

Measuring the Resilience of Supply Chain Networks

Till Sahlmüller

Westfälische Wilhelms-Universität Münster
till.sahlmüller@wi.uni-muenster.de

Bernd Hellingrath

Westfälische Wilhelms-Universität Münster
bernd.hellingrath@wi.uni-muenster.de

ABSTRACT

With increasing supply chain complexity, it gets more likely that disruptions ripple through the supply chain network, affecting supply chain performance. As the severity of disruptions depends on the supply chain network structure, it is important to assess the network structure in terms of its resilience. This article presents the results of a literature review (LR) to provide a comprehensive overview of measures used for evaluating the resilience of supply chain networks. The results indicate a wide range of measures applied in literature, focusing on either nodes, paths, or subgraphs of the network. The identified measures are compared regarding the structural characteristics they study and the aspects of supply chain performance they investigate.

Keywords

Resilience, Supply Chain Network, Graph Theory, Measures, Ripple Effect

INTRODUCTION

In recent decades, caused by an increase in complexity of production, reduced lead times, and branching out in new markets, supply chains have become more complex (Hearnshaw and Wilson 2013). However, these complex supply chains are more prone to disruptions, making it necessary to increase resilience. The concept of supply chain resilience is based on the premise that not all disruptions can be prevented. Here, a supply chain disruption is any unanticipated or unforeseen event that disturbs the expected flows of goods, products, and materials in a supply chain network (SCN) (Hosseini and Ivanov 2019). Causes might be natural disasters, political conflicts, terrorism, or the destruction of infrastructure, all of which have a long-term impact (Sokolov et al. 2015). Great harm to the supply chain performance occurs in case the effects of disruptions do not remain local but instead spread to other, initially not affected, parts of the SCN. This effect is also called the *ripple effect* (Park et al. 2021). How far disruptions spread through supply chains, depend on their SCN structure, as the structure defines what entities are connected and how they rely on each other (Basole and Bellamy 2014). Even more, the network structure can elevate the negative effects of disruptions (Zhao, Scheibe, et al. 2019).

As disruptions are highly unpredictable, it is essential to analyze and change the SCN structure proactively (Ivanov et al. 2014). A broad area of literature, therefore, analyzes SCNs to identify structural characteristics they inherit and to verify how changing the structure changes the outcome of possible disruptions (Kim, Choi, et al. 2011; Kim, Chen, et al. 2015; Falasca et al. 2008; Mari et al. 2015; Y. Li and C. W. Zobel 2020). Based on the central idea that certain properties of entities and network connections are important for the functioning of supply chains in the post-disaster phase, choosing appropriate metrics for analyzing the network structure is crucial. That is, the choice of metric determines what characteristics of the supply chain network are assessed.

Metrics can also be used to evaluate how changing the network structure increases certain structural aspects. However, improvement of the network structure in certain perspectives might degrade it in others. Therefore, it is important to consider both the aspects metrics consider and those they do not consider.

In this research, we concentrate on structural measures for assessing supply chain resilience. Our goal is to give an overview and categorization of existing measures applied to assess the resilience of supply chain networks. We furthermore illustrate what aspects are captured by each measure and how different measures compare to each other. We further sum up what performance aspects the measures assess. For our research, we conducted a systematic literature review. To guide our research, we set the following research questions:

RQ1 What network measures are used to assess SCN resilience?

RQ2 What different aspects of the network structure do these measures assess?

RQ3 How do these measures assess supply chain performance in face of disruptions?

The remainder of the paper is organized as follows: We first provide an overview of literature related to measuring supply chain network resilience. We then propose our research methodology, followed by the results of the literature search. The latter encompasses the different network measures identified. After that, we give a discussion of our findings. We conclude with a summary and outlook.

LITERATURE REVIEW

There exists no coherent definition for Supply Chain Resilience. However, it is accepted that it captures both the resistance capability to a disruption at initial impact as well as the recovery to the pre-disruption state or a new, more desirable state after disruption (Hohenstein et al. 2015).

To assess resilience, the resilience triangle, introduced by the Multidisciplinary Center for Earthquake Engineering (Bruneau et al. 2003) presents a concept to evaluate supply chain resilience by assessing the performance loss due to disruption as well as the time it takes the system to recover. This concept is based on the idea of a system having a certain pre-disruption performance, which is set to 100%. After disruption at time t_0 , the performance loss, given by $100 - Q(t)$, until recovery (t_1) is measured, where $Q(t)$ is the performance at time t .

$$\mathbb{R} = \int_{t_0}^{t_1} [100 - Q(t)] dt \quad (1)$$

This concept gives a reasonable illustration of resilience, as it captures both the direct impact of disruptions and the recovery. It, therefore, is often applied and adapted by supply chain researchers (C. W. Zobel 2011; R. Li et al. 2017; Y. Li and C. W. Zobel 2020; Falasca et al. 2008; Adenso-Díaz et al. 2018; Park et al. 2021).

