam (2016)	—	A high-end server manufacturing company
Behzadi et al. (2017)	Agricultural	A kiwifruit supply chain in New Zealand
Bottani et al. (2019)	—	A supply chain for ready-made UHT tomato sauce
Cardoso et al. (2014a)	Closed-loop	A European supply chain
Cardoso et al. (2014b)	Closed-loop	A European supply chain
Carvalho et al. (2012)	—	A Portuguese automotive supply chain
Dehghani et al. (2018)	—	A Photovoltaic (solar) cells supply chain
Fahimnia & Jabbarzadeh (2016)	Sustainable	An Australian sportswear production and distribution company
Fattahi et al. (2017)	—	An Iranian glass supply chain
Ghavamifar et al. (2018)	Competitive	An Iranian automotive parts and services supplier
Ghomi-Avili et al. (2018)	Closed-loop, Competitive, Green	A filter manufacturing company
Ghomi-Avili et al. (2019)	Closed-loop	An Iranian glass company
Haeri et al. (2020)	—	An Iranian blood supply chain
Hamdan & Diabat (2020)	—	A Jordanian blood supply chain
Hamidieh et al. (2018)	—	An Iranian supply chain for fertilizers
Hasani & Khosrojerdi (2016)	—	A global electro-medical device manufacturer
Hosseini et al. (2019)	Agricultural	An Iranian wheat supply chain
Ivanov (2017)	—	A European supply chain
Ivanov (2018)	Sustainable	A global supply chain in electronics
Jabbarzadeh et al. (2016)	—	An Iranian engine oil company
Jabbarzadeh et al. (2018a)	Sustainable	A plastic pipe industry
Jabbarzadeh et al. (2018b)	Closed-loop	An Iranian glass supply chain
Jabbarzadeh et al. (2019)	Green	An electricity supply chain in Iran
Jiang et al. (2009)	—	A beef supply chain in China
Lenort et al. (2016)	—	A supply chain from automotive industry
Li et al. (2017)	—	A Chinese mobile phone supply chain
Lim-Camacho et al. (2017)	—	Three Australian resource industries: fisheries, agriculture, and mining
Maheshwari et al. (2017)	Agricultural	Procurement of corn stover, switchgrass, and Miscanthus in US
Mari et al. (2014)	Sustainable	A garment manufacturing firm based in Pakistan
Margolis et al. (2018)	—	A food processing company
Mehrjerdi & Lotfi (2019)	Closed-loop, Sustainable	An automobile assembly company
Mohammed et al. (2018)	Green	A meat supply chain in the UK
Mohammed et al. (2019)	Green	A meat supply chain
Mousavi Ahranjani et al. (2020)	Agricultural	An Iranian bioethanol supply chain
Prakash et al. (2017)	Closed-loop	—
Rezapour et al. (2017)	Competitive	An automotive supply chain
Ribeiro & Barbosa-Povoa (2018a)	Closed-loop	A European chemical process supply chain
Sabouhi et al. (2018)	—	An Iranian pharmaceutical company
Sadghiani et al. (2015)	—	An Iranian retail chain
Soren & Shastri (2019)	Agricultural	—
Taleizadeh et al. (2020)	Competitive	—
Tucker et al. (2020)	—	A drug supply chain in US
Wicher et al. (2015)	—	A supply chain from automotive industry
Yavari & Zaker (2019)	Closed-loop, Green	An Iranian dairy company
Yavari & Zaker (2020)	Closed-loop, Green	An Iranian dairy company
Zahiri et al. (2017)	Sustainable	A pharmaceutical supply chain network
Zahiri et al. (2020)	—	An Iranian hazardous-materials supply chain
Zhao & You (2019)	—	A biofuel supply chain in US

4.2. Simulation-Optimization Methods in SCND

Hybrid sim-opt methods refer to the interaction between optimization and simulation "to find near-optimal solutions to complex or stochastic optimization problems" (Juan et al., 2015). In particular, this section analyzes the use of such methods for designing and assessing supply chains. Table 8 shows both the optimization and the simulation approaches used by each analyzed paper. Regarding optimization, MILP is the most used approach (53%). Regarding simulation, DES is the preferred one (59%). The mix between these particular approaches is the most used hybridization (31% of the papers).

