



Review of quantitative methods for supply chain resilience analysis

Seyedmohsen Hosseini^{a,*}, Dmitry Ivanov^b, Alexandre Dolgui^c



^a Industrial Engineering Technology, University of Southern Mississippi, 730 East Beach Boulevard, Long Beach, MS, USA

^b Supply Chain Management, Berlin School of Economics and Law, Berlin, Germany

^c Automation, Production and Computer Sciences Dept., IMT Atlantique LS2N - CNRS UMR 6004, La Chantrerie, France

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ABSTRACT

Supply chain resilience (SCR) manifests when the network is capable to withstand, adapt, and recover from disruptions to meet customer demand and ensure performance. This paper conceptualizes and comprehensively presents a systematic review of the recent literature on quantitative modeling the SCR while distinctively pertaining it to the original concept of resilience capacity. Decision-makers and researchers can benefit from our survey since it introduces a structured analysis and recommendations as to which quantitative methods can be used at different levels of capacity resilience. Finally, the gaps and limitations of existing SCR literature are identified and future research opportunities are suggested.

1. Introduction

In today's global and increasingly dynamic and turbulent environments, supply chains (SC) are confronted with numerous events that threaten to disrupt SC operational activities and jeopardize efficient and effective performance. Disruption risks are events caused by natural catastrophes, such as hurricanes, earthquakes, or floods, or by man-made threats, such as terrorist attacks or labor strikes. Disruption risks typically refer to low likelihood, but high impact events, which unpredictably vary in type, scale and nature, are intermittent and irregular to be identified, estimated and forecasted well, and may have short or long term negative effects (Ho et al., 2015, Torabi et al., 2015, Dolgui et al., 2018, He et al., 2018).

For example, as a result of the tsunami and earthquake that struck Japan in 2011, Toyota's parts suppliers were unable to deliver parts at the expected volume and time. This forced Toyota to halt production for several days. Similarly, General Motors was forced to stop production because of a shortage of raw materials from their Japanese suppliers (Huffington Post, 2015). Nissan suffered significant setbacks: the company had a high level of dependency on raw materials from suppliers who were located in the tsunami and earthquake zone and supplied 12% of Nissan's engines (BBC News, 2011). Nissan had to temporarily shut down production at its Sunderland UK plant.

The Japanese tsunami and earthquake also impacted the aerospace industries. Boeing Company retained collaboration with Japanese manufacturers and suppliers because of the punctuality of their deliveries and their quality of production. Five Japanese companies, including Mitsubishi Heavy Industries Ltd., produce structural parts comprising 21% of the 777 wide body jet and 35% of the 787 jet aircraft, making Japan the largest supplier of the 777 and 787, after the U.S. (Bloomberg, 2011). The Japanese tsunami shook aerospace SCs. Three first-tier aerospace suppliers, Mitsubishi Heavy Industries, Kawasaki Heavy Industries, and Fuji Heavy Industries, were located in a disruption-prone zone. Shares of those three companies dropped a minimum of 1.2% and a maximum of

* Corresponding author.

E-mail addresses: mohsen.hosseini@usm.edu (S. Hosseini), divanov@hwr-berlin.de (D. Ivanov), alexandre.dolgui@imt-atlantique.fr (A. Dolgui).

6%, following the disaster ([Reuters, 2011](#)).

The examples given provide evidence that SC systems must be designed so that they can withstand disruptions (low vulnerability) and recover from disruptions quickly and at a minimal cost (high recoverability). In other words, the question of SC resilience (SCR) arises when designing global supply networks. SCR manifests when the network is capable to withstand, adapt, and recover from disruptions to meet customer demand and ensure performance.

In the last decade, SCR has been transitioning from an emerging topic to a rapidly growing research area: model taxonomies need to be developed, and different types of operational research techniques and generic applications and trends classified. Though there are very few literature reviews on SCR, existing ones are conceptually and empirically-oriented. Notwithstanding the growing number of publications on SCR, there are few studies that focus on quantifying attributes of resilience in SCs. Existing surveys tend to focus on the qualitative (conceptual) aspects of SCR.

[Fiksel \(2003\)](#) provided insights on how firms, corporations, and SC companies can handle disruptive events, such as loss of a supplier, labor strikes, or transportation disasters, in order to maintain acceptable competitive advantages. [Tukamuhabwa et al. \(2015\)](#) presented a survey paper that defines and reviews conceptual factors that could improve the resilience of SCs. [Kamalahmadi and Mellat-Parast \(2016\)](#) analyzed the definitions and drivers of enterprise resilience, as well as the principles of SCR. Several commonalities can be observed across existing surveys. The authors aim to identify and analyze the factors that contribute to SCR from a qualitative standpoint. The majority of factors discussed in these surveys are qualitative or semi-qualitative. For example, Japanese automotive companies tried to collaborate with auto part suppliers being geographically dispersed to reduce the risk impact likelihood of their SCs. Auto manufacturing companies reconsidered their backup and emergency inventory. Geographic separation of suppliers and holding excess backup and emergency inventory are considered as a two resilience enhancement features for auto manufacturers. When reviewing disruptive examples in the SCs and suggested mitigation and recovery policies in literature, the analysis highlights a greater geographic distribution of production facilities, protection of manufacturing sites as well as operational redundancies and flexibilities in capacity and inventory. Left ignored, however, was the deciphering of the SCR factors according to different levels of disruption severity – an important SCR dimension which our study is pertained to.

The importance of quantitative methods to studying SC disruption risk has been highlighted in surveys by [Fahimnia et al. \(2015a\)](#), [Ho et al. \(2015\)](#) and [Snyder et al. \(2016\)](#). [Pires Riberio and Barbosa_Povoa \(2018\)](#) survey highlighted the importance of quantitative analysis of SCR. The reviews of quantitative methods by [Ivanov et al. \(2017b\)](#) and [Dolgui et al. \(2018\)](#) direct attention to specific aspects of SCR, i.e., recovery stages, and the ripple effect in the SC, respectively. [Ivanov and Dolgui \(2018\)](#) developed a classification scheme for analyzing SC disruption risk literature. None of these studies, though, presented a systematic review of the recent literature on quantitative SCR modeling considering in a structured way different levels of SCR – a distinctive and significant contribution made by our study relying on the original concept of resilience capacity. In addition, the existing surveys do not systematically specify how the qualitative SCR factors can be operationalized in the quantitative models. As a result, it is not yet clear how to develop recommendations on using specific quantitative methods and relate them to inherent SCR properties.

This study aims to provide a comprehensive review of the quantitative analyses of SCR. Such a review can be particularly beneficial for researchers who seek to develop analytical models for SCR. The particular contribution of this paper is exploring and analyzing quantitative drivers of SCR around the resilience capacity concept ([Biringer et al., 2013](#), [Hosseini and Barker, 2016b,c](#)) that is also used for analysis, classifications, and identification of future research areas. The capacity resilience concept suggests building three lines of defense, which is close to the three level resilience classification of LCN (low-certainty-need) SCs proposed by [Ivanov and Dolgui \(2018\)](#), i.e., parametric redundancy or absorptive capacity in the form of redundant inventory, process flexibility or adaptive capacity in the form of backup suppliers established, and structural variety or restorative capacity in the form of technology diversification. Such a combination is unique in SCR literature and explicitly incorporates a variety of decision-making dimensions at different levels of disruption severity accounting for prioritizing investments in building and maintaining SCR. It mimics the complexity of business reality affording more comprehensive understanding of SCR and realistic application of quantitative methods for its analysis.

Firms usually encounter all three stages when coping with disruptions. Even if the methods of SC resilience increase according to the three lines of defense visible in literature, they have been mostly considered fragmented in previous surveys; we consolidate them, for the first time, into an integrated framework. This paper also suggests and classifies several methodologies that can be applied in the future to formulate and quantify SCR problems. Our survey can be of value for decision-makers and researchers since it proposes a structured analysis and recommendations as to which quantitative methods to use, at different levels of defense, according to the capacity resilience concept. The usage of resilience capacity concept for SCR literature analysis is the unique feature of this paper that differentiates it from the other existing quantitative surveys ([Fahimnia et al., 2015a](#), [Ivanov et al., 2017b](#), [Pires Riberio and Barbosa_Povoa, 2018](#)).

The theoretical foundations of this study build on three main perspectives, namely:

- (1) Analyzing and visualizing existing SCR literature, particularly from an analytical and mathematical modeling standpoint;
- (2) Reviewing and classifying the quantitative contributions of SCR based on capacity for resilience; and
- (3) Identifying the gaps and limitations of current research and proposing potential research opportunities.

The paper is organized around these perspectives as follows. [Section 2](#) presents the research methodology of a structured literature review. An analysis of data visualization in current literature is presented in [Section 3](#). [Section 4](#) is devoted to definitions and qualitative analysis of SCR literature, with a focus on factors of particular importance for quantitative models. Quantitative analysis approaches to SCR and its measurement are presented in [Section 5](#). [Section 6](#) highlights current gaps and future research

opportunities. The paper is concluded in [Section 7](#) with a summary of major findings in research and their implications.

2. Research methodology of literature review

We conducted a systematic survey to evaluate the body of literature on SCR. This systematic literature review has been carried out through an iterative process of defining appropriate research terms, reviewing the literature, completing analysis, and finalizing classification results. The details of the research methodology utilized in this paper are as follows:

- (1) *Search methodology*: The literature review considers publications about SCR over the last 15 years from 2002 to 2017. It includes definitions of SCR, quantitative and analytical modeling of SCR, and follows an extensive, systematic search of academic peer-reviewed literature. The review also contains both empirical and non-empirical studies, although the main focus is on non-empirical results. An initial search was carried out through the Google Scholar and Scopus citation databases to identify relevant papers. The list of papers was obtained from different publishers, including Elsevier (www.sciencedirect.com), Informs (<http://pubsonline.informs.org/>), Springer (<https://link.springer.com/>), Taylor & Francis (<http://www.tandfonline.com/>), Emerald (www.emeraldinsight.com), JSTORE (<http://www.jstore.org/>), InderScience (www.inderscience.com), IEEE (ieeexplore.ieee.org/xpl/periodicals.jsp), and some library services (e.g., Engineering Village www.engineeringvillage.com). In order to ensure recent publications are covered in this literature review, the same procedure was implemented to locate papers published between 2016 and 2018 according to set keywords, as explained below. Information clustering has been carried out using CiteSpace software ([Chen, 2016](#)) to distinguish between the relevant and irrelevant categories of academic papers. Resilience is a multi-disciplinary concept that has been widely receiving attentions by researchers from different disciplines. With the help of CiteSpace, we were able to identify some clusters that are not relevant to the SCR papers such as computer science and civil engineering.
- (2) *Methodology implementation*: The literature search was conducted using Boolean keywords combinations “(SC vulnerability OR supply disruptions) AND (SC resilience OR SC resiliency)”. The keywords used were “SC resilience”, “resilience supplier”, “SC vulnerability”, “supply disruptions”, “resilience”, “resilient supply”, “SC disruption”, “flexibility”, “resilience distribution networks”, “supply resilience strategy”, “SC flexibility”, “resiliency in SC”, and “enterprise resilience”.
- (3) *Reviewing, refining, and filtering database*: The papers identified in the search were then analyzed and evaluated by reviewing abstracts, then reading the full-text of each article. Irrelevant papers were filtered out, based on academic judgment, after being read in full. We also utilized information clustering techniques implemented using CiteSpace software to filter out irrelevant papers. We scanned the references of papers that have been found through the searching process to find relevant papers not identified through the search process. Reference chasing was also performed to find relevant papers not identified through the search process. The reviewing, refining, and filtering of papers not only established a breadth and width coverage, but also captured important elements of the overall picture of SCR literature. In total, 168 papers are reviewed in this study.