To evaluate the resilience of the underlying SCN, choosing an appropriate structural performance measure (see $Q(t)$ in (1)) is crucial. Structural metrics provide quantitative insights into the network's topology, which allow the characterization of the network structure concerning specific dynamics (da F. Costa et al. 2007). In terms of SCNs, measures have to be chosen that successfully depict network characteristics that are important for the functioning of the supply chain in the face of disruption and, especially in case some of its entities or transportation routes might be disturbed. Metrics can be calculated both on the level of entities/connections or on the level of the whole network (Kim, Choi, et al. 2011). Metrics on the entity/connection level are helpful to identify entities/connections that are important by being central or responsible for production and transportation of materials and products. On the other side, metrics on the whole network level provide information about the structure of the whole network, the overall connectivity between its entities and potential bottlenecks.

There exists research that uses an overview of measures to illustrate the general properties of supply chain networks. For example, Kim, Choi, et al. 2011 use the degree centrality, closeness centrality, and betweenness centrality to identify key firms in supply networks. Perera et al. 2017 use modularity and assortativity to illustrate the overall network structure of supply chain networks and find out that in most of them exist several highly connected hubs that are not interconnected to each other. With a focus on supply chain resilience, Hosseini, Ivanov, and Dolgui 2019 present a literature review on quantitative modeling methods for supply chain resilience, including an overview of metrics and objective functions used. However, the focus is more on operational measures than on metrics based on the supply chain network structure. Han et al. 2020 provide an overview of performance metrics used in the area of supply chain resilience, including metrics applied for the reconstruction of supply chains. However, the focus is more on the distinction between different categories than on more detailed information of specific metrics. Finally, Bier et al. 2020 conducted a literature search on methods for mitigating disruptions in supply chain structures and highlight the importance of considering the complexity of supply chain networks. They also provide an overview of applied metrics, including structural network metrics. However, the outline is rather broad and also encompasses probabilistic measures.

In contrast to the above mentioned publications we here concentrate on structural measures that are used to assess the resilience of the supply chain network. By conducting a literature search, we give an overview of applied measures and furthermore group the measures in plausible categories. We then analyze the purpose of applying those measures, how they differ and highlight the aspects that are not captured by them. We furthermore sum up what aspects of supply chain performance are assessed by each of the measures.

METHODOLOGY FOR LITERATURE SEARCH

Concerning the discussion above, we here look for resilience measures that consider the structure of the SCN. To avoid bias and guarantee rigor, we conducted a literature search following vom Brocke et al. 2009 to review existing literature on structural metrics for SCNs. The databases Scopus and Web of Science were considered to cover literature from an interdisciplinary field from different sources. Furthermore, both contributions from journals and conferences were incorporated, even widening the range of sources. The search, however, is limited to publications written in English.

Relevant keywords were defined as search criteria to select appropriate literature. As the focus is on the network structure of supply chains, we included both "supply chain network" and "supply network" as these terms are often used interchangeably (Braziotis et al. 2013). Furthermore, "topology" is often used instead of "structure". Finally, we included "measur*", "metric*" and "assess*" for measures. Therefore, we used the following search term:

TITLE-ABS-KEY(("supply chain network" OR "supply network") AND "resilien*" AND ("structur*" OR "topolog*") AND ("measur*" OR "metric*" OR "assess*")).

This led to a total of 95 publications, which resulted in 71 publications after deleting duplicates. Subsequently, the title, abstract, and the publications' keywords were examined to determine whether the publication addresses the stated research focus. Reasons for exclusion were mainly that the publications considered operational instead of network structure-based metrics. The thereby identified papers were read in total. Additional publications were added by forward and backward search, which finally led to 16 articles.

RESULTS OF LITERATURE REVIEW

Characteristics of Articles

Figure 1 shows the number of publications per year. There is an increase in publications per year from 2014 onwards. This finding is consistent with observations, that from this time on, there is an increased number of publications centered around analyzing the structure of supply chains to improve supply chain resilience (Sahlmüller and Hellingrath 2021).

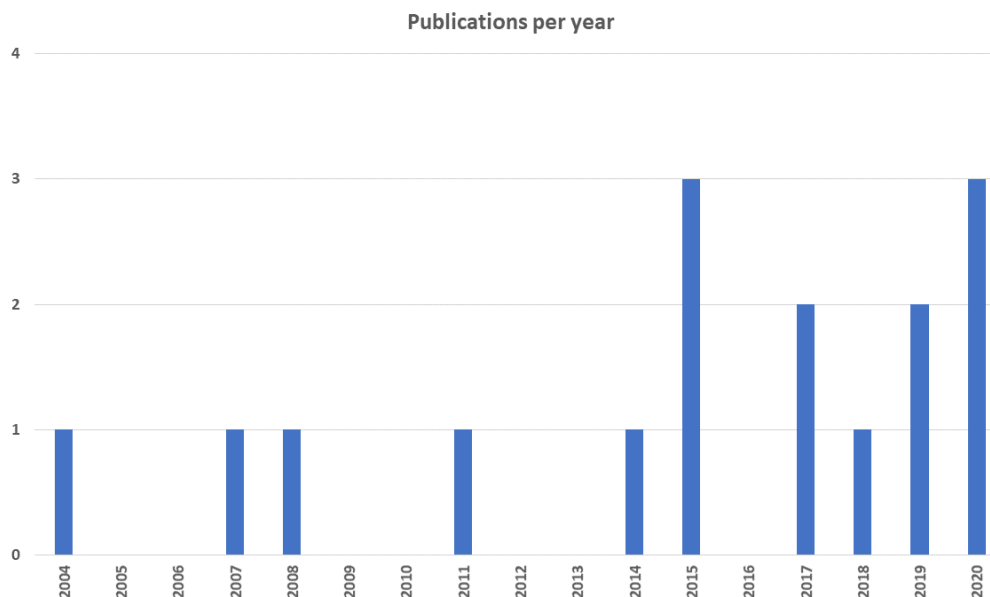


Figure 1. Identified publications per year.