All papers combine two methods, with the exception of Costa et al. (2017), who hybridize three methods. They propose a sim-opt model to design a Colombian supply chain for bio-diesel production and distribution from palm oil feedstock. Firstly, a deterministic simulation model is used to design the production process and obtain the production cost. This feeds a MILP model for locating production plants. Finally, a goal programming model is proposed to perform a micro-location considering social aspects.

Table 8: Sim-opt references according to the mathematical approach.

Mathematical approach	**Authors**
Mixed integer linear programming	Chiadamrong & Piyathanavong (2017), Costa et al. (2017), De Armas et al. (2017), de Keizer et al. (2015), Ebadian et al. (2013), Ekşioğlu et al. (2013), González-Hernández et al. (2019), Guerrero et al. (2018), Gumus et al. (2009), Karabakal et al. (2000), Ko et al. (2006), Leonzio et al. (2019), Martins et al. (2017), Salem & Haouari (2017), Truong & Azadivar (2003), Villareal & Flores (2009), Zhang et al. (2019)
Optimizer	Costa-Salas et al. (2017), Ding et al. (2009), Keramydas et al. (2017), Koo et al. (2008), Yoo et al. (2010)
Stochastic programming	Dai & Zheng (2015), Kim et al. (2011), Salehi et al. (2019), Ye & You (2015)
Mixed integer non-linear programming	Correll et al. (2014), Kristianto & Zhu (2017)
Robust optimization	de Mattos et al. (2019), Wang et al. (2008)
Goal programming	Costa et al. (2017)
Fuzzy programming	Ji et al. (2007)
Concave mixed-integer programming	Saif & Elhedhli (2016)
Discrete-event simulation	Chiadamrong & Piyathanavong (2017), Correll et al. (2014), Costa-Salas et al. (2017), Costa et al. (2017), de Keizer et al. (2015), Ding et al. (2009), Ebadian et al. (2013), Ekşioğlu et al. (2013), González-Hernández et al. (2019), Karabakal et al. (2000), Keramydas et al. (2017), Ko et al. (2006), Koo et al. (2008), Kristianto & Zhu (2017), Martins et al. (2017), Saif & Elhedhli (2016), Truong & Azadivar (2003), Ye & You (2015), Yoo et al. (2010)
Monte Carlo simulation	Dai & Zheng (2015), De Armas et al. (2017), de Mattos et al. (2019), Guerrero et al. (2018), Kim et al. (2011), Leonzio et al. (2019), Salehi et al. (2019), Salem & Haouari (2017), Villareal & Flores (2009), Wang et al. (2008), Zhang et al. (2019)
Artificial neural network	Gumus et al. (2009)
Fuzzy simulation	Ji et al. (2007)

Exact methods are used by 59% of papers (Table 9). The other half uses heuristic or metaheuristic methods. These are preferred in those cases in which fast solutions are required and near-optimal solutions are enough to most decision makers. Most metaheuristic papers use *genetic algorithms* (7 out of 11), which shows open opportunities for other techniques such as iterated local search

(De Armas et al., 2017), tabu search (Correll et al., 2014), or any other metaheuristic (Gendreau et al., 2010) or simheuristic (Juan et al., 2015).

Table 9: Sim-opt references according to the solving approach.

Authors	**Exact method**	**Heuristic**	**Metaheuristic**
Chiadamrong & Piyathanavong (2017)	X		
Correll et al. (2014)			TS[4]
Costa et al. (2017)	X		
Costa-Salas et al. (2017)			GA[5], EP[6]
Dai & Zheng (2015)	X		
De Armas et al. (2017)			ILS[7]
de Keizer et al. (2015)	X		
de Mattos et al. (2019)	X		
Ding et al. (2009)			GA
Ebadian et al. (2013)	X		
Ekşioğlu et al. (2013)	X		
González-Hernández et al. (2019)	X		
Guerrero et al. (2018)	X		
Gumus et al. (2009)	X		
Ji et al. (2007)			GA
Karabakal et al. (2000)	X		
Keramydas et al. (2017)			OptQuest
Kim et al. (2011)	X		
Ko et al. (2006)			GA
Koo et al. (2008)			NSGA-II[8]
Kristianto & Zhu (2017)	X		
Leonzio et al. (2019)	X		
Martins et al. (2017)	X		
Saif & Elhedhli (2016)	X		
Salehi et al. (2019)	X		
Salem & Haouari (2017)			PSO[9]
Truong & Azadivar (2003)			GA
Villareal & Flores (2009)	X		
Wang et al. (2008)			GA
Ye & You (2015)		OAA[10]	
Yoo et al. (2010)		NP[11], OCBA[12]	
Zhang et al. (2019)	X		