A block diagram of the methodology is illustrated in [Fig. 1](#).

The outcomes of the literature review conducted to allow for data visualization analysis, analysis of geographic distribution of

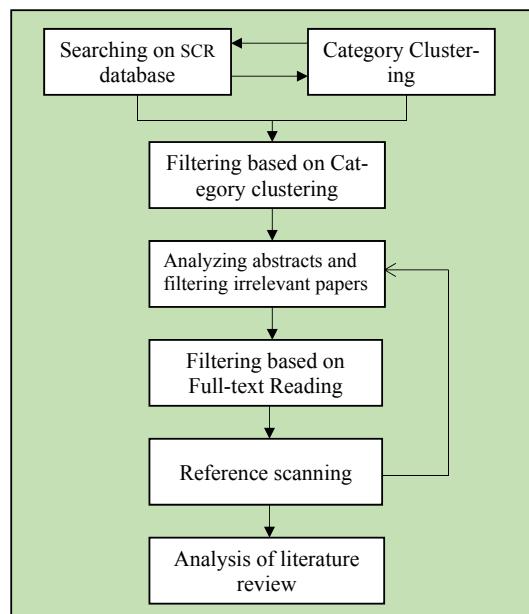


Fig. 1. The flowchart of literature-review methodology.

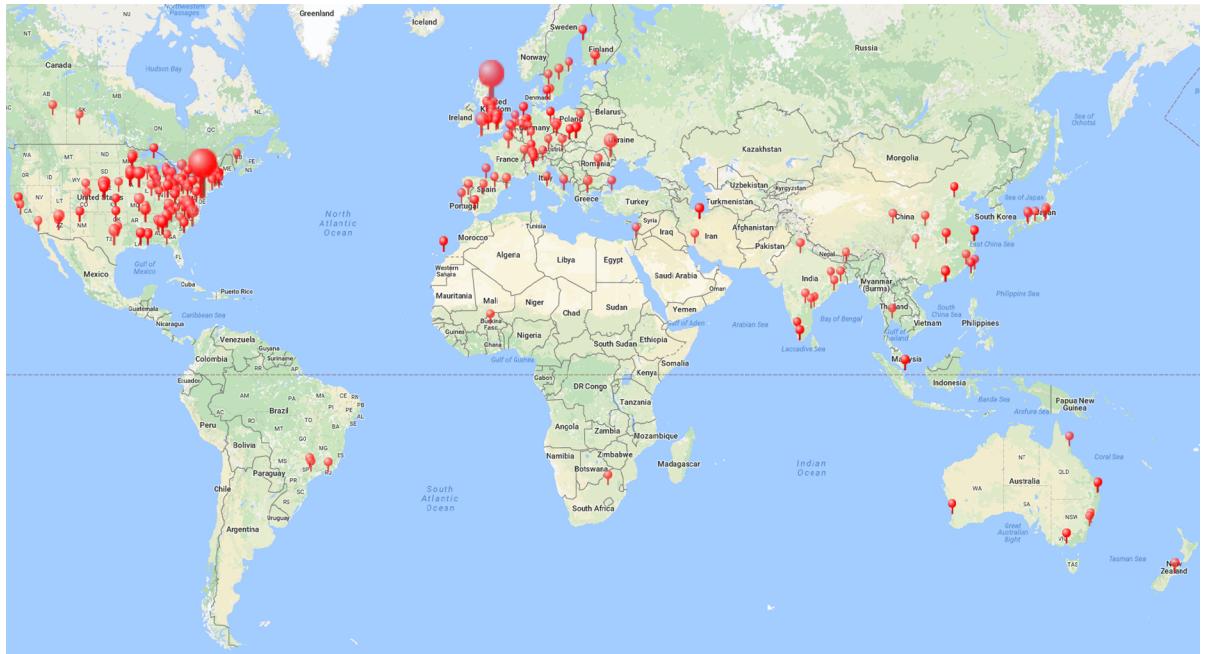


Fig. 2. Geographical locations of all contributing organizations.

contributed organization, as well as category, journal and keyword information clustering.

3. Data visualization analysis of literature review

This section presents a visualization-based scientometric analysis to examine the current state and explore developments in the field of SCR. Analyzing how data was visualized in literature using visualization software has recently received a great deal of attention by researchers conducting state of the art reviews, i.e., [Fahimnia et al. \(2015a\)](#), [Li et al. \(2017\)](#), [Yu and Xu \(2017\)](#), [Hosseini et al. \(2016a\)](#), [Fahimnia et al. \(2015b\)](#). The results of such an analysis help to answer the following questions: (1) Which subject category is the most popular in the domain of SCR?; (2) Which journals extensively publish about SCR?; (3) Organisations of which countries are most productive in producing SCR research?; (4) What are emerging trends and developments in SCR research?

3.1. Geographical distribution of contributing organizations

An interesting bibliometric analysis is to uncover the geographical distribution of all organizations (research institutes) contributing to SCR literature. We used BibExcel to analyze bibliographical data in SCR research. Fig. 2 illustrates the geographical distribution of all contributing organizations. The size of the red circles is proportional to the contribution degree of each organization. It becomes evident that U.S. research institutes have the highest contributions to SCR literature, and remarkable that most of these are located on the east coast. Our findings indicate that England and China are the second and third most productive in terms of SCR literature. The degree of contribution from other countries can be seen in Fig. 2. Notably, AGH University Science & Technology from Poland is the most productive research institute, while MIT and Northwestern University from the U.S. are the second and third most productive research institutes.

3.2. Category information clustering

An important analysis carried out in this study was to develop information clustering in SCR from the perspective of categories. To do so, CiteSpace visualization software was utilized. CiteSpace has been used by many researchers to visualize and analyze trends and patterns in literature ([Yu and Xu, 2017](#); [Chen et al., 2016](#); [Xiang et al., 2017](#)). Category information clustering, using CiteSpace, helped us identify and exclude irrelevant papers, during our search process, such as those concerning ecology and environmental science and food science and technology. For example, Fig. 3 depicts one snapshot of the visualization results from CiteSpace that demonstrates clusters of papers. These clusters are comprised of papers which share the same keywords. The size of the cluster is proportional to the number of papers that use the specific keyword representing the cluster. As a result, irrelevant papers could be filtered out according to keywords in the category information clustering.

It should be noted that CiteSpace implements spectral clustering technique to identify clusters. Generally speaking, spectral clustering outperforms traditional clustering methods such as *k*-means or single linkage ([Shi & Malik, 2000](#), [Luxburg, 2006](#)). For

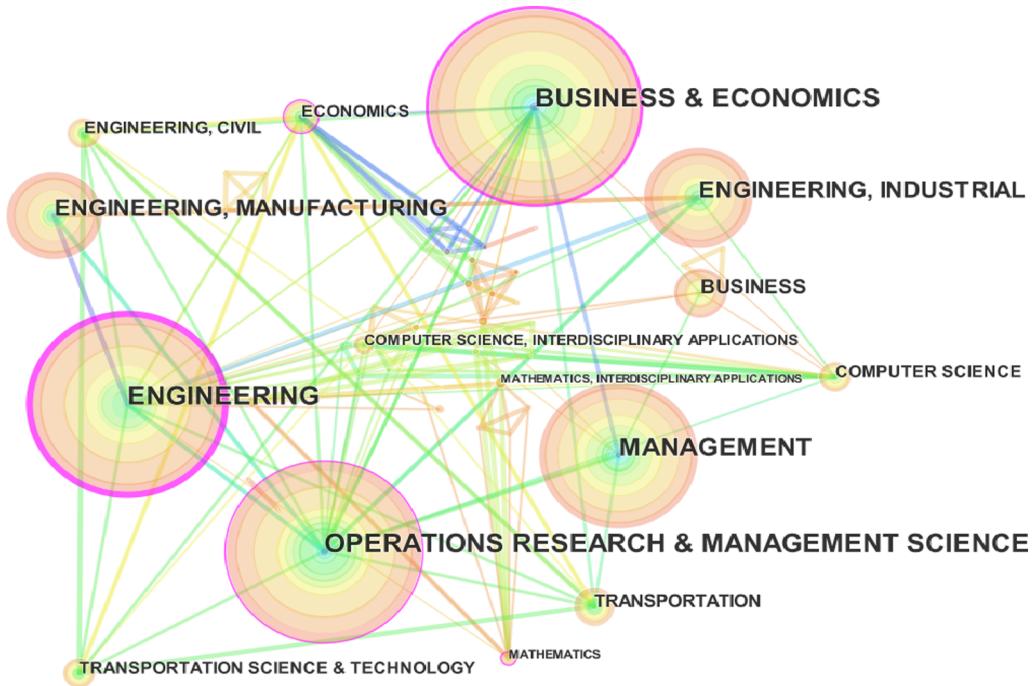


Fig. 3. Category information clustering.

example, spectral clustering is more flexible and robust and does not imply any assumptions on the forms and number of clusters unlike the k -means clustering. Hence, the number of clusters is uniformly determined by the spectral clustering algorithm based on the optimal cut method. It is notable that cluster labels are based on the keywords and abstracts of citing papers determined by log-likelihood ratio (LLR). More technical information about spectral clustering and LLR on co-citation clustering can be found in (Chen et al., 2009).

3.3. Keyword information clustering

Another visualization performed for this study was to analyze how frequently certain keywords were used in SCR literature. The

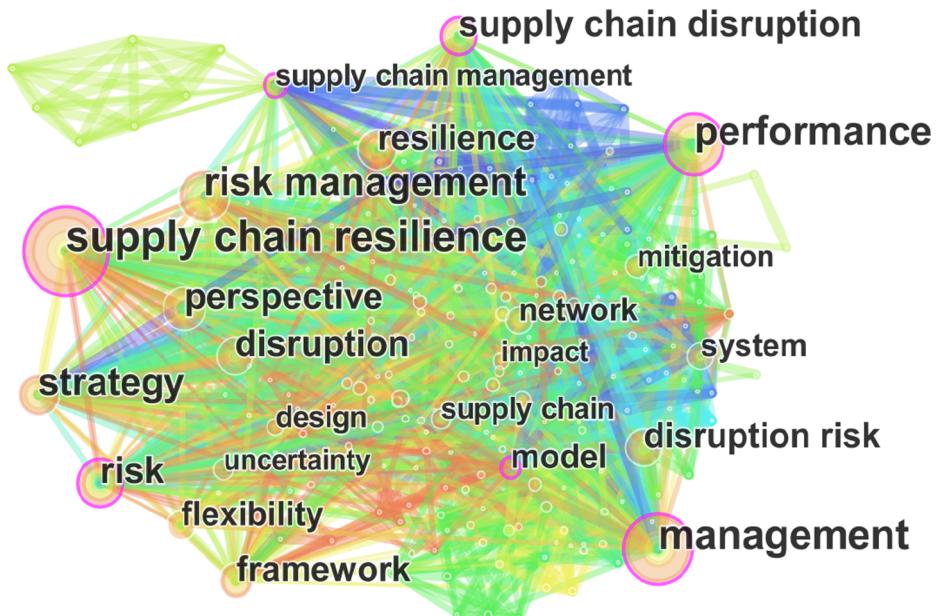


Fig. 4. Keyword information clustering of SCR research area.