The publications were primarily published in journals (13) and to a minor degree in conference proceedings (3). Most publications were published in either business journals, engineering journals, or journals that are centered in the intersection of those two topics, including the International Journal of Production Economics (4 times), Sustainability (2 times), the International Journal of Industrial Engineering: Theory, Applications and Practice, Complexity, IEEE Transactions on Engineering Management, Decision Sciences, IEEE Intelligent Systems, IEEE Systems Journal and the International Journal of Production Research. Publications in conference proceedings were published in the proceedings of the Conference on Intelligent Autonomous Agents, Networks and Systems, in the

proceedings of the Conference on Advances in Social Network Analysis and Mining, and the proceedings of the International Conference on Information Systems for Crisis Response and Management. Considering the identified publications, they come from an interdisciplinary research area.

Research Methodology

Supply Chain networks consist out of nodes and links, where nodes represent firms and links define the exchange relationships between firms (in this publication, the material flow) (Hearnshaw and Wilson 2013). Most of the metrics investigated in the identified publications can be assigned to those groups, assessing either node or link characteristics. For example, they calculate the number of suppliers or existing paths between nodes. However, some are restricted to only a subgraph of the initial graph, requiring both a certain connectivity and the existence of specific nodes. Therefore, we categorized the metrics into node-based, path-based, and subgraph-based metrics. We then further divided the categories into appropriate sub-categories based on structural characteristics they consider (see Figure 2).

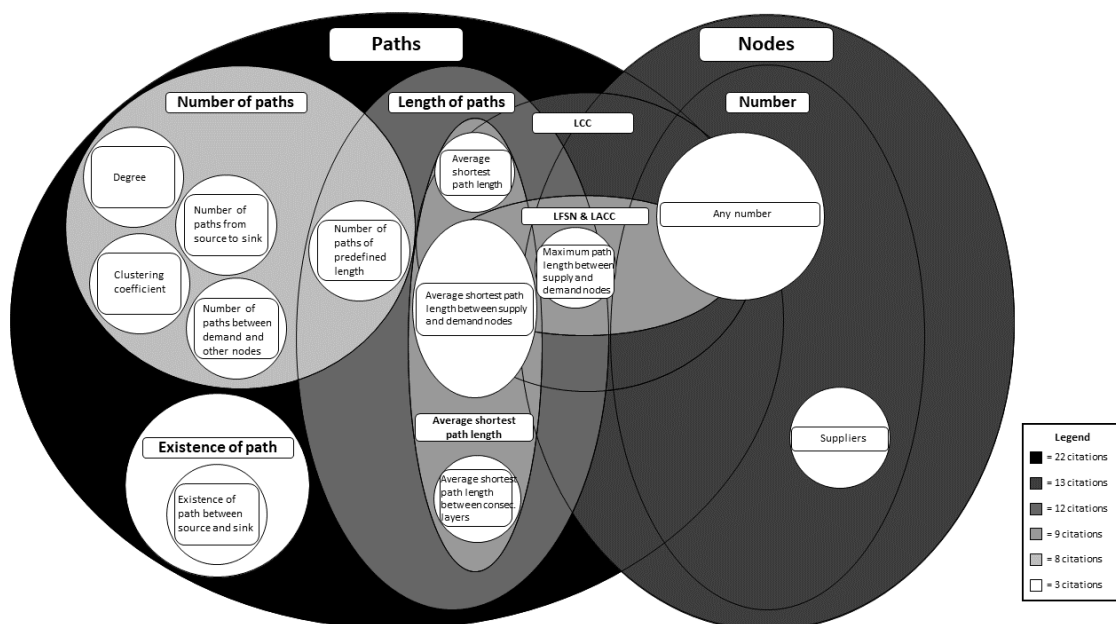


Figure 2. Overview of identified metrics. Here, "LCC" and "LFSN & LACC" are subgraph metrics. As publications often consider more than one metric, the total number of metrics surpasses the number of publications.

METRICS

Table 1 contains the identified publications, the applied measures, and how they were explicitly calculated.