Figure 4 shows the frequency in which the analyzed papers mix each simulation technique with each solving approach. Open opportunities are identified in the use of artificial neural networks, fuzzy simulation and Monte Carlo simulation. Most papers combine an exact method with DES, although this simulation approach is also frequently combined with a metaheuristic. As an example of the first case, Chiadamrong & Piyathanavong (2017) propose a hybrid model that, in early stages, solve independently both the deterministic and the stochastic models for designing a SCN. Then, authors combine these models and compare results with the analytical model and a simulation-based optimization model. The solving time required by this hybrid approach is shorter than the one employed by traditional simulation-based optimization models. As an example of the second case, Ko et al. (2006) design and assess a distribution network through a hybrid sim-opt model. A strategic-tactical MILP model is proposed and a genetic algorithm is used as a solving approach combined with DES.

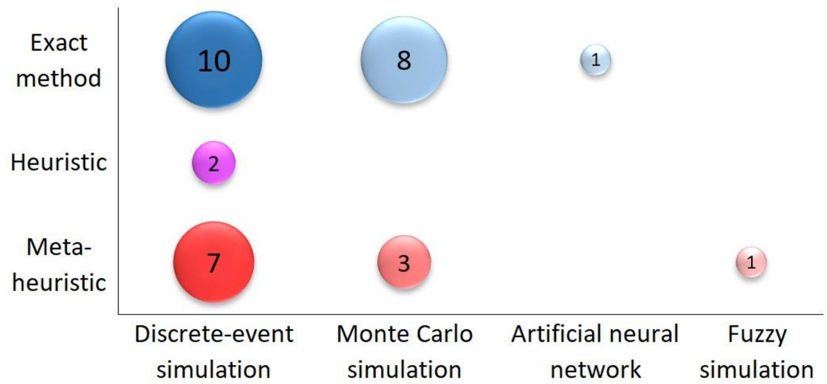

Figure 4: Number of analyzed sim-opt papers according to the simulation and solving approaches.

Sim-opt papers make little use of scenarios with probabilities, as well as fuzzy numbers (Table 10). Probability distributions are the most used uncertainty approach (23 out of 32 papers). For instance, Martins et al. (2017) propose a sim-opt approach to redesign a pharmaceutical wholesaler SCN. They affirm that literature addressing supply chain network redesign is very scarce, and that a redesign process should be carried out carefully because it is different to the design one –in the former, the company has already a market share that can be severely affected if the redesign process is not performed well. A MILP model is used for strategic and tactical decisions of redesign, and a DES model is also employed for operational decisions related to the evaluation of the impact of redesign in daily activities.

It is very unusual to combine different uncertainty approaches. Only Wang et al. (2008) model *demand uncertainty* through scenarios with probabilities. They also model *costs uncertainty* through fuzzy numbers. Other modeled uncertain parameters are shown in Table 11, such as *cost* (28% of the papers) and *supply* (25% of the papers). Nevertheless, *demand* is also the most addressed uncertain parameter: 75% of the papers consider it. For instance, a set of 7 strategic-tactical decisions are considered by Truong & Azadivar (2003) to design and assess a SCN. Qualitative and policy decisions are tackled by a genetic algorithm and quantitative decisions by a MILP model. Simulation is used to assess the performance of the obtained supply chain configurations.

Only 8 out of 32 papers model a single uncertain parameter. The rest address at least 2 of them. Moreover, some of these parameters are considered by only one paper. For instance, only Costa-Salas et al. (2017) consider *arrival frequency*, *pick-up time*, *delivery time* and *trans-shipment time* as uncertain. They combine DES with scenario-optimization methods to design a tire collection process. Firstly, a simulation model is proposed. Then, by determining the best fleet size, variables such as *economic benefit* and *negative environmental impact* are optimized through an optimizer module based on genetic algorithms