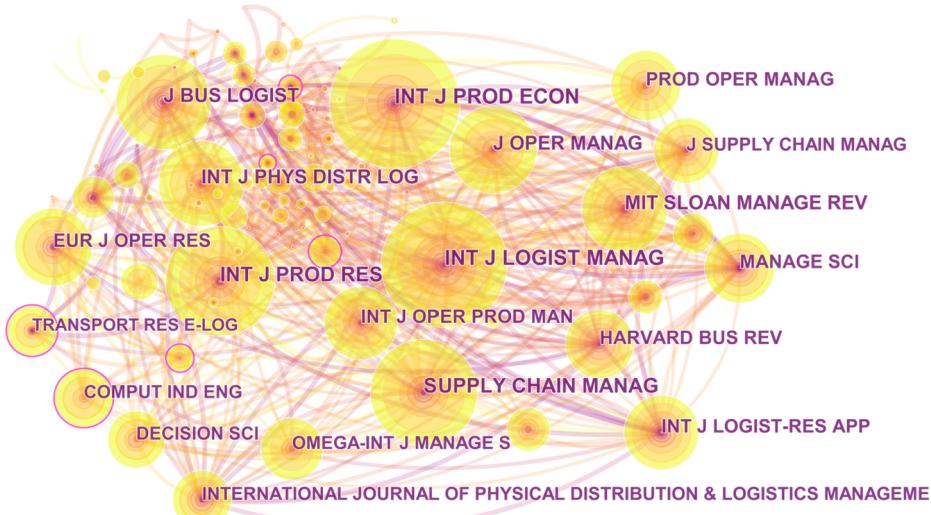


Fig. 5. Main journal clusters in SCR research area.

results illustrated in Fig. 4 show that “SCR” is the main keyword, followed by “management”, “performance”, “SC disruption”, “risk”, and “disruption”. For greater specificity, a pairwise comparison between keywords used across SCR literature was examined. For example, Fig. 4 shows that “SC resilience”, “management”, “performance”, and “SC disruption” are the most common keywords used together across the SCR papers analyzed. The thickness of the line between two given words denotes the degree of connection: a thicker line means a greater frequency of connection. We found that “strategy” used in SCR papers refers to a resilience strategy implemented before and after disruptive events. Literature has also extensively dealt with “risk”, “flexibility”, and “framework” as the next most popular keywords used in tandem with “SC resilience”.

3.4. Journal information clustering

We used CiteSpace to visually cluster the SCR literature, based on source of publication. According to the results represented in Fig. 5, International Journal of Production Economics, International Journal of Logistics Management, International Journal of Production Research, and Supply Chain Management: An International Journal, are the top four cited journals contributing to the SCR literature, followed by Journal of Business Logistics and MIT Sloan Management Review. The analysis of journal clusters shows that Operations Research Journals, such as European Journal of Operational Research, Computers & Operations Research, Transportation Research-Part E, and Decision Science, have smaller cluster size in comparison with journals, such as International Journal of Logistics Management, International Journal of Physical Distribution & Logistics Management, MIT Sloan Management Review, and Journal of Business Logistics, which focus on the qualitative aspect of SCR. This analysis emphasizes the need for more quantitative research on SCR in the future.

4. Definitions and qualitative analysis of SCR literature

Companies that operate at global scale with inherent uncertainty at the structural SC design level have a common question to ask. How do some companies obtain better performance than others under conditions of severe disruptions? In this section we introduce the notion of SCR in the framework of resilience capacity. Resilience is a multidisciplinary concept that was initially discussed in sciences, such as psychology (Bonanno et al., 2005; Bonanno and Galea, 2007), ecology (Hartvigsen et al., 1998; Webb, 2007; Kerkhoff and Enquist, 2007), economics, and organizations (Rose, 2007; Hollnagel, 2006). In ecology literature, resilience is loosely defined by Webb (2007) as “the ability of the system to maintain its function when faced with novel disturbance”. More generic definitions of resilience can be found in (Hosseini et al., 2016a).

The concept of SCR is relatively new, along with a broader focus of research in SC risk management. SCR has been defined by various scholars. Christopher and Peck (2004) defined SCR as “the ability of SC system to return to its original or move to a new, more desirable state after being disrupted”. Sheffi and Rice (2005) defined SCR as “the firm’s ability to absorb disruptions or enable the SC network to return to state conditions faster and thus has a positive impact on firm performance”. Ivanov and Sokolov (2013) understand SCR as the ability to maintain and recover (adapt) planned execution, as well as to achieve planned (or adapted, yet still acceptable) performance. Appendix A summarizes a comprehensive list of SCR definitions proposed in recent literature.

Despite of variations in SCR definitions proposed, some commonalities can be observed. Definitions shared several key elements, such as anticipating unforeseen disruptive events, withstanding disruptions, responding quickly to disruptions, recovering from disruptions, and returning to steady state conditions. Closs and McGarrell (2004) and Poins and Koronis (2012) highlighted that anticipating unexpected disruptions ensures better readiness and preparedness. Kim et al. (2015), Pettit et al. (2010), and Closs and

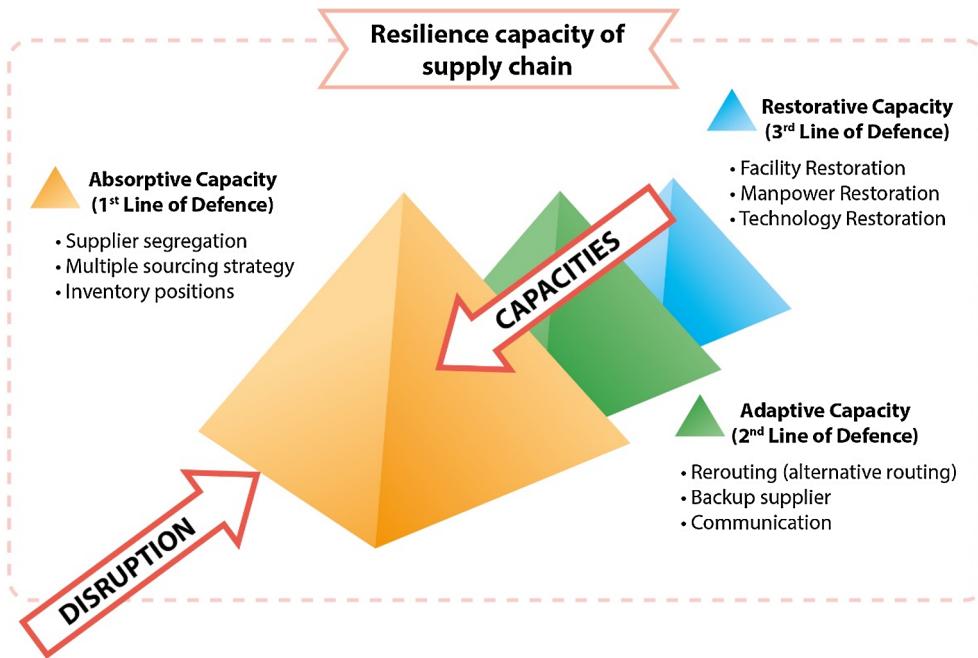


Fig. 6. Resilience capacity of supply chain systems with three lines of defense.

McGarrell (2004) stated that strengthening the capability of SC firms to withstand disruptions is a key proactive strategy that makes SCs more resilient. Many definitions underscore that the capability of a SC to recover and return to normal operations after a disruption is an essential factor of resilience (Longo and Oren, 2008; Falasca et al., 2008; Guoping and Xinqiu, 2010; Poins and Koronis, 2012; Roberta Peria et al., 2014; Ponomarov, 2012; Kamalahmadi and Mellat-Parast, 2016; Govindan et al., 2016).

Although formal definitions of SCR do not appear to highlight the cost of a resilience strategy, some researchers acknowledged the impact of cost-effectiveness in resilience practices. Christopher and Rutherford (2004) highlighted that SCR can be accomplished efficiently and cost effectively using the agile six sigma methodology. Haimes (2006) and Haimes et al. (2008) argued that resilience not only aims to recover the desired states of a system within an acceptable time, but also at an acceptable cost. Ivanov et al. (2014a,b, 2016a, 2017a,b) discussed that disruptions should be mitigated by means of cost-efficient recovery policies. Ivanov and Dolgui (2018) suggested a new approach to SC disruption risk management, where SC behavior is less dependent on the certainty of our knowledge about the environment and its changes, i.e., low-certainty-need (LCN) SCs. Two efficiency capabilities of the LCN SC are a low need for uncertainty consideration in planning decisions and a low need for recovery coordination efforts, based on a combination of lean and resilient elements into SC *resileanness*.

4.1. SCR definition by the resilience capacity concept

In order to present our new definition of SCR, we first need to elaborate on the concept of resilience capacity (Fig. 6).

First and principally, resilience capacity is a new and important dimension of system performance under uncertainty which consists of the resilience enhancement features that could increase the ability of a system to absorb, adapt, and restore itself after disruption (Hosseini and Barker, 2016c). It is based on three lines of defense (Fig. 6), which is close to the three level resilience classification of LCN (low-certainty-need) SCs proposed by Ivanov and Dolgui (2018). Biringer et al. (2013) introduced the concept of resilience capacity with three categories, each of which represents temporal attributes before, during, and after a disruption: absorptive capacity, adaptive capacity, and restorative capacity.

According to Biringer et al. (2013), *absorptive capacity* is the capability of a system to absorb or withstand the impact of system perturbations and minimize the negative consequences of disruption with relatively low levels of energy or effort. Lücker et al. (2018) and Ivanov and Dolgui (2018) refer to multiple sourcing, risk mitigation inventory and supplier segmentation as usual resilience mechanism at this level. For example, PepsiCo uses a backup packing plant in the US and carries a risk mitigation inventory to cope with the disruptions in coconut water supply from South Asia (HBS, 2017). Absorptive capacity refers to all implementations put in place prior to a disruption occurring. Absorptive capacity can be thought of as the first line of defense against disruptions that lessens the effort necessary to recover after a disruption occurs. While development of absorptive capacity is desirable and indeed critical to withstand the disruptions, exploiting the resilience capabilities to achieve the desired performance outcomes through effective adaptation is becoming increasingly important (Ivanov and Sokolov, 2013).

Adaptive capacity is defined by Biringer et al. (2013) as the degree to which a system can adapt itself and attempt to overcome disruption by implementing nonstandard operating practices without any recovery activities. Adaptive capacity is the second line of



Fig. 7. The proposed hierarchy for SCR.

defense against disruption when absorptive capacity is not sufficient to harness disruption. Hosseini and Barker (2016c) identified quick evacuation of port, mode flexibility, and repositioning of containers at the port as primary features of adaptive capacity for increasing the resilience of inland waterway ports. Biringer et al. (2013) described reorganization as a key element of adaptive capacity of companies and SCs. Transportation companies or industries like railroads may normally be prohibited to collaborate with each other by antitrust law however, temporary executive orders can be passed to give permit collaboration to the railroad transportation companies in order to recover quicker in case of national disasters. Finding and re-routing a backup connection between customer and distribution center is highlighted as an adaptive capacity in the case of disruption by Turnquist and Vugrin (2013).

Restorative capacity is defined by Biringer et al. (2013) as the ability of a system to be restored quickly and efficiently in the case if the absorptive and adaptive capacities of that system are not able to maintain an acceptable level of performance. Restorative capacity is the third and last line of defense when the system is broken and unable to perform. Hosseini and Barker (2016c) stated that budget restoration and resource restoration are two factors of restorative capacity for ports.

Based on the notion of resilience capacity for a system, we define SCR as “*SC capability to utilize the absorptive capacity of SC entities to repulse and withstand the impacts of perturbations, to minimize the consequences of disruptions and their propagation by utilizing adaptive capacity and to recover performance level to normal operations in a cost-efficient manner using restorative capacity when absorptive and adaptive capacities are not sufficient.*”

Based on the definition of SCR presented above, we present a resilience hierarchy for SCR, as illustrated in Fig. 7.