Table 1. Resilience measures for Supply Chain Network Structures

Reference	Measure	Definition
Valenzuela et al. 2018	communicability between nodes	<i>weighted number of walks of pre-definded length between nodes</i>
R. Li et al. 2017	(i) Amount of production delivered (ii) Average delivery distance	(i) <i>number paths from source to sink</i> (ii) <i>weighted delivery distance</i>
Ponnambalam et al. 2014	closeness centrality	<i>average length of shortest paths between nodes</i>

Dixit et al. 2020	based on density (D), centrality (CT), connectivity (CV), network size (NS)	$\frac{connectivity \cdot network\ size}{density \cdot centrality}$
Y. Li and C. W. Zobel 2020	(i) number of healthy nodes (ii) size of largest connected component (LCC) (iii) size of LCC in relation to average path length (APL) of the LCC	(i) $\frac{number\ of\ healthy\ nodes\ at\ time\ t}{network\ size}$ (ii) $\frac{size\ of\ LCC\ at\ time\ t}{network\ size}$ (iii) $\frac{size\ of\ LCC\ at\ time\ t / APL\ of\ LCC\ at\ time\ t}{network\ size / APL\ of\ network}$
Zhao, Scheibe, et al. 2019	(i) size of the largest functional sub-network (ii) average supply path length	(i) <i>size of largest connected component containing at least one supply node</i> (ii) <i>average shortest path between supply and demand nodes</i>
Y. Li, C. Zobel, et al. 2019	(i) size of the LCC at initial impact (ii) size of the LCC at full impact (iii) number of healthy nodes at full impact	(i) $\frac{size\ of\ LCC\ at\ initial\ impact}{network\ size}$ (ii) $\frac{min_{0 \leq t \leq T} size\ of\ LCC\ at\ time\ t}{network\ size}$ (iii) $\frac{min_{0 \leq t \leq T} number\ of\ healthy\ nodes}{network\ size}$
Kim, Chen, et al. 2015	network disruption	<i>disrupted path from source to sink</i>
Craighead et al. 2007	network size	<i>number of nodes available after disruption</i>
Falasca et al. 2008	network size	<i>number of nodes available after disruption</i>
Wang et al. 2015	multiple-path reachability of demand nodes	<i>aggregated multiple path reachability of demand nodes, weighted by length of path and significance of reached nodes</i>
Thadakamalla et al. 2004	(i) size of LCC (ii) average shortest path lengths (iii) clustering coefficient	(i) <i>size of LCC</i> (ii) <i>average shortest path length</i> (iii) $\frac{number\ of\ edges\ among\ node's\ first\ neighbors}{possible\ number\ of\ edges\ between\ first\ neighbors}$
Zhao, Kumar, Harrison, et al. 2011	(i) supply availability rate (ii) size of the largest functional sub network (LFSN) (iii) average supply path length in the LFSN (iv) maximum path length in the LFSN	(i) <i>percentage of demand nodes with access to supply nodes</i> (ii) <i>LCC containing at least one supplier</i> (iii) <i>average of shortest path length between supply and demand nodes in LFSN</i> (iv) <i>maximum path length between supply and demand nodes in LFSN</i>
Pourhejazy et al. 2017	(i) average node degree (ii) average clustering coefficient (iii) number of supply nodes (iv) total distance	(i) <i>average number of connections per node</i> (ii) <i>mutual exchange connections among nodes</i> (iii) <i>total number of supply nodes</i> (iv) <i>distance between supply and demand nodes</i>

Shi et al. 2020	(i) size of the largest all-role connected component (LACC) (ii) weighted average path length of LACC (iii) maximal vertical path length of LACC	(i) size of LCC that includes at least one supplier, manufacturer, distributor, retailer (ii) weighted average path length between consecutive layers and average of all other paths (iii) longest path length of all vertical paths in LACC
Mari et al. 2015	(i) supply availability rate (ii) size of the LFSN (iii) average supply path length in LFSN (iv) clustering coefficient	(i) percentage of retailer nodes with access to manufacturers and suppliers (ii) size of LCC with at least one supplier and manufacturer (iii) average shortest path length between supplier and retailer nodes in LFSN (iv) ratio between the number of edges among a node's first neighbours and total possible number of edges between them

Node-based measures

Based on the identified publications, there are two measures based on node properties: The total number of nodes available after disruption (Dixit et al. 2020; Y. Li and C. W. Zobel 2020; Y. Li, C. Zobel, et al. 2019; Craighead et al. 2007; Falasca et al. 2008) and the number of suppliers available after disruption (Pourhejazy et al. 2017), respectively.

In network theory, the number of available nodes after disruption is a prominent measure for evaluating the spread of processes such as diseases or information (Dorogovtsev and Mendes 2002). In terms of supply chain performance, a higher number of functioning nodes after disruption means that more nodes can ship and receive goods (Craighead et al. 2007) and therefore represents an overall health status of the network (Y. Li and C. W. Zobel 2020). Furthermore, it accounts for an additional "buffer" (Dixit et al. 2020) as there might be a second option for a failed supplier or customer. Pourhejazy et al. 2017 stress out that a high number of failed suppliers might increase the demand on the remaining suppliers, which may lead to an imbalance of supply and demand.

Path-based measures

The subsequent measures assess nodes' involvement in the walk structure of the network. Thus, they evaluate the volume or length of walks that originate, terminate, or pass through nodes (Borgatti and Everett 2006). The number of path-based measures is more elevated than the node-based measures and can be categorized in measures based on the existence of paths, the length of paths, and the number of paths.