Table 10: Sim-opt references according to the uncertainty approach

Authors	Uncertainty approach			
	Probability distribution	Fuzzy numbers	Scenarios with probabilities	Scenarios without probabilities
Chiadamrong & Piyathanavong (2017)	X			
Correll et al. (2014)				X
Costa et al. (2017)				X
Costa-Salas et al. (2017)	X			
Dai & Zheng (2015)	X			
De Armas et al. (2017)	X			
de Keizer et al. (2015)	X			
de Mattos et al. (2019)	X			
Ding et al. (2009)	X			
Ebadian et al. (2013)	X			
Ekşioğlu et al. (2013)				X
González-Hernández et al. (2019)	X			
Guerrero et al. (2018)	X			
Gumus et al. (2009)		X		
Ji et al. (2007)		X		
Karabakal et al. (2000)	X			
Keramydas et al. (2017)	X			
Kim et al. (2011)			X	
Ko et al. (2006)	X			
Koo et al. (2008)	X			
Kristianto & Zhu (2017)				X
Leonzio et al. (2019)	X			
Martins et al. (2017)	X			
Saif & Elhedhli (2016)	X			
Salehi et al. (2019)			X	
Salem & Haouari (2017)	X			
Truong & Azadivar (2003)	X			
Villareal & Flores (2009)	X			
Wang et al. (2008)		X	X	
Ye & You (2015)	X			
Yoo et al. (2010)	X			
Zhang et al. (2019)	X			

Table 11: Sim-opt references according to the uncertain parameter.

Uncertain parameter	**Authors**
Demand	Chiadamrong & Piyathanavong (2017), Dai & Zheng (2015), de Mattos et al. (2019), Ding et al. (2009), González-Hernández et al. (2019), Gumus et al. (2009), Ji et al. (2007), Karabakal et al. (2000), Keramydas et al. (2017), Kim et al. (2011), Ko et al. (2006), Koo et al. (2008), Kristianto & Zhu (2017), Leonzio et al. (2019), Martins et al. (2017), Saif & Elhedhli (2016), Salehi et al. (2019), Salem & Haouari (2017), Truong & Azadivar (2003), Villareal & Flores (2009), Wang et al. (2008), Ye & You (2015), Yoo et al. (2010), Zhang et al. (2019)
Costs	Correll et al. (2014), De Armas et al. (2017), de Mattos et al. (2019), Guerrero et al. (2018), Ji et al. (2007), Kim et al. (2011), Koo et al. (2008), Kristianto & Zhu (2017), Wang et al. (2008)
Supply	de Keizer et al. (2015), de Mattos et al. (2019), Ekşioğlu et al. (2013), Kim et al. (2011), Kristianto & Zhu (2017), Koo et al. (2008), Salehi et al. (2019), Salem & Haouari (2017)
Yield	Correll et al. (2014), Ebadian et al. (2013), González-Hernández et al. (2019), Kim et al. (2011), Koo et al. (2008), Kristianto & Zhu (2017)
Selling price	Dai & Zheng (2015), Kim et al. (2011), Koo et al. (2008), Kristianto & Zhu (2017), Leonzio et al. (2019)
Lead time	Chiadamrong & Piyathanavong (2017), Ding et al. (2009), Keramydas et al. (2017)
Capacity	Chiadamrong & Piyathanavong (2017), Ekşioğlu et al. (2013)
Product quality	de Keizer et al. (2015), Koo et al. (2008)
Weather conditions	Ebadian et al. (2013), Ekşioğlu et al. (2013)
Temperature	de Keizer et al. (2015), González-Hernández et al. (2019)
Arrival frequency	Costa-Salas et al. (2017)
Pickup time	Costa-Salas et al. (2017)
Delivery time	Costa-Salas et al. (2017)
Trans-shipment time	Costa-Salas et al. (2017)
Order-picking time	Ko et al. (2006)
Travel time	Ko et al. (2006)
Raw material quality	Koo et al. (2008)
Harvest schedule	Ebadian et al. (2013)
Moisture	Ebadian et al. (2013)
Machine efficiency	Ebadian et al. (2013)
Transportation delay	Karabakal et al. (2000)
Yield variability	Correll et al. (2014)
Processing time	de Keizer et al. (2015)
Loading time	de Keizer et al. (2015)
Degradation time	González-Hernández et al. (2019)
Product losses	Guerrero et al. (2018)
CO_2 emissions	Guerrero et al. (2018)
Purchase price	Zhang et al. (2019)

and evolutionary programming.