The hierachal structure of SCR is compounded of four levels. The bottom level is occupied by features of SCs which enhance resilience these factors, such as surplus inventory at the manufacturer or having a backup supplier, will be discussed in detail in Section 5. Identifying resilience enhancement features enables a better understanding of SCR. SC resilience enhancement features make up the resilience capacity of an SC which, in turn, is comprised of absorptive, adaptive, and restorative capacities. Vulnerability and recoverability of an SC are functions of resilience capacity in the sense that SCs with higher capacity for resilience are less vulnerable to disruption and need fewer recovery efforts. SCs with lower resilience capacity are more vulnerable and require more effort to achieve recovery. Finally, SC resilience, located on the top level of the hierarchy, is a function of the vulnerability and recoverability of the SC.

4.2. Conceptual drivers of SCR

Literature has extensively tried to identify the key characteristics and drivers of SCR from a qualitative point of view. In this subsection, we outline qualitative drivers that could improve the resilience of SCs. These drivers are identified by relevant authors who have identified, referred to, or examined particular resilience strategies (proactive vs reactive). Key characteristics and elements considered are agility, visibility, flexibility, collaboration, information sharing (Blome et al., 2013, Bode and Macdonald, 2017, Dubey et al., 2017, 2018). Although sometimes these elements have been used interchangeably by different authors, we attempt to explicitly specify them and to identify the key drivers that contribute to building SCR taxonomy from the quantitative perspective.

4.2.1. Agility

Christopher and Lee (2004) argued that agility is one of the most powerful means of achieving resilience in the SC. They stated that SC networks with higher agility are capable of more quickly responding to turbulent conditions. Agility is defined as the ability of SC firms to respond quickly, smoothly, and cost-efficiently to sudden changes in supply or demand (Wieland and Wallenburg, 2013). Agility is also defined as a SC firm's ability to respond promptly to unexpected market changes and convert those changes to business opportunities (Jain et al., 2008). SC agility usually refers to the SC ability to quickly adapt the network structure and operations policy to dynamic and turbulent requirements of the customer (Dubey et al., 2018). Wieland and Wallenburg (2013) stated that resilience is formed by two dimensions: agility, which is a reactive resilience strategy, and robustness, which is a proactive resilience

strategy. They highlighted that agility cannot only enhance SC resilience, but also must have a positive effect on the value created for the SC customer.

4.2.2. Visibility

Visibility is defined by [Francis \(2008\)](#) as “the identity, location and status of entities transiting the SC, captured in timely message about events, along with the planned and actual dates/times of these events.” SC visibility has also been defined as a transparent view of upstream and downstream inventories, demand and supply conditions, and production and purchasing schedules ([Christopher and Peck, 2004](#)). [Saenz and Revilla \(2014\)](#) discussed how SC visibility was beneficial to improving Cisco’s resilience of their response to the Japanese tsunami and earthquake of 2011. Although the Japanese tsunami and earthquake resulted in total economic losses of \$217 billion, Cisco suffered almost no revenue loss. Within 12 h of the disaster occurring, Cisco was able to identify all of its suppliers in the disrupted region, from tier 1 suppliers to suppliers of raw materials, and within 24 h was able to map its customers and field 118 inquiries ([Saenz and Revilla, 2014](#)). [Chopra and Sodhi \(2014\)](#) pointed out that visibility in SC entities is a key strategy to protect SCs from disruptions. Visibility is a proactive strategy that contributes to SCR.

4.2.3. Flexibility

[Erol et al. \(2010\)](#) defined flexibility as the ability of firms and enterprises to adapt themselves to changing environments and stakeholders with minimum effort and time. [Millar \(2015\)](#) argued that flexibility, as a feature of SCR, determines a firm’s ability to respond to changes in the market, such external impact being beyond the immediate scope and control of SC ecosystem. [Rice and Caniato \(2003\)](#) recommended a hybrid flexibility approach to enhance SCR. Literature revealed that flexibility practices, including flexible transportation, flexible sourcing, flexible labor arrangement, and postponement, could all contribute to the resiliency of SCs ([Tang, 2006a; Tang, 2006b; Christopher and Holweg, 2011; Pettit et al., 2013](#)). [Christopher and Holweg \(2011\)](#) argued that flexibility makes SCs more resilient by enhancing rapid adaptability during turbulent conditions. In literature, flexibility has been interchangeably used with the term “adaptive capability” ([Soni et al., 2014](#)). [Pettit et al. \(2013\)](#) discussed that SCs with a lower level of flexibility in sourcing and order fulfillment are more vulnerable to disruptions and less resilient.

4.2.4. Collaboration

Empirical and conceptual SCR literature has shown that collaboration is a key factor for building resilient SCs ([Christopher and Peck, 2004; Juttner and Maklan, 2011; Pettit et al., 2013](#)). Although there is agreement among researchers that collaboration can positively enhance SCR, it is not clear exactly how collaboration influences SCR.

Collaboration in SC relates to the capability of two or more autonomous firms to work effectively together, planning and executing SC operations toward common goals ([Cao et al., 2010; Scholten and Schilder, 2015](#)). According to a report released by [BCI in 2013](#), 58% of SC disruptions originate from first tier suppliers and these suppliers are of the most concern for companies in terms of sources or risk. [Blackhurst et al. \(2011\)](#) stated that collaboration between supplier and buyer can significantly reduce the likelihood of SC disruption in the upstream SC and prevent the negative impact of disruption propagation throughout the whole SC.

4.2.5. Information sharing

Information sharing is considered a key driver of SCR by some researchers ([Soni et al., 2014; Datta et al., 2007](#)). [Faisal \(2010\)](#) argued that information sharing can help SCs to mitigate risk in the case of disruptions. They suggest that exchanging and sharing between SC entities prior to and after a disruption is necessary for the resiliency of the SC. [Saghafian and Oyen \(2012\)](#) pointed out that information sharing coupled with emergency backup and storage facilities can make SCs more resistant to disruptions and less vulnerable. [Christopher and Peck \(2004\)](#) argued that lack of information sharing is a key source of SC vulnerability, because SC firms use forecast-driven rather than demand-driven data, which prevents them from sharing information and eventually increases the bullwhip effect.

[Yang and Fan \(2016\)](#) applied an approach based on integrating control theory and simulation to show the impact of information-sharing on reducing the bullwhip effect under demand disruptions. [Brandon-Jones et al. \(2014\)](#) analyzed survey data collected from 264 U.K. manufacturing companies and suggested that information sharing, along with SC connectivity, can improve SCR and robustness. [Li et al. \(2017\)](#) investigated the impact of incorporating information sharing across different echelons of the SC to achieve higher resilience and mitigate uncertainty regarding supplier capacity. Information availability is an important determinant in reliable/unreliable sourcing literature and, more specifically, the availability of information to some players and the non-availability of this information to other players ([Yang et al., 2009; Gupta et al., 2015](#)).

5. Quantitative analysis of SCR

In this section, we use the concept of resilience capacity, introduced in [Section 4](#), to classify the analytical papers of SCR.

5.1. Absorptive capacity

5.1.1. Supplier segregation

Separating suppliers geographically can effectively reduce the disruption risk imposed on a manufacturing facility, specifically in the event of a regional natural disaster. After the Japanese tsunami and earthquake, which saw many auto-part suppliers on the east coast severely impacted, several automakers, including Toyota, tried to work with geographically dispersed suppliers. Purchasing raw

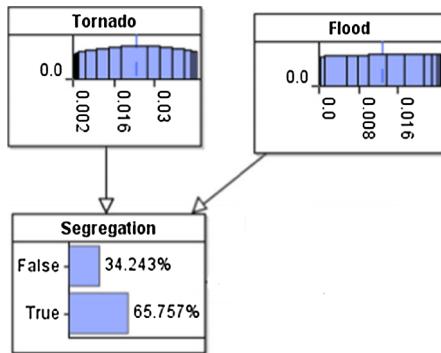


Fig. 8. Bayesian network modeling of supplier segregation from natural disaster (Hosseini and Barker, 2016b).

materials from suppliers located in different regions could potentially reduce the likelihood of a regional natural disaster negatively affecting the suppliers of a manufacturing facility.

Hosseini and Barker (2016b) used Bayesian networks, a well-known statistical tool that works based on conditional probability, to model the likelihood that a supplier would be separated from a natural disaster zone. A supplier with a higher likelihood of separation from a disaster zone is considered to be more resilient. The authors introduced three variables segregation, tornado, and flood. The likelihood that a supplier is separated from disaster is conditioned on the occurrence of flood and tornado, as illustrated in Fig. 8. The prior probability of flood and tornado occurrences is modeled by truncated normal distribution. The variable for the marginal probability of segregation is obtained by a conditional IF statement. The authors stated that a supplier is considered to be located in a disaster-safe zone if the occurrence probability of flood and tornado is less than 0.03, i.e., IF (probability of tornado and probability of flood < 0.03, "True", "False"). As shown in Fig. 8, the likelihood that the supplier is separated from the disaster zone (True state) is 65.76%.

Hosseini et al. (2019) used optimization methodology to consider segregation among suppliers. The objective function is to maximize the smallest distance between the locations of any pair of suppliers. Consider the following notations:

Input parameters:

d_{ij} : Shortest distance between locations of suppliers i and j

L : Smallest segregation distance between every pair of suppliers

M : A constant large number

Decision variable:

z_i : 1, if supplier i is assigned to the firm; and 0 otherwise

$$Z = \text{Max} \sum_{i=1}^n \sum_{j=i+1}^n z_i z_j d_{ij} \quad (1)$$

where

$$L \leq d_{ij}(1 + M(1 - z_i) + M(1 - z_j)) \quad \forall i, j \in n | i < j \quad (2)$$

The model related to supplier separation is represented in Eqs. (1) and (2), where the objective function is to maximize the segregation distance between suppliers. Hasani and Khosrojerdi (2016) modeled facility dispersion and facility fortification as resilience strategy using a mixed-integer, non-linear robust optimization model.

5.1.2. Multiple sourcing strategy

Evidently, sourcing strategies are of greater importance in achieving SCR (Yildiz et al., 2016, Yoon et al., 2018). Namdra et al. (2017) developed a scenario-based mathematical model for SCR under single and multiple sourcing. Their findings stress that, when decision-makers are risk-averse and cautious, multiple sourcing results in better service level with a lower conditional value of risk compared to single sourcing. Lücker and Seifert (2017) presented a mathematical model which shows that, under some conditions, dual sourcing can be considered a substitute for risk mitigation inventory at manufacturing sites in a pharmaceutical SC. The authors also show that an optimal dual source production rate can greatly reduce disruption time. Bicer (2015) showed how Extreme Value theory (EVT) can be applied to price the value of flexibility in the case of disruptive events. The author investigated the impact of dual sourcing with a single product under conditions of high demand fluctuation. The EVT was used to characterize the tail heaviness of demand distribution. The author concluded that companies could potentially improve cost efficiency if customer demand distribution is more heavy-tailed demand when the cost of sourcing from supplier is relatively low.

Torabi et al. (2015) considered multiple sourcing in a mathematical model to select resilient suppliers. Other researchers, including Sawik (2011), Sawik (2013), Meena and Sarmah (2013), Sadghiani et al. (2015), Zhang et al. (2015), Kamalahmadi and Mellat-Parast (2016), Ivanov et al. (2017a,b), and Ivanov (2018a) underline that manufacturing facilities must reduce the supplier

dependency and recognize the value of sourcing diversification by collaborating with multiple suppliers rather than a single supplier.