The existence of paths

Some publications (Kim, Chen, et al. 2015; Zhao, Kumar, Harrison, et al. 2011; Mari et al. 2015) measure network resilience based on the existence of a path between source and sink.

The existence of a path between two nodes, i and j , means that a flow starting from node i can pass through the network to reach node j . A high number of existing paths between a particular node, i , and all other nodes, $j \neq i$, indicates that that specific node i is of importance (Grubestic et al. 2008). The total number of mutually existing paths between nodes in a network gives an indicator for the general accessibility of that network. However, it neither indicates the length of paths nor provides information about the lack of connectivity between nodes (Grubestic et al. 2008).

In terms of supply chain performance, the existence of paths between specific nodes illustrates transportation routes between the firms the nodes represent. Therefore, they ensure delivery of necessary supplies to maintain operation (Zhao, Kumar, Harrison, et al. 2011), allow firms to respond to market demand quickly (Mari et al. 2015) and prevent the whole network from failing due to missing resources (Kim, Chen, et al. 2015).

The length of paths

This section covers measures that consider the distance between nodes. The applications of these measures differ as they consider different sets of nodes: Some publications (R. Li et al. 2017; Ponnambalam et al. 2014; Thadakamalla et al. 2004) measure the delivery distance/average (shortest) path length between any two nodes, whereas others (Zhao, Scheibe, et al. 2019; Pourhejazy et al. 2017) restrict the assessment to paths between source and sink.

Generally, the length of a path between two nodes, i and j , is defined as the number of edges the flow has to traverse

to arrive at node j starting from node i (Grubestic et al. 2008). Built on the premise that most communication between entities takes place in the shortest way possible, most publications assess the *shortest path length* (Estrada and Hatano 2008) or the *average shortest path length*. The latter serves as a measure for the whole network and is also called the *characteristic path length* (Watts and Strogatz 1998). The characteristic path length is mainly influenced by long paths (Rubinov and Sporns 2010), as even a single, significantly longer path might greatly increase the average shortest path length. Moreover, it highly depends on structural bottlenecks, such as highly connected nodes (Estrada and Hatano 2008). That is, in case there exists a structural bottleneck in the network, it is likely that most of the shortest paths pass through it (see Figure 3) (Estrada and Hatano 2008). As a consequence, in case of disruption, the shortest path tends to increase as nodes are removed from the network, and it will increase significantly in case highly connected nodes are affected (Motter and Lai 2002). As node-removals also may result in fragmented subgraphs, paths can even be of infinite length, increasing the characteristic path length to infinity (Achard and Bullmore 2007).

In terms of supply chain performance, shorter paths ensure lower cost and product delivery time (R. Li et al. 2017; Thadakamalla et al. 2004) as well as how comfortable a node can be accessed (Ponnambalam et al. 2014). Furthermore, shorter paths facilitate delivery from supply to demand nodes along the supply chain network (Zhao, Scheibe, et al. 2019).

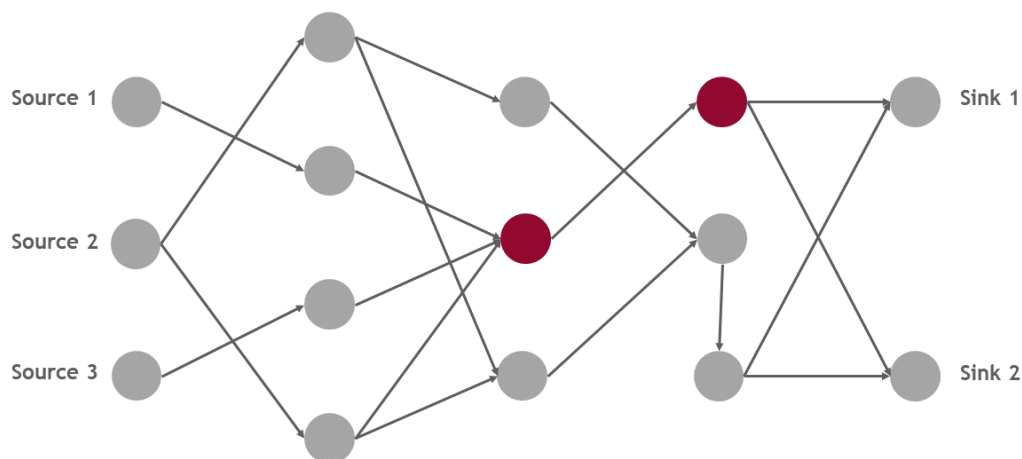


Figure 3. All of the shortest paths between source and sink nodes depend on the two highlighted nodes.

The number of paths

Instead of the sheer existence of paths, measures in this category focus on the number of paths between particular nodes. Paths are said to differ if one contains at least one edge the other does not. Naturally, different paths can be of different lengths as they consist of a different number of edges.

Measures considering the number of paths are the *average degree* (Pourhejazy et al. 2017), the *clustering coefficient* (Thadakamalla et al. 2004; Pourhejazy et al. 2017; Mari et al. 2015), the *number of paths between demand and other nodes* (Wang et al. 2015), the *number of paths between source and sink* (R. Li et al. 2017; Dixit et al. 2020) and the *number of paths of certain length* (Valenzuela et al. 2018).