An open opportunity is identified in the optimization of criteria different than cost, since *cost minimization* is the most addressed objective criterion (Table 12): 78% of the papers seek to optimize it, either as a single objective or jointly with other criterion in a multi-objective model (identified with an asterisk in the table). For instance, a paper by Saif & Elhedhli (2016) minimizes both operation costs and costs associated to global warming impact. The latter objective is important here due to the environmental impact that the designed cold supply chain can yield. Two cases that require warehousing and transportation with a controlled temperature are analyzed through a hybrid sim-opt approach.

Table 12: Sim-opt references according to objective criterion.

Objective criterion		**Authors**
Minimize	Costs	Correll et al. (2014), De Armas et al. (2017), de Keizer et al. (2015), de Mattos et al. (2019), Ding et al. (2009)*, Ebadian et al. (2013), Ekşioğlu et al. (2013), Guerrero et al. (2018)*, Gumus et al. (2009), Ji et al. (2007), Karabakal et al. (2000), Keramydas et al. (2017)*, Ko et al. (2006), Kristianto & Zhu (2017)*, Leonzio et al. (2019), Martins et al. (2017), Saif & Elhedhli (2016)*, Salehi et al. (2019), Salem & Haouari (2017), Truong & Azadivar (2003), Villareal & Flores (2009), Wang et al. (2008), Ye & You (2015), Yoo et al. (2010), Zhang et al. (2019)
	CO_2 emissions	Guerrero et al. (2018)*, Keramydas et al. (2017)*, Saif & Elhedhli (2016)*
	Social goals deviations	Costa et al. (2017)*
	Emission costs	Kristianto & Zhu (2017)*
	Environmental impact	Costa-Salas et al. (2017)*
	Product losses	Guerrero et al. (2018)*
Maximize	Profit	Chiadamrong & Piyathanavong (2017), Costa et al. (2017)*, Costa-Salas et al. (2017)*, Dai & Zheng (2015), González-Hernández et al. (2019), Kim et al. (2011), Koo et al. (2008)*
	Customer service level	Ding et al. (2009)*, Koo et al. (2008)*
	Ecological credits	Costa et al. (2017)*

Finally, Table 13 shows papers that consider some supply chain special case or a real-world case. The latter is considered by 21 out of 32 papers, which shows the relevance that most authors give to apply their models to real-life cases. For instance, a two-part paper is written by Pitty et al. (2008) (not included in the table) and Koo et al. (2008) (in the table). The former one proposes an integrated refinery supply chain dynamic simulator. The latter combines this simulation tool with a non-dominated sorting genetic algorithm to design and operate a petroleum refinery SCN with the objectives of maximizing profit margin and customer satisfaction.

Only 11 out of 32 papers papers consider explicitly a supply chain special case, being the agricultural SCN the most addressed one. For instance, an agricultural SCN is designed and assessed by de Keizer et al. (2015) through a hybrid MILP and DES model. The objective is to minimize the total cost taking into account the high perishability of fresh cut flowers. Therefore, the product quality decay is modeled as a function of time and temperature. Data from a real-world Dutch company that distributes flowers across Europe is used to test the proposed approach.

Table 13: Sim-opt references according to the supply chain special case and real-world case.

Authors	Supply chain special case	Real-world case
Correll et al. (2014)	Agricultural	A biomass supply chain
Costa et al. (2017)	Sustainable	A Colombian first generation biodiesel production from palm oil feedstock
Costa-Salas et al. (2017)	Reverse	A Colombian city used tire collection process
de Keizer et al. (2015)	Agricultural	A Dutch cut flower retail chain
de Mattos et al. (2019)	—	Distribution of long-lasting insecticidal nets in Ivory Coast
Ding et al. (2009)	—	A European automotive production-distribution network
Ebadian et al. (2013)	Agricultural	A Canadian agricultural biomass supply chain
Ekşioğlu et al. (2013)	Agricultural	A supply chain for biocrude production
González-Hernández et al. (2019)	Agricultural	A supply chain of prickly pear in Mexico
Guerrero et al. (2018)	Closed-loop	—
Gumus et al. (2009)	—	A multinational company in alcohol free beverage sector
Karabakal et al. (2000)	—	Volkswagen distribution system
Keramydas et al. (2017)	—	A white goods retailer who serves the Greek market
Kim et al. (2011)	—	A biorefinery network in US
Koo et al. (2008)	—	A petroleum refinery supply chain
Kristianto & Zhu (2017)	Agricultural	Ethanol production from rice straws in Indonesia
Leonzio et al. (2019)	—	A carbon capture, utilization and storage supply chain in Germany
Martins et al. (2017)	—	A pharmaceutical wholesaler
Saif & Elhedhli (2016)	Green	Prepared meats in Canada, A cold supply chain for publicly-funded vaccines in Canada
Salehi et al. (2019)	Humanitarian	A blood supply chain network in a possible earthquake in Tehran
Villareal & Flores (2009)	—	A wood distribution company in Mexico
Zhang et al. (2019)	—	A natural gas supply chain