5.1.3. Inventory positioning

[Tomlin \(2006\)](#) highlighted the impact of inventory control strategies on mitigating disruption risk in SC. Inventory strategies are part of the absorptive capacity of a supplier or manufacturer in terms of ordering and stocking decisions. This fact needs to be taken into account prior to disruption. The resilience degree of a manufacturing facility does not depend on its initial capacity alone, but also on its additional initial capacity. Some manufacturing companies prefer to reduce inventory holding costs. Those who implement lean manufacturing principles may not carry excess inventory at all, instead accepting the disruption risk and associated cost. [Tomlin \(2006\)](#) investigated the impact of accepting disruption risk (acceptance strategy) and not carrying excess inventory in a single-product supply system with two suppliers. He showed that the optimal mitigation strategy can be achieved for short disruptions by utilizing the acceptance strategy, but holding excess inventory could be an optimal strategy for rarer, but longer disruptions. [Turnquist and Vugrin \(2013\)](#) formulated a stochastic optimization model to design resilient distribution networks. In this work, it is assumed that each distribution center can carry excessive inventory in addition to the normal holding inventory. The optimization model determines the additional initial inventory each distribution center must carry prior to the disruption, to ensure that the total cost of initial additional capacity at distribution centers is minimized. [Khalili et al. \(2016\)](#) considered an integrated production-distribution planning problem in a two-echelon SC, where transportation links, distribution centers, and active capacity levels of the production facilities are vulnerable to disruption and operational risks. The authors proposed a two-stage scenario based on a mixed stochastic-possibilistic programming model, where two types of inventory are taken into account: (1) additional initial production capacity of the production facility, and (2) emergency inventory of a specific product type in the distribution center. [Elluru et al. \(2017\)](#) also highlighted the impact of expanded inventory at the distribution facility as a key mitigation strategy when designing resilient networks using the location-routing problem.

[Spiegl et al. \(2012\)](#) studied automatic pipeline inventory and order-based production systems using control engineering theory. The pipeline inventory is characterized by a feedback loop. The integral of “time absolute error” is a measurement of resilience, which quantifies the error level between actual and desired inventory after disruption. The authors analytically examined the trade-off between the resilience level of inventory systems and the costs of inventory. The authors explored reduction of recovery time and work in progress using an ordering control algorithm: moving from a leveling strategy to a chase strategy can enhance resilience, but may increase the cost of the SC. [Barker and Santos \(2010\)](#) applied an input-output model to evaluate the impact of disruption on SCR.

5.1.4. Multiple transportation channels

[Khalili et al. \(2016\)](#) investigated the impact of resilience enhancement under multiple transportation channels and rerouting options for an integrated production-distribution system. The impact of availability and size of different transportation modes under different disruption scenarios are analyzed. The authors concluded that utilizing multiple transportation channels in conjunction with prepositioning of emergency inventory at distribution centers could significantly enhance the resilience and reduce the recovery time. [Kamalahmadi and Mellat-Parast \(2016\)](#) echoed those results considering the impact of multiple transportation channels on the SCR.

5.2. Adaptive capacity

5.2.1. Backup supplier

Contracting between a manufacturing facility and a backup supplier is a preparatory action that can enhance SCR. [Torabi et al. \(2015\)](#) found that having a backup supplier is an effective strategy to mitigate SC disruption. [Ho et al. \(2010\)](#) studied a scenario in which a buyer has two supply options: an inexpensive, but vulnerable one (primary supplier), or a highly reliable, but expensive one (backup supplier). The authors then considered a buy-back contract between the buyer and backup supplier when the primary supplier has experienced a disruption. [Chakraborty et al. \(2016\)](#) used game theory to mitigate SC disruption with random demand and price where suppliers are prone to disruption. A backup supplier is incorporated into the model as a key, pre-disaster resilience strategy. Using a rigorous quantitative methodology, [Saghafian and Van Oyen \(2016\)](#) investigated the impact of contacting a secondary flexible backup supplier on SC mitigation. The authors measured the true value of a flexible backup supplier and determined the upper bounds for the amount a risk-averse manufacturing plant should be willing to pay to implement a flexible backup supplier strategy. [Jabarzadeh et al. \(2018\)](#) developed a multi-objective stochastic programming model, where primary and backup suppliers are separately modeled as binary decision variables. The primary objective function of their model is to minimize the total cost of the SC under different disruption scenarios, as represented in Eq. (3). Let's consider the input parameters and decision variables given below:

Input parameters:

x_n : fixed cost of evaluating and selecting primary supplier n

z_l : fixed cost of contracting with backup supplier l

π_s : probability of occurrence of disruption scenario s

δ_m : defective rate of primary supplier n for raw material type r

γ_l : defective rate of backup supplier l for raw material type r

u_{rlm} : unit cost of purchasing raw material type r from backup supplier l and transporting it to factory m

q_{rnm} : unit cost of purchasing raw material type r from primary supplier n and shipping it to factory m

Decision variables:

X_n : a binary decision variable, equal to 1 if primary supplier n is selected, and 0 otherwise.

Z_l : a binary decision variable, equal to 1 if backup supplier l is selected, and 0 otherwise.

Q_{rnms} : quantity of raw material type r transported from primary supplier n to factory m under scenario s

U_{rlms} : quantity of raw material type r transported from backup supplier l to factory m under scenario s

$$\text{MinZ} = \sum_{n \in N} x_n X_n + \sum_{l \in L} z_l Z_l + \sum_{s \in S} \pi_s \left[\sum_{r \in R} \sum_{n \in N} \sum_{m \in M} \frac{q_{rnms} Q_{rnms}}{1 - \delta_m} + \sum_{r \in R} \sum_{n \in N} \sum_{m \in M} \frac{u_{rlms} U_{rlms}}{1 - \gamma_l} \right] \quad (3)$$

The first and second terms of objective function are the cost of selecting primary and backup suppliers, respectively, while the third term is the total cost of shipping raw materials from the primary and backup suppliers to factories. It is notable that the model developed by [Jabarzadeh et al. \(2018\)](#) determines primary and backup supplier decisions prior to disruption. Despite this work, [Torabi et al. \(2015\)](#) developed a two-stage programming model where the primary suppliers are determined in the first stage, prior to disruption, and the backup supplier is determined in the second stage, post-disruption. Primary and backup suppliers can be determined prior to disruption, but the selection of a backup supplier depends on the severity of impact of the disruption on the capacity of the primary supplier. Hence, utilizing two-stage stochastic programming models that determine backup suppliers in the post-disruption stage based on the lost capacity of primary suppliers seems to be more appropriate. [Turnquist and Vugrin \(2013\)](#) developed a stochastic optimization model to design resilient distribution networks. A backup supplier is modeled in the form of a set of constraints that allow one backup connection for each customer, but do not force these connections to be made. [Kamalahmadi and Mellat-Parast \(2015\)](#) modeled a mixed integer linear programming model where supplier flexibility, or the ability of a supplier to provide more items than initially requested, is considered as a decision variable of mitigation strategy.

5.2.2. Rerouting

Redundancy within transportation networks in the event of a natural disaster could enable a SC to use nonstandard and more expensive routing options to ensure continuity. For example, droughts halted critical barge traffic on some portions of the Mississippi river in 2012. Many shipping companies were forced to switch from waterway transport, one of the most inexpensive forms of long distance bulk transportation, to railroad transport. Many cargo shipping companies may consider rerouting options from a primary port to an alternative port if the primary one is congested due to disruption. [Liu and Lam \(2013\)](#) presented a simplified model of SCs with two echelons, supplier and customers, connected through a transportation network with one primary port. The authors investigated the impact of disruption at the primary port and the possibility of rerouting from the supplier to an alternative port. Duration and frequency of disruption were modeled by a discrete time Markov chain distribution. The Markov reward-based methodology demonstrates that the best performance, which includes minimal backlog, reasonable inland traffic, and a reliable shipping schedule, can be achieved through a balance of contingency routing and capacity expansion. [Khaled et al. \(2015\)](#) proposed an optimization model for rerouting under high congestion due to disruption at links and nodes. [Wang et al. \(2016\)](#) examined the rerouting strategy to enhance SCR from the supplier's perspective. The authors developed a mathematical model that finds an optimal rerouting strategy for multiple suppliers' SC in terms of product allocation and supplier selection. The findings of their model show that a higher level of resilience is achievable if a rerouting strategy is carried out sooner. [Hosseini and Khaled \(2016\)](#) developed a hybrid ensemble and AHP for a resilient supplier selection problem. The authors considered rerouting and reorganization as two key factors of adaptive capacity.

5.2.3. Communication

Communication and cooperation are resilience enhancing features of adaptive capacity that help SCs to overcome disruptions through appropriate communication and collaboration, in a timely manner, among members of the SC. Although the role of communication among SC businesses and enterprises is acknowledged by qualitative studies ([Scholten and Schilder, 2015; Mandal et al., 2016; Wieland and Wallenburg, 2013](#)), there are very few quantitative papers that explore the role of communication in SCs. [Reyes Levalle and Nof \(2015a\)](#) studied supply network resilience as it is influenced by network level interactions and communication with other agents. The authors used collaborative control theory, where supply networks are modeled as a set of interconnected, autonomous agents that interact to enable a flow of physical goods, tasks, and/or information, and a set of control protocols that regulate the behavior of agents. The results show that communication and collaboration among agents can help to effectively ensure resilient supply networks. In another paper, [Reyes Levalle and Nof \(2015b\)](#) studied the impact of resilience by training (RBT) on SC topology and resilience under random and targeted disruptions. The outcomes of their research indicate that communication within SC networks not only can increase the service level of normal business operations, but can also increase the post-disruption service level significantly.

5.2.4. Substitution

Substitution is the capability of a manufacturing facility to temporarily substitute raw material with alternatives until operations return to a steady state. For example, consider a power SC where the production capacity of a combined cycle power plant is affected by a shortage of natural gas. Switching between natural gas and coal fuel could temporarily sidestep disruption of the power supply. Of course, technical issues arising from raw material replacement must be considered by the manufacturer prior to disruption. [Mancheri et al. \(2018\)](#) applied dynamic simulation to measure the resilience of a tantalum SC. The authors argued that material

substitution in product design could enhance the resilience of tantalum SC.

5.3. Restorative capacity

Hosseini and Barker (2016b) discussed suppliers' restoration budgets and technical resource restorations as two arms of restorative capacity, which significantly help suppliers to recover quickly. The authors modeled these two factors using a Bayesian network (BN) approach for selecting resilient suppliers. Sahebjamnia et al. (2015) proposed a multi-objective, mixed integer, linear programming (MOMILP) model, where budget restoration availability is modeled as a restriction in the resource allocation problem. Sahebjamnia et al. (2018) integrated disaster recovery planning with business continuity to build organizational resilience. To do so, the authors developed a MOMILP, where external and internal restoration resources of the manufacturing facility are taken into account. The authors argued that reducing organizational resources, including human resources, facilities, and equipment, can disrupt a number of critical functions of the manufacturing facility. Restoration level as a time unit is considered a key variable of post-disaster strategy. Turnquist and Vugrin (2013) proposed a stochastic, mixed integer, programming model to design resilient distribution centers (DCs), where restoration capacity investment (unit/period) is considered a resilience-enhancing feature of DCs.

5.4. Modeling and solution methodologies

Analyses performed in Sections 5.1–5.3 allow the modeling approaches considered to be divided into five categories. These categories are as follows: Category I: mathematical and optimization modeling; Category II: structural equations modeling; Category III: Bayesian networks; Category IV: simulation techniques; Category V: multi-criteria decision-making.