The (average) degree of a node, i , illustrates the number of nodes to which node i has an edge (Grubestic et al. 2008). Generally, the node degree is a representation of direct interactions between entities in the network (Jordán and Scheuring 2004). Furthermore, nodes with a higher degree are deemed more critical for networks as they are more closely associated with other nodes in the network (Grubestic et al. 2008). As before, the *average node degree* is a network measure.

For supply chains, Pourhejazy et al. 2017 highlight that a higher degree ensures alternatives to supply goods.

The (average) clustering coefficient measures how close the neighbors of a node are connected by mutual links (Jordán and Scheuring 2004). It, therefore, reflects the connectivity around individual nodes (Rubinov and Sporns 2010) or any node in case the average clustering coefficient is considered. High average clustering ensures general availability of alternative paths (Jordán and Scheuring 2004).

For supply chains, a high clustering coefficient allows rapidly shifting the production among suppliers (Mari et al. 2015). It ensures both alternative transportation routes (Pourhejazy et al. 2017) and flexibility in the exchange of goods in the neighborhoods of nodes (Thadakamalla et al. 2004).

The number of paths between nodes serves as an indicator of importance as nodes that are connected to other nodes by a high number of paths are likely to be essential for the network flow. However, one has to consider that more peripheral nodes have, in principle, more unique paths than more central nodes as the latter are connected by shorter paths, which leave less option for alternatives (Grubestic et al. 2008).

In terms of supply chains, Wang et al. 2015 focus on the number of paths between demand nodes and all other nodes as this ensures that demand nodes can be reached after disruptions. Other publications (R. Li et al. 2017; Dixit et al. 2020) concentrate on the number of paths from source to sink. Generally, a high number of paths from source to sink indicates a more connected network as there are more connected nodes between them (Grubestic et al. 2008). Furthermore, a high number of paths from source to sink guarantees the ability to deliver a minimum amount of product, which ensures a certain service level (Dixit et al. 2020; R. Li et al. 2017).

The number of paths of a predefined length is a measure based on both the number and the length of paths. It is considered by Valenzuela et al. 2018, who measure the number of paths with a maximal, pre-specified length. The upper bound on the path length ensures that only transportation routes are considered that are not too long.

Subgraph-based measures

The above measures consider properties of the whole network, such as the longest path or the total number of available nodes in the entire network. However, as nodes or edges are removed from the network due to failure, the initial graph may fragment into smaller subgraphs. The nodes in the different subgraphs are still linked to each other so that flow may pass from one node to another but not between distinct components. If a failure is rippling through the network, research shows that in the beginning, only single nodes and small clusters of nodes break down from the initial graph (Albert et al. 2000). Whereas nodes in smaller subgraphs are connected to just a few nodes, there remains a very large subgraph, and the nodes in it are still connected to an extensive fraction of the entire network. This remaining largest subgraph, which is called the *largest connected component*, LCC, is widely used across disciplines to assess the impact of failures on networks (such as the Internet as connections between routers, the world wide web, power grids, and transportation networks) (Motter and Lai 2002). Whereas the *presence* of the largest connected component now often serves as an indicator if the network is at least partly performing its intended function, the *size* is an indicator of how much of the initial network is working (Newman 2010) (see Figure4).

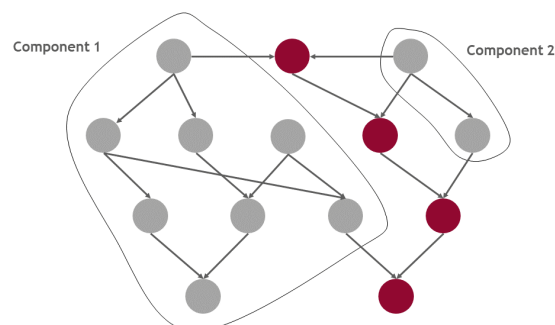


Figure 4. Post-disruption the highlighted nodes are disrupted. Compared to the pre-disruption network with size 14, the LCC (component 1) has size 8.

Some identified publications concentrate on the LCC (Y. Li and C. W. Zobel 2020; Y. Li, C. Zobel, et al. 2019; Thadakamalla et al. 2004). Refined concepts of the LCC that were investigated are the *largest functional sub-network*,

LFSN, and the *largest all-role connected component*, LACC. The LFSN is defined as the LCC with at least one supplier (Zhao, Kumar, Harrison, et al. 2011; Zhao, Scheibe, et al. 2019) or with at least one supplier and one manufacturer (Mari et al. 2015) in it. The LACC is the LCC that contains at least one supplier, one manufacturer, one distributor, and one retailer (Shi et al. 2020) (see Figure 5).