5. Insights and Future Research Directions

The increasing concerns about operational and disruption risks in SCND lead to use methods that model them as accurately as possible. As discussed in previous sections, designing and assessing resilient SCNs requires to take into account many factors altogether, from uncertainty in several parameters of the optimization model that need to be considered (e.g., random occurrence of disruptions, random customers' demands or links availability, etc.) to dynamic conditions that might affect daily operations (e.g., continuous changes in availability of raw materials, transport costs, or customers' demands, among others). Consequently, solving methods need to be able to address all these characteristics of real-world SCNs together with the fact that, in most cases, SCNs constitute large-scale complex systems (Gen et al., 2018). Modeling these concerns means: *(i)* considering uncertainty to represent operational and/or disruption risks (inherent in supply chain resiliency research) coherently with real-world features; *(ii)* optimizing the supply chain design according to suitable criteria, such as costs, profit, environmental impact, or resilience; and *(iii)* using time-efficient methods when designing and assessing resilient supply chains considering their complexity.

Under these circumstances, pure optimization or pure simulation methods alone do not seem to have the flexibility and power to provide answers to increasingly demanding decision-makers. On the contrary, hybrid sim-opt methods, such as those from stochastic programming (Santoso et al., 2005) or simheuristics, which combine metaheuristic frameworks with simulation, seem to be more appropriate to deal with problems under uncertainty. In particular, simheuristics have shown to be an effective method to deal with large-scale *NP-hard* optimization problems under uncertainty conditions (Juan et al., 2018). For instance, Pagès-Bernaus et al. (2019) propose a simheuristic algorithm to design SCNs in the context of e-commerce, and shows that it tends to outperform classical stochastic programming approaches when solving large-sized instances. Since they are based on the use of simulation and therefore can provide rich information on any design plan, simheuristics are well suited for estimating SCN risk-related properties such as: reliability, robustness, and resilience.

Likewise, when dealing with large-scale SCNs under dynamic conditions, the combination of metaheuristics with machine learning methods might also be quite appropriate. In effect, learnheuristics are based on the use of learning mechanisms that allow the metaheuristic algorithm to improve their capacity to adapt to the existence of dynamic inputs (Calvet et al., 2017). For instance, Calvet et al. (2016) address a SCN in which both distribution costs and customers' demands might be influenced by the way customers are assigned to the heterogeneous facilities or retail centers.

Although traditional SCND has focused on long-term and costly to reverse strategic decisions, there might be situations in which the design, re-design and assessment of a SCN needs to be performed in a fast way and several times in a short time period, thus calling for 'agile' SCND. This is the case, for example, of emergency situations associated with natural or human-caused disasters, where a set of mobile facilities (e.g., first-aid centers) need to be quickly deployed over a territory and then re-allocated as new events happen (e.g., some areas get stabilized while others require more attention and resources). In this cases, decisions on the SCND (e.g., facility location, customers' allocation, or transport modes) need to be made almost in real time and are required to be re-evaluated every few days or even hours. In these cases, the use of biased-randomized algorithms (Grasas et al., 2017) constitute an interesting tool yet to be fully explored, specially when they are combined with parallelization techniques in order to generate high-quality solutions in real-time. Finally, with the advent of the internet of things (IoT), real-time information obtained of sensors distributed by all the elements of the supply chain can be used to design SCN. Hence, the design process would not only become more efficient, but also much more reliable, since the IoT provides to supply chain managers a coherent stream of real-time data, by which they can develop flexible contingency plans and strategies to respond to disasters (Ivanov et al., 2019). Furthermore, as IoT allows the continuous self-assessment of the supply chain, it is possible to predict eventualities during supply chain operation. Thus, decision makers can assess and re-design the SCN in function of the time period of the disaster, providing a flexible and fast recuperation of the system, designing intelligent supply chains networks (Cui, 2015).