The solution methodologies are divided into five main categories. Some researchers have tried to solve optimization models using exact methods, which is difficult and limited in terms of large-size problems. Some authors utilized exact solver commercial software like GAMS, CPLEX, Lingo, AnyLogic, and anyLogistix. For large-scale problems, particularly stochastic programming models with large numbers of disruption scenarios, meta-heuristic algorithms have been applied. Multi-criteria decision-making, such as AHP, ANP, and VIKOR, has been used to evaluate the performance of SC systems. Fuzzy logic and grey set theory are also used to deal with SCR problems. Examples of modeling and solution approaches are presented in Appendix B.

Fig. 9 summarizes the causal relationship between SCR capacity and its drivers. Here, we consider a two-stage SC with

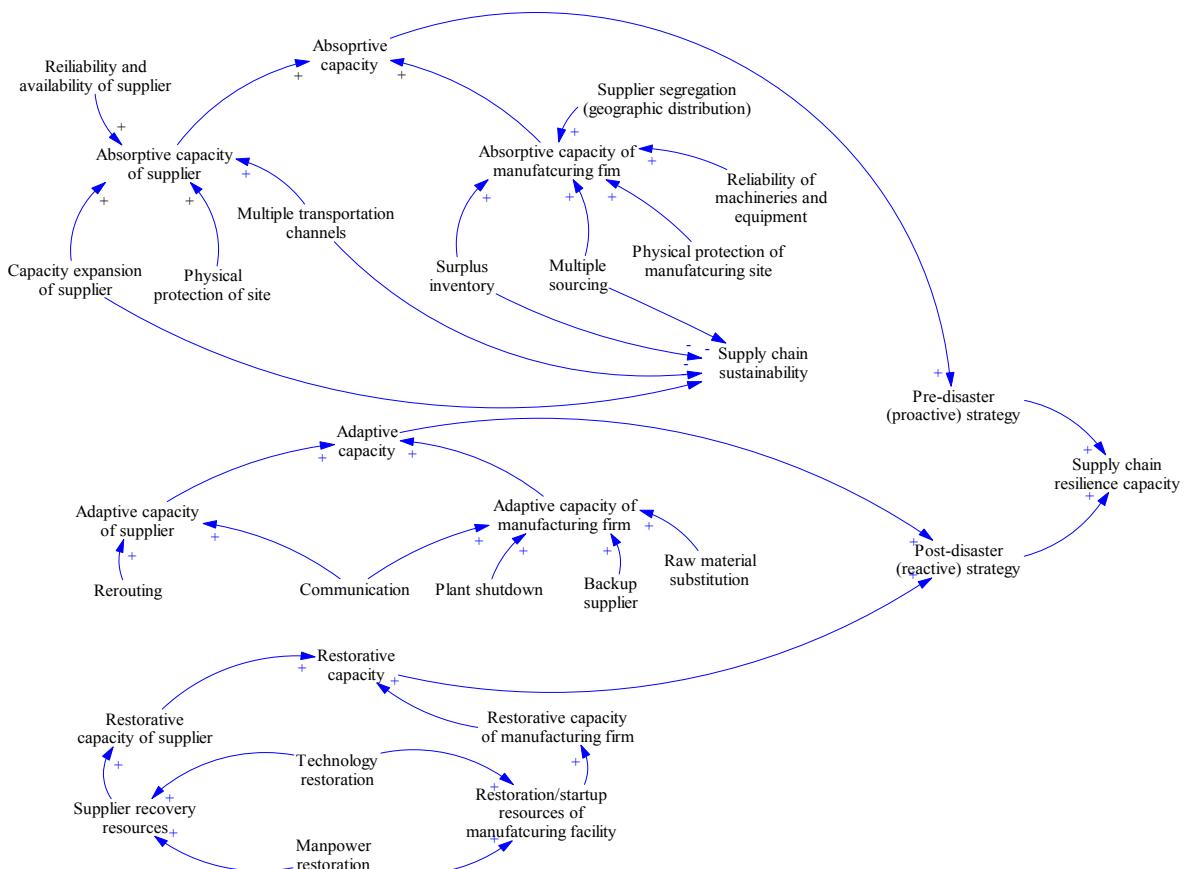


Fig. 9. Causal diagram of supply chain resilience capacity and its drivers.

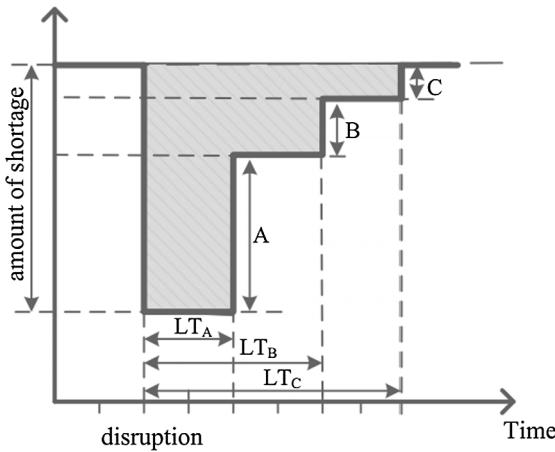


Fig. 10. The recovery process of disrupted supplier (Torabi et al., 2015).

manufacturer and supplier. In Fig. 9, each arrow is represented by either a positive or negative sign. An arrow from factor A to factor B , with a positive sign, denotes a positive relationship between those two factors, meaning that increase (decrease) in A will lead to increase (decrease) in B subsequently, while a negative sign means that an increase in A leads to a decrease in B , or vice versa. As is represented by the causal diagram, supplier resilience capacity is influenced by pre-disaster and post-disaster strategies. Absorptive capacity forms pre-disaster (proactive) strategy, while adaptive and restorative capacity together form post-disaster (reactive) strategy. The enhancement resilience drivers of absorptive, adaptive, and restorative capacities for supplier and manufacturer are illustrated. Among drivers of resilience capacity, there are some drivers, including multiple sourcing, multiple transportation channels, surplus inventory of manufacturer, and capacity expansion of supplier, that could influence SC sustainability. From the sustainability perspective, less inventory, single sourcing, and use of a single transportation channel is more desirable than multiple channels. As such, those factors enhance SCR, but may not be the best features from the sustainability point of view.

5.5. SCR metrics

The analysis of literature shows that resilience in the context of SC management is modeled and quantified in two different ways. The first way is to develop metrics that quantify the SCR. These metrics are usually bounded between [0, 1] and considered as objective functions that must be maximized in addition to minimizing SC cost as primary objective. For example, Torabi et al. (2015) developed a resilience metric that is a function of absorptive capacity (inventory pre-positioning), adaptive capacity (backup supplier), and restorative capacity (restoration of disrupted supplier). Let's assume that the amount of lost capacity recovered by inventory prepositioning, backup supplier, and restoration of disrupted supplier is denoted by A , B , and C , respectively, and that LT_A , LT_B , and LT_C denote the time of receiving items associated with the A , B , and C resilience strategy. The loss of resilience RE' can be shown graphically as the shaded area in Fig. 10 and can be mathematically calculated by Eq. (4)

$$RE' = A \times LT_A + B \times LT_B + C \times LT_C \quad (4)$$

It is clear that a lower value of RE' results in higher supply resilience. The authors then calculated the resilience of the supply base by Eq. (5):

$$RE = 1 - \frac{RE'}{Q \times T^*} \quad (5)$$

where Q is the total amount of items the manufacturer needs from the supplier and T^* is the upper bound on the length of the recovery process (Fig. 10).

Ojha et al. (2018) developed a metric to quantify the resilience as a measure of service loss aftermath of disruption. Suppose there are n nodes (suppliers) in the supply network, and the resilience index of node n denoted by RI_k is measured by:

$$RI_k = 1 - \frac{\sum_{w=w_0}^{w_n} \left(1 - \frac{SL_{kw}}{SL_{k0}}\right)}{(w_n - w_0)} \quad (6)$$

where w_0 and w_n are the weeks when disruption occurs at the SC node, and the time when disruption ends plus the time to recover from the disruption. SL_{k0} and SL_{kw} are the service levels of node k prior to and after the disruption. The similarity that can be observed across these two measures, proposed by Torabi et al. (2015) and Ojha et al. (2018), is that resilience is calculated by 1 minus fraction of loss, so both metrics are bounded between 0 and 1. Torabi et al. (2015) measured the loss of supplier capacity, while Ojha et al. (2018) considered the loss of service level.

Despite the metrics developed by Torabi et al. (2015) and Ojha et al. (2018) that quantify the resilience of the supply network,

**Fig. 11.** Objective functions of SCR.

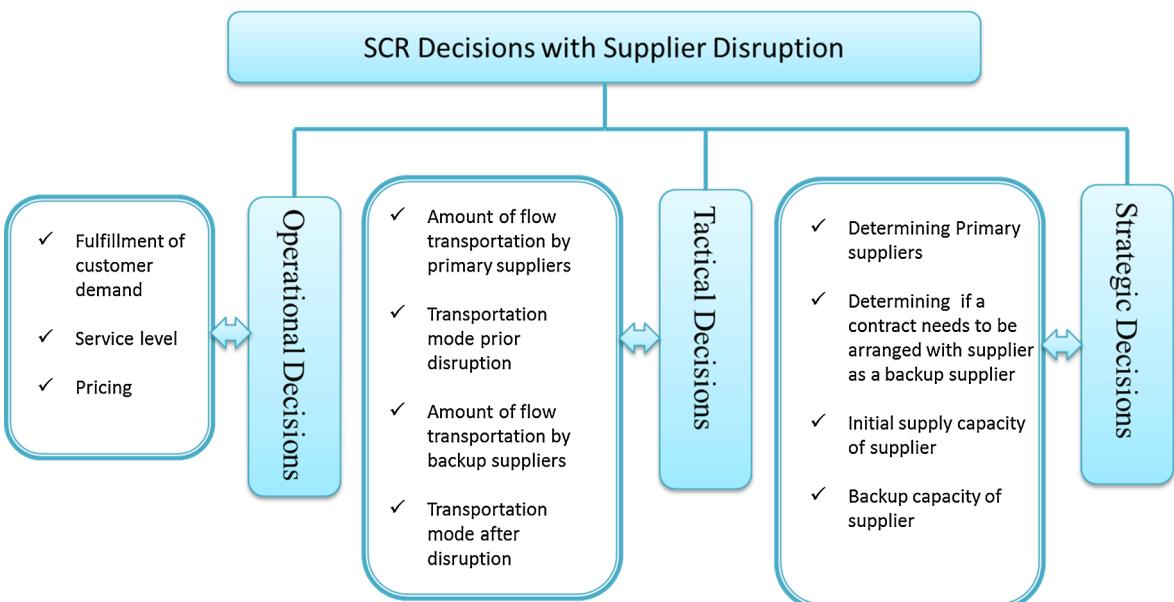
many researchers have not measured SCR directly, but rather have tried to measure the drivers of resilience. Käki et al. (2015) developed a metric using Bayesian models that measures the risk deduction in supply networks. The proposed metric is capable of quantifying the impact of disruption propagation throughout multi-tier supply networks. The authors argued that the risk deduction metric can help to identify vulnerable suppliers, and enhance risk mitigation. Mogre et al. (2016) measured the SC vulnerability using a multi-input output economic model for different mitigation strategies. Jabarzadeh et al. (2018) considered backup supplier and surplus inventory as a resilience strategy to meet customer demand, and the costs associated with utilizing backup supplier and holding surplus inventory to be minimized. Hosseini et al. (2018) quantified SCR as a measure of supplier segregation that aims to select a set of geographically dispersed suppliers.

5.6. Objectives and decision variables in SCR problems

The major objective in designing a resilient supply network is to strengthen the capability of SC entities to withstand against disruptions and recover quickly from disruption with minimal costs and efforts when they are disrupted. In this step, various objective functions and decision variables were specified in the growing body of literature. In this section we summarize some key objectives and decision variables of SCR optimization problems (Figs. 11 and 12).