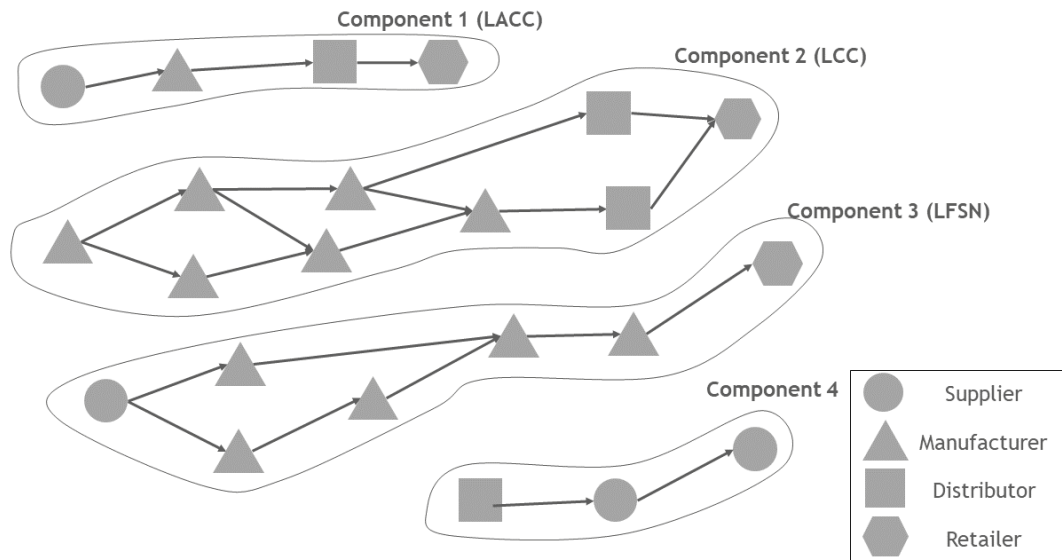


Figure 5. Different sizes of the LCC, LFSN and LACC in a post-disruption network.

Focused on the LCC, respectively LFSN and LACC, the majority of publications measure supply chain resilience by the *size of the LCC/LFSN/LACC*, that is, the number of nodes in the LCC/LFSN/LACC (Y. Li and C. W. Zobel 2020; Y. Li, C. Zobel, et al. 2019; Thadakamalla et al. 2004; Zhao, Scheibe, et al. 2019; Zhao, Kumar, Harrison, et al. 2011; Shi et al. 2020; Mari et al. 2015). Compared to counting the number of available nodes in the whole network, measuring the available nodes in the LCC/LFSN/LACC gives a better overview of the network performance against disruptions as a bigger LCC/LFSN/LACC implies that the whole supply chain suffers less and needs less effort to recover (Y. Li and C. W. Zobel 2020). Therefore, it ensures system robustness (Y. Li, C. Zobel, et al. 2019), overall network connectivity (Zhao, Scheibe, et al. 2019; Thadakamalla et al. 2004) and that firms can deploy contingency plans efficiently and effectively (Mari et al. 2015). Other publications measure the average shortest path length in the LCC/LFSN/LACC (Shi et al. 2020; Zhao, Kumar, Harrison, et al. 2011; Y. Li and C. W. Zobel 2020; Mari et al. 2015), which evaluates the accessibility of nodes. This guarantees that supplies are close to customers (Zhao, Kumar, Harrison, et al. 2011), speed of transportation (Shi et al. 2020; Mari et al. 2015) and an efficient transportation of goods (Y. Li and C. W. Zobel 2020). Considering the shortest path length, however, can be misleading as the average shortest path length is highly correlated to the size of the considered subgraph (Y. Li and C. W. Zobel 2020). Finally, the maximum path length (Shi et al. 2020; Zhao, Kumar, Harrison, et al. 2011) assesses the worst-case post-disaster speed of transportation.

DISCUSSION

In this section, we want to discuss our findings towards the proposed research questions:

Concerning the first research question, the considered measures can be divided into three main categories (node-based, path-based, and subgraph-based) and several sub-categories. The subgraph-based measures pose a sub-group of the other two as they assess both the connectivity and node characteristics (such as the number of connected nodes). Despite the differences between the categories, the measures in specific categories differ in the set of nodes they assess: Some authors evaluate supply chain resilience by considering all nodes, others only a subset (e.g., suppliers, customers).

As the aspects of the network structure the identified measures consider and the elements of supply chain performance that are assessed are in tight relation, we answer RQ2 and RQ3 together:

In general, the node-based measures assess resilience regarding how many of the initial nodes are still available after a disruption. In a post-disruption situation, a higher number of available nodes indicates a higher ability of

the network to fulfill its intention. The node-based measures, however, do not give any information about the connectivity between nodes. More specifically, focusing on supply chains, they measure how many initial suppliers, manufacturers, etc., are still delivering goods, producing, etc. The metrics, however, do not capture information concerning the transportation of products to and from these nodes. However, the latter is crucial for supply chain networks where specific nodes perform specific tasks and where the failure of a transportation route connecting a single source might halt the whole supply chain.

The path-based measures are the most used ones, and further differ in the degree of detail they capture network connections. Some measures monitor whether a path still connects nodes. In the aftermath of disruptions, existing paths indicate that flows can still pass between nodes. However, this measure does not provide any information about the length of paths or the existence of alternative paths. For supply chains, applying this metric assesses the number of nodes for which a transportation route exists, which allows the exchange of goods. However, it does not capture the delivery distance, nor whether or not there exist alternative transportation routes.