6. Conclusions

This paper has provided a literature review on recent works related to the design of resilient supply chain networks via simulation and optimization approaches. A systematic literature review approach was followed. Our review shows that this is an emerging topic, which has been gaining 'momentum' during the last years. Simulation-optimization methods are specially designed to deal with considerations regarding uncertainty, time-efficiency and optimization of suitable criteria. The simulation side provides efficient tools to address uncertainty. *Discrete-event simulation* stands out in analyzed papers, although *Monte Carlo simulation* is also a useful tool. Nevertheless, simulation does not allow itself to obtain optimal or near-optimal solutions. Therefore, the optimization side is intended to achieve them. Here, we find that most used mathematical approaches are *stochastic programming*, *mixed-integer linear programming*, *fuzzy programming*, and *robust optimization*.

Hence, a hybrid simulation-optimization approach is particularly useful due to the following facts: *(i)* both operational and disruption risks are subject to uncertainty in real-world problems. The use of a deterministic approach would lead to a supply chain design whose resilience is not coherent with this reality, increasing potential high economic losses after a disruption event; and *(ii)* instead of just measuring resilience or costs, as pure simulation would do, resilience should be optimized in order to face risks properly. However, extremely resilient supply chains design would be highly expensive. A trade-off between resilience and any economic performance indicator would be very useful. Solving methods considering multiple objectives become relevant in these cases.

Analyzed papers show that *costs minimization* is still the widely preferred optimization objective, but given the contemporary concerns about environment, sustainability, and resilience, other objectives have been taken into account, such as *environmental impact* or *CO_2 emissions minimization*. Nevertheless, only a few authors have tackled them. Consequently, the consideration of multiple-objective approaches constitutes an open challenge. In addition, *demand* is the most addressed uncertain parameter, which shows its relevance when designing and assessing supply chain networks. However, other parameters subject to uncertainty, such as *costs*, *capacity*, *supply*, *node disruption*, *link disruption*, and many others should also be considered together with *demand*. Clearly, these combinations are also open research lines, especially when considering both operational and disruption risks. The uncertainty regarding these parameters is mostly addressed through *probability distributions* and *scenarios with assigned probabilities*. *Fuzzy numbers* are used to a lesser extent.

Six supply chain design special cases were identified: *sustainable, closed-loop, agricultural, green, competitive* and *reverse supply chain*. About 37% of the papers address at least one of these. In addition, real-world cases are considered by most papers. Economic sectors, such as the automotive industry, the pharmaceutical industry, or the clothing industry are tackled.

Most real-life supply chain networks are large-sized and associated problems easily become *NP-hard* as realistic constraints are included into the mathematical models. Furthermore, if several uncertain parameters and multiple objectives are considered, an exact optimization may become time-prohibitive. Hence, it is somewhat surprising that the use of *metaheuristic methods* is still relatively scarce in sim-opt methods for resilient supply chain network design. Most authors prefer to use *exact methods* as solving approach. Besides, only about 9%

of the papers use hybrid simulation-optimization methods to design resilient supply chain networks. Therefore, the open opportunities are huge when considering the hybridization and metaheuristics to carry out the design process.

In consequence, our paper proposes the use of emerging hybrid methods, such as simheuristics and learnheuristics, to deal with the design of supply chain networks under uncertainty and dynamic conditions. We point out the need of considering agile methods, such as parallelized versions of biased-randomized algorithms, to address a new type of supply chain networks characterized by the need of re-designing facility location, customers' allocation, and transport modes every few hours or days.

Although there are some advantages when following a systematic review protocol in comparison with narrative reviews, such as the reduction of sources of bias and the increase in objectivity for the selection and analysis of research works, there are some limitations as well. Indeed, the combination of terms to search for documents and the selection of databases may lead to the exclusion of some research papers. Unfortunately, it is not possible to provide the list of such excluded studies. In addition, as analyzing papers addressing the use of simulation and optimization techniques for resilient supply chain network design and assessment is a criterion for this paper, some studies on this topic *not* developing or applying any of these techniques are also excluded.

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