Consider the examples of objective functions in Fig. 11 more detailed.

First, the most common objective in the SCR optimization models is monetary (e.g., minimizing the total cost or maximizing overall profit). Second, the vulnerability objective functions measure the performance or service level loss in the SC (e.g., inventory capacity loss, lead time increment, stock out rate, fill rate) due to the disruption. Third, in the recovery time/resource consideration, vulnerability and recovery are two aspects of SCR. The optimization models generally aim at maximizing the recovery level of production capacity of disrupted manufacturer, or supply capacity of supplier, distribution center or warehouse. Hereupon, minimizing the length of recovery time or maximizing the recovery level of a disrupted SC entity is conceptualized as a primary objective of SCR in optimization models by some researchers (Torabi et al., 2015; Kamalahmadi and Mellat-Parast, 2015; Cardoso et al., 2015; Dixit et al., 2016; Khalili et al., 2016; Kaur and Singh, 2016; Elluru et al., 2017; Namdra et al., 2017; Duhadway et al., 2018; Margolis et al., 2018; Ni et al., 2018; Mohammed et al., 2019; Ojha et al., 2018; Sabouhi et al., 2018; Wang et al., 2018; Hosseini et al., 2019).

**Fig. 12.** Primary decisions of SCR with focus on supply vulnerability.

Fourth, uncertainty can be modeled in SCR problems in different ways: (i) disruption uncertainty such as occurrence likelihood of disruptive events like natural disasters, power outage, labor strikes, etc., (ii) operational uncertainty such as the a likelihood of unmet demand and shortage on supplier's capacity. The analysis of literature shows that the majority of SCR problems are presented in the form of stochastic scenario based optimization models in order to tackle demand and supply uncertainty under different disruptive event scenarios (Turnquist and Vugrin, 2013; Torabi et al., 2015; Khalili et al., 2016; Namdra et al., 2017; Hosseini et al., 2019; Morshedlou et al., 2018). Fifth and finally, an important objective in the reviewed models is to enhance the resilience of SCs by maximizing the resilience enhancement drivers (e.g., flexibility, redundancy, reliability) of SC entities. Backup capacity of supplier and emergency inventory of manufacture are considered as two key drivers of resilience enhancement features to meet customer demand by Turnquist and Vugrin, 2013; Garcia-Herreros et al., 2014; Kamalahmadi and Mellat-Parast, 2015; Sahebjamnia et al., 2015; Torabi et al., 2015; Namdra et al., 2017; Rezapour et al., 2018; Sahebjamnia et al., 2018; Fahimnia et al., 2018; Sahebjamnia et al., 2018; Sawik, 2018).

6. Current gaps and future research opportunities

In this section, we suggest potential research opportunities based on analysis of the research gap and existing limitations in the SCR literature.

6.1. Mathematical modeling

Two-stage stochastic programming is one of the most appropriate ways to deal with uncertainty originating from disruption. The decision variables in the first stage are related to the absorptive capacity of SCs, such as the level of prepositioned inventory at the supplier/manufacturer, or additional capacity carried by the supplier/distribution center. The second stage is scenario-based and helps to determine whether a backup supplier should be used, and the quantity of items that should be shipped from the backup suppliers to the customer or manufacturer. Future attempts can be made to develop two-stage stochastic models, where the objective function of the model is to minimize the traditional SC cost (procurement cost + supplier evaluation cost + transportation costs, etc.), and the second-stage objective function measures the resilience of the SC under all possible disruption scenarios. Analyses of SCR literature show that robust optimization has not been well-studied. Hence, exploring robust optimization modeling in the context of SCR might result in interesting findings. Application of chance constrained programming to the SCR problems would be an interesting topic since SCR problems are intrinsically involved with several stochastic parameters such as expected capacity loss, expected capacity/resource restoration, and expected time recovery.

6.2. Bayesian network (BN) modeling

BN is a powerful methodology for handling uncertainty, risk assessment, and decision-making. BNs are structured based on conditional probability and Bayes' theorem, which captures the dependency between different suppliers or between supplier and manufacturer in a supply network. The likelihood that a manufacturing facility fails to operate due to failure at the supplier can be modeled by BNs. An important challenge in large interconnected and complex supply networks is to control the ripple effect. The ripple effect can occur when the impact of disruption propagates throughout the entire SC and cascades downstream, rather than remaining localized or being contained to only one part of the SC. Forward and backward propagation analysis is a unique feature of BNs that does not exist in any other methodology, including regression models, structural equation modeling, or neural network modeling that captures the relationships among variables. Using forward propagation analysis, we can enter any number of disruption observations and use propagation to update the marginal probabilities of all unobserved variables. Forward and backward propagation analysis can be used in the future to analyze the ripple effect in complex supply networks with a large number of nodes and links. Lists of successful applications of BNs in the field of risk assessment can be found in (Garvey et al., 2015; Hosseini and Barker, 2016b; Hosseini and Barker, 2016c; Hosseini et al., 2016d; Qazi et al., 2017; Qazi et al., 2018).

6.3. Markov chain modeling

Resilience is a stochastic and time-dependent concept, which is a function of systems' vulnerability and recoverability. The multi-state Markov process is a good way to model the vulnerability and recoverability of SC elements, such as ports, suppliers, and manufacturing facilities. A discrete-time, Markov chain process for a port with three states is represented in Fig. 13.

State 1 represents the operational capacity of the port under normal conditions (prior to disruption), state 3 represents the state of the port when it is fully disrupted, and state 2 is an intermediate state, i.e., the port is partially disrupted or 50% of the port's operational capacity is disrupted. In Fig. 13, α_1 represents the probability that the port absorbs the shock of disruption without losing operational capacity. α_2 represents the probability that the port loses 50% of its operational capacity due to disruption, while α_3 represents the probability that the system will be fully disrupted. The recoverability probability between the different states is represented by β_1 , β_2 , β_3 .

6.4. Multi-criteria decision-making

Although multi-criteria decision-making (MCDM) methods have been applied to the resilient supplier selection problem by some

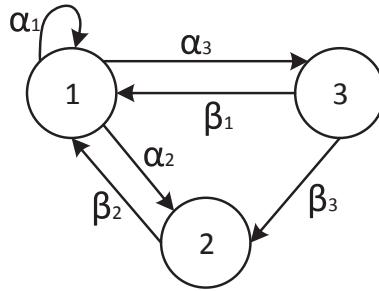


Fig. 13. A discrete time Markov chain model with three states simulating the operational capacity of the port.

researchers (Kull and Talluri, 2008; Yoon et al., 2016; Lima-Junior and Carpinetti, 2016; Mizgier et al., 2017; Amindoust, 2018), MCDM methods, such as TOPSIS, AHP, ANP, ELECTRE, VIKOR, have not been well-studied in the context of SCR. Future research works could focus on exploring the applications of MCDM methods on resilient supplier and vendor problems. MCDM would also be useful for evaluating SC networks with respect to resilience, green, and organizational criteria, simultaneously.

6.5. Dynamic versus static modeling

As we discussed earlier, the degree of resilience in a system is a function of its vulnerability and recoverability. A disrupted system bounces back to its steady state over a period of time (recovery time) after the disruption. Few of the current mathematical models in SCR literature considered the dynamicity of resilience. Future optimization models are expected to consider time periods prior to and after disruption. In addition to this, we observed very few papers that consider time recovery constraints. Time and budget recovery constraints are among the most important restrictions on recovery operations in practice. Because the problem statements concerning SC disruptions deal with time-dependent settings, which include dynamic inventory control, transportation control, sourcing control, and production control policies, the simulation methodology for the given problem domain has earned an important role in academic research (Ivanov, 2017a, 2017b, 2018a, 2018b). In comparison to analytical, closed-form analysis, simulation has the advantage of being able to handle complex problem settings with situational behavior changes in the system over time. This is inevitable in considering dynamic changes in production-ordering policies and SC design structures (Ivanov and Rozhkov, 2017).

6.6. Ripple effect and low-certainty-need (LCN) SC designs

The ripple effect manifests itself when the impact of a SC disruption cannot be localized and cascades downstream, resulting in a high impact effect on SC performance (Dolgui et al., 2018). Analysis of the ripple effect in the framework of SCR is a promising research avenue. Low-certainty-need (LCN) SC designs suggest a new approach to disruption risk management where SC behavior is less dependent on the certainty of our knowledge about the environment and its changes (Ivanov and Dolgui, 2018). Structural variety, process flexibility, and parametrical redundancy are key LCN SC characteristics that ensure efficient disruption resistance, as well as recovery resource allocation. Two efficiency capabilities of the LCN SC are low need for uncertainty consideration in planning decisions and low need for recovery coordination efforts based on a combination of lean and resilient elements. Future research in bridging LCN and resilience will allow the identification of an LCN SC framework, as well as concepts and technologies for its implementation. Special focus might be directed on digital technology in the implementation of an LCN framework.

6.7. Hybrid approaches using digital technologies

Industry 4.0 has received much attention in recent years, but only a few efforts have been made to design resilient digital technology and Industry 4.0. There are few works that assess the impact of Industry 4.0 and digital technology on SC risks (e.g., Ivanov et al., 2016b; Ivanov et al., 2019) and analytics and SC risks (Choi and Lambert, 2017, Choi et al., 2017). Industry 4.0-driven SCs could, potentially, be vulnerable because of the integration of cyber-physical systems, additive manufacturing, robotics, high-performance computing, cognitive technologies, and advanced materials. At the same time, digital technologies could provide new ways to reduce disruption risks (Ivanov et al., 2019). Developing resilience strategies based on recovery and vulnerability measures of Industry 4.0-driven decentralized SC designs is an interesting direction for research.

6.8. Integrating resilience and sustainability

As SCs become more complex and more operations are being outsourced, managing disruption risks and achieving resilience have become more critical. Global SCs and transportation networks form the backbone of the modern economy and directly influence such sustainability issues as fueling trade, green consumption, employment rates, etc. A desirable SC design should consider not only sustainability issues, such as awareness of environmental protection and social responsibilities, but also consider the proactive and reactive resilience strategies in the case of disruptions. Although there are perceptible intersections between resilience and sustainability issues, very few papers, such as Fahimnia and Jabarzadeh (2016), have studied the interface of resilience and

sustainability.

SCR enhancements, in practice, are driven by utilizing the backup supplier, capacity buffer, surplus inventory, and multiple sourcing, while using single sourcing, less stored inventory, and less redundancy (e.g., multiple transportation systems) are more important for sustainability (Ivanov, 2018a). Future research works should aim for bridging resilience and sustainable issues by developing multi-objective stochastic optimization models capable of making trade-offs between sustainable and resilience decisions.

6.9. Digital supply chain twins to improve resilience

A combination of simulation, optimization and data analytics constitutes a full package of technologies to create a digital SC twin – a model that always represents the state of the network in real-time (Ivanov et al., 2019). At each point of time, a digital twin represents the physical SC with the actual transportation, inventory, demand, and capacity data and can be therefore used for planning and real-time control decisions. If there is a strike at an international logistics hub, this disruption can be spotted by a risk data monitoring tool and transmitted to the simulation model as a disruptive event. Then, simulation in the digital twin can help show disruption propagation and quantify its impact. In addition, simulation enables efficient recovery policy testing and the adaptation of contingency plans according to the situation – for example, reconsidering alternative network topologies and back-up routes on-the-fly. Since a digital twin can represent the network state for any given moment in time, it allows for complete end-to-end SC visibility to improve resilience and test contingency plans.