A measure that overcomes this weakness is the one that measures the average shortest path length between nodes. Additionally to the pure existence, this measure also captures the distance between nodes. On the downside, it does not monitor the presence of alternative paths and is prone to structural bottlenecks. More specifically: The average shortest distance is measured by considering only the shortest path between nodes. Consequently, if one of those considered paths fails, the average shortest path might elongate highly. Secondly, due to the natural structure of networks, many shortest paths probably depend on the connection pattern of just a few nodes. In case one of those highly connected nodes is affected, it is likely that many paths elongate greatly. Lastly, a general problem with the average shortest paths-metric is that in case of a fragmentation of the initial graph, the path length increases to infinity as there is no longer a connecting path. To resolve the latter, considering the average *inverse* shortest path length is recommended. This measure is regarded as a measure of global efficiency (Rubinov and Sporns 2010) and has the advantage that infinite paths add a value of zero. It, therefore, concentrates on the length of paths in the connected subgraphs (Achard and Bullmore 2007). In terms of supply chain performance, assessing the length of paths evaluates if products and materials can be delivered rapidly. However, this is prone to bottlenecks such as airports and harbors. Many short transportation routes likely depend on those bottlenecks, which might be problematic in the aftermath of disruptions as they might be overburdened.

A measure that evaluates the existence of alternative routes is the one that determines the number of paths between nodes. The application of this measure alternates in that some publications consider the number of paths a single node has in general (degree), between neighbors (clustering coefficient), or between any nodes. Compared to the existence of paths, these metrics also assess the lack of connectivity as nodes with fewer paths are subsequently less connected. On the downside, compared to the average shortest path length, these measures do not guarantee short paths and are also sensitive to bottlenecks as a high number of alternate paths might depend on a few nodes. Towards supply chain performance, these metrics assess the existence of alternative transportation routes. Alternative transportation routes ensure flexibility as destroyed transportation routes or failed suppliers can be replaced by alternative routes or other suppliers to which exist a transportation route. However, this metric is sensitive to bottlenecks as it is still possible that different transportation routes depend on specific infrastructure such as harbors. Lastly, the measure that assesses the size of the largest connected component already includes some of the characteristics captured by other measures: It measures the number of still functioning nodes provided that they are connected. Therefore, it assesses the performance of the whole network as it entails how the network can operate compared to the pre-disruption situation. One benefit of this measure is that it makes the validation of the connectivity of particular sets of nodes unnecessary (for example, suppliers and customers): In case one supplier is part of the LCC, by definition, this supplier is connected to all customers that are also part of the LCC. On the downside, however, this measure restricts the assessment of the network to the largest subgraph. If the initial graph fragments into several subgraphs of similar size, the assessment might be erroneous as many still-functioning nodes are not considered.

In terms of supply chain performance, this metric on one glance provides a quick view on the performance of the whole supply chain network: In case the size of the largest connected component is about as big as the initial network, the supply chain is likely able to fulfill its intended goal. However, as long as there are alternative routes (which ensures connectivity of the LCC), it does not capture disrupted transportation routes. Assessing the path length in the LCC further evaluates speed of transportation.

CONCLUSION

In this research, we conducted a systematic literature review to identify measures that are applied to evaluate the resilience of SCNs.

We posed three research questions that guided our research: RQ1 focused on the kind of structural metrics that were applied. We could answer the question by classifying the metrics into appropriate categories. RQ2 was centered

around the benefits and limitations that come along with applying the specific measures. We highlighted network characteristics each measure focuses on and stated what structural characteristics might be closely related but not captured. RQ3 examined how the metrics assess supply chain performance when struck by disruption. We answered this research question by highlighting different performance aspects that are linked to specific structural characteristics.

Our literature search clearly is not without limitations. We made an effort to choose appropriate keywords to encompass a broad field of literature and find all relevant publications. But, of course, it might be possible that we missed essential publications.

Our research has theoretical and practical implications: Our overview of metrics shows that a couple of measures are deemed suitable for assessing supply chain resilience. Each of them focuses on particular structural characteristics and, therefore, specific aspects of supply chain performance that are considered. It should be verified if and what measures are deemed appropriate from a practitioner's perspective and applicable.

From a theoretical perspective, we see that quite some metrics are prone to structural bottlenecks. Maybe the identification of those bottlenecks should be more in focus. Furthermore, after choosing a metric, a subsequent step in SC resilience research is increasing supply chain resilience by changing the SCN. The goal is to alter the underlying network so that when hit by disruption, the network still possesses structural characteristics captured by the metrics of choice. In this regard, however, we see a strong focus on approaches that concentrate on the size of the LCC/LFSN/LACC (Mari et al. 2015; Zhao, Kumar, and Yen 2011; Thadakamalla et al. 2004). Those approaches create networks that have a scale-free structure and therefore remain close to the initial network size despite nodes being disrupted. Due to the result of our research, we urge it essential to look for approaches that can also change the SCN in terms of other characteristics, like the number and length of paths.

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