7. Discussion and conclusions

In this paper, a systematic literature review of SCR was presented, aimed at identifying resilience-enhancing features of SCs and understanding analytical approaches, especially mathematical modeling of SCR problems. We presented a new definition for SCR, based on the resilience capacity of SCs. We reviewed both the qualitative and quantitative drivers of SCR. We classified quantitative drivers that contribute to the resilience of SCs based on resilience capacity, which was further divided into absorptive capacity, adaptive capacity, and restorative capacity. Absorptive and adaptive capacities are the first and second lines of defense for SC systems and measure the internal capability of a SC to withstand disruption, while restorative capacity is the third line of defense and measures the exogenous capability of SC. Different quantitative methodologies for modeling SCR are reviewed. The objective functions, decision variables, and constraints of mathematical models of SCR problems are discussed.

Some significant contributions emerge. The analysis of optimization models of SCR models show that future research efforts could explore multi-objective optimizations with primary objectives, such as minimizing total SC cost (e.g., sum of supplier evaluation cost, transportation cost, production cost) and secondary objectives, such as maximizing the resilience of the SC or minimizing the recovery time of a disrupted component of the SC. We predict that future OR models will focus on developing multi-objective, two-stage stochastic programming, where some decisions should be made in the first stage, prior to disruption, such as (i): who are the selected suppliers; (ii): how much surplus inventory should a selected supplier carry prior to disruption; (iii): how many products should be transported from a selected supplier. The second stage should determine those decision variables that depend on the disruption scenario and are determined after realization of disruption, such as (i) selection of backup suppliers; (ii) proportion of customer demand that can be met by backup supplier due to disruption at the primary supplier; (iii) restoration capacity of disrupted primary supplier. Of course, decision variables can be differentiated depending on the structure and components of the given SC.

Finally, we recommended potential future research avenues, which are divided into two classes: methodology-based and subject-based. From the methodology side, future research efforts could explore the applications of Markov chain modeling, Bayesian network, optimization models, and, particularly, multi-objective, two-stage stochastic programming models of the SCR problem. From the subject side, exploring the interface between green and resilience SCs, as well as the effect of achieving resilience in Industry 4.0 and using digital technology, would be highly beneficial.

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Appendix A. Definitions of SCR

Authors/year	SCR definition
Rice and Caniato (2003)	The ability of SC to react to unexpected disruption and restore normal supply network operations.
Christopher and Peck (2004)	The capability of SCs to operate in the face of disturbances and disruptions with or without a limited decrease in their performance.
Gaonkar and Viswanadham (2007)	The ability of a SC to maintain, resume and recover operations aftermath of a severe disruptive event.
Falasca et al. (2008)	The capability of SC to reduce the likelihood of disruption, to reduce the consequences of those disruptions when they occur and to reduce the time to recover normal performance.
Ivanov and Sokolov (2013)	The ability to maintain, execute and recover (adapt) the planned policies along with achievement of the planned (or adapted, but yet still acceptable) performance.

Longo and Oren (2008)	The capability of chain to respond to external/internal disruptions and vulnerabilities, and quickly recovering an equilibrium state capable of guaranteeing high performance and efficiency levels.
Ponomarov and Holcomb (2009)	Ability of SC to prepare for unexpected events, respond to disruptions, and restore from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function.
Pettit et al. (2010)	The ability of chain to withstand, adapt and grow in the face of turbulent changes.
Guoping and Xinqiu (2010)	The ability of SC to return to its original status under emergency risk environment.
Barroso et al. (2011)	The ability of chain to react to the negative effects caused by disturbances that occur at a given moment in order to maintain the SC's objectives.
Poins and Koronis (2012)	The ability of SC to proactively plan and design the SC network for anticipating unexpected disruptive events, respond adaptively to disruptions while maintaining control over structure and function and transcending to a robust state of operations.
Kim et al. (2015)	A network-level attribute to withstand disruptions that may be triggered at the node or arc level.
Kamalahmadi and Mellat-Parast (2016)	The adaptive capability of a SC to reduce the probability of facing sudden disturbances, resist the spread of disturbances by maintaining control over structures and functions, and recover and respond by immediate and effective reactive plans to transcend the disturbance and restore the SC to a robust state of operations.

Appendix B. Examples of solution approaches and technology for SCR modeling

Authors	Modeling approach	Software technology	Type of model	Vulnerable part	Key Drivers of SCR
Brusset and Teller (2017)	Structural equations modeling	–	Deterministic	Supply	Flexibility, external and integration capabilities
Carvalho et al. (2012)	Discrete event simulation	–	Stochastic	Supply and manufacturing facility	Additional stock (redundancy in inventory), restructuring existing transport (flexibility in transportation)
Chowdhury and Quaddus (2017)	Dynamic capability theory	–	Deterministic	Supply	Reverse capacity, flexibility, financial strength
Dixit et al. (2016)	Bi-objective programming	NSGAII + Co-kriging	Deterministic	Supply network	Surplus capacity of supplier
Hosseini and Barker (2016b)	Bayesian network	–	Stochastic	Supply	Geographic segregation, backup supplier, surplus inventory, physical protection, rerouting, technical resource, budget resource
Hosseini and Khaled (2016)	Hybrid ensemble and AHP	–	Deterministic	Supply	Backup supplier, surplus inventory, reliability of supplier, rerouting, raw material replacement
Hosseini et al. (2016d)	Bayesian network	–	Stochastic	Supply and manufacturing facility	Reliability, supplier separation, production restoration, plant shutdown
Ivanov (2017)	Simulation	anyLogistix	Stochastic	Supply	Multiple sourcing, facility fortification
Ivanov and Rozhkov (2017)	Discrete-event simulation	AnyLogic	Stochastic	Supply	Production-ordering policy
Ivanov et al. (2014)	Dynamic control	–	Stochastic	Supply	Flexibility, surplus inventory
Ivanov et al. (2014b)	Hybrid optimal control-mathematical programming	CPLEX	Deterministic	Supply, Distribution centers	Backup sources, rerouting
Jabarzadeh et al. (2018)	Bi-objective stochastic programming	GAMS/CPLEX	Stochastic	Supply and manufacturing facility	Backup supplier, production capacity of factory
Kamalahmadi and Mellat-Parast (2015)	Stochastic programming	CPLEX	Stochastic	Supply	Flexibility of supplier's capacity
Kamalahmadi and Mellat Parast (2017)	Two stage stochastic programming	–	Stochastic	Supply	Backup supplier, pre-positioning inventory
Khalili et al. (2016)	Bi-objective two stage stochastic programming	GAMS/CPLEX	Stochastic	Production capacity	Surplus inventories, transportation capacity
Liu et al. (2018)	Structural equations modeling	–	Deterministic	Manufacturing facility	Agility, integration
Mancheri et al. (2018)	Dynamic simulation	–	Stochastic	Supply and manufacturing facility	Resistance, rapid recovery, flexibility
Margolis et al. (2018)	Bi-objective programming	Gurobi	Deterministic	Manufacturing facility	Surplus capacity of manufacturing facility
Namdra et al. (2017)	Two-stage stochastic programming	GAMS/CPLEX	Stochastic	Supply	Multiple sourcing, backup supplier, spot purchasing
Pramanik et al. (2017)	AHP + TOPSIS + QFD	–	Fuzzy	Supply	Surplus capacity, responsiveness
Saheljamnia et al. (2018)	Bi-objective robust possibilistic programming	Epsilon constraint	Stochastic	Manufacturing facility	Restoration resource, budget recovery
Spiegler et al. (2012)	Control engineering	–	Stochastic	Supply	Inventory stock level
Torabi et al. (2015)	Bi-objective two stage stochastic programming	Differential evolution algorithm	Stochastic	Supply	Backup supplier, surplus capacity of supplier,

Turnquist and Vugrin (2013)	Stochastic programming	Lingo	Stochastic	Distribution centers	Extra capacity of distribution center (DC), restoration capacity of DC, additional connections between DC and customers
Hasani and Khosrojerdi (2016)	Mixed integer, non-linear robust programming	Taguchi based memetic algorithm	Deterministic	Supplier, manufacturer and warehouse	Multiple sourcing, facility dispersion, facility reinforcement
Ojha et al. (2018)	Bayesian network	–	Stochastic	Supply	Backup inventory

* It is notable that papers without a specific software technology are marked by “–”. *

Appendix C. Summary of main SCR key drivers, classified in terms of absorptive capacity, adaptive capacity and restorative capacity.

Absorptive capacity		
Reference	Key drivers	Explanation
Hosseini and Barker (2016a,b,c), Hosseini et al. (2019)	Geographic distribution	Collaborations of manufacturers with geographically dispersed suppliers increase the risk of supply discontinuity.
Tomlin (2006), Spiegl et al. (2012), Ivanov et al. (2014a), Turnquist and Vugrin (2013), Sawik (2013), Torabi et al. (2015), Sahebjamnia et al. (2015), Kamalahmadi and Mellat-Parast (2016), Kamalahmadi and Mellat-Parast (2017), Khalili et al. (2016), Elluru et al. (2017), Ivanov (2018a), Rezapour et al. (2018), Jabarzadeh et al. (2018), Ivanov et al. (2018), Lücker et al. (2018), Sawik (2018), Tan et al. (2019)	Emergency inventory of manufacturer and backup capacity of supplier	Backup capacity and emergency inventory could reduce vulnerability of SC and enhance the SC's resilience.
Sawik (2011), Sawik (2013), Sadghiani et al. (2015), Meena and Sarmah (2013), Zhang et al. (2015), Bicer (2015), Torabi et al. (2015), Namdra et al. (2017), Lücker and Seifert (2017), Ivanov et al. (2017a,b), Ivanov (2018a)	Multiple sourcing strategy	Multiple sourcing strategy has a higher level of association with SCR as compared with single sourcing strategy.
Hosseini and Barker (2016c), Hosseini et al. (2019)	Maintenance and reliability	Manufacturers could improve their resilience by collaborating with reliable suppliers with lower disruption rates.
Khalili et al. (2016), Kamalahmadi and Mellat-Parast (2016)	Multiple transportation channels	Utilizing multiple transportation channels could enhance the SCR in the case of transportation damages.
<i>Adaptive capacity</i>		
Ho et al. (2010), Turnquist and Vugrin (2013), Torabi et al. (2015), Chakraborty et al. (2016), Saghafian and Van Oyen (2016); Hosseini and Barker (2016b), Kamalahmadi and Mellat Parast (2017), Jabarzadeh et al. (2018)	Backup supplier	Utilizing backup supplier when facing a disruption may improve the SCR
Liu and Lam (2013), Khaled et al. (2015), Khalili et al. (2016), Hosseini and Barker (2016b), Hosseini and Khaled (2016), Wang et al. (2016)	Rerouting	Freight rerouting particularly in multi-modal transportation systems in the case of damage to transportation mode could enhance the SCR
Wieland and Wallenburg (2013), Scholten and Scilder (2015), Reyes Levalle and Nof (2015a, 2015b), Mandal et al. (2016); Biringer et al. (2013), Mancheri et al. (2018)	Communication	Lack of information sharing, organizations and collaboration among SC partners in the case of disruption could delay recovery process and reduce resilience of SC as whole.
	Substitution	Alternative power sources in power plants with dual fuel capability could enhance the resilience when the primary fuel supply is disrupted. Substituting raw materials of manufacturer with an alternative choice could reduce the likelihood of SC disruption.
<i>Restorative Capacity</i>		
Reference	Key drivers	Explanation
Turnquist and Vugrin (2013), Sahebjamnia et al. (2015), Hosseini and Barker (2016b), Morshedlou et al. (2018)	Budget and resource restoration	SC companies with a higher budget and resource (man/hour) restoration capability will have a shorter recovery time from disruption, resulting in higher resilience achievement.

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