Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 58-19 (2024) 1150–1155

Network science indicators and their relationship with performance during disruptions: a case study

Michele Martignago*, Phu Nguyen, Niloofar Katiraee*, Martina Calzavara*, Dmitry Ivanov****

**Department of Management and Engineering, University of Padua, Vicenza, Italy (e-mail: michele.martignago@phd.unipd.it, niloofar.katiraee@unipd.it, martina.calzavara@unipd.it)*

***Berlin School of Economics and Law, Badensche Str. 50, 10825 Berlin, Germany (e-mail: phu.nguyen@hwr-berlin.de, dmitry.ivanov@hwr-berlin.de)*

Abstract:
Interest in supply chain (SC) resilience has increased in the wake of the pandemic and other crises, including those related to political and environmental instability. The literature offers some contributions to proactive indicators to assess the resilience of a system before a disruption occurs. Other studies provide metrics to assess resilience from the reactive perspective after the onset or end of a disruption. This paper examines the application of some proactive indicators from network science to some post-disruption measure of resilience, especially how these measure evolves as a function of time. We examine this by testing different supply chain designs against disrupted scenarios and using data from a real-life industry. The focus is on service level as a performance metric. The tested indicators correlate well with performance loss but show a limited ability to correlate with metrics representing SC dynamics. The practical contribution of this paper is an approach to measure SC resilience as an inherent property of the system, which can aid in designing future SCs, rather than measuring resilience as a response to a disruptive event. The paper also provides theoretical contributions, including the further validation of certain indicators from the literature and the identification of research areas in need of new metrics.

Keywords: Supply network design, viability, digital twin, adaptation, simulation, fill-rate, KPIs.

1. INTRODUCTION

Disruptive events impact supply chains (SCs) negatively affecting the profitability of companies and even threatening the ability to meet some of society's basic survival needs in the long term (Aldrighetti et al., 2021; Ivanov and Dolgui, 2022). The ability to overcome disruptions is known as resilience: SC resilience (SCR) studies have focused much on definitions, while SCR quantification is still an open research topic (Ribeiro and Barbosa-Povoa, 2023). The optimization approach in SC design (SCD) typically deals with the costs of opening and operating distribution centers (DCs), integrated with predictable costs related to transportation and inventory. In fact, academic literature has long dealt with forecastable time-dependent elements in SCs, calling them "risks" (Tang, 2006). In contrast, disruptions are rare and hard-to-predict events, sometimes even unprecedented in causes and effects (Queiroz et al., 2022; Ivanov, 2021). The focus of this paper is on the performance of SCs in times of disruption, and we measure it using key performance indicators (KPIs). KPIs are tools typically used in companies to monitor business processes and alignment with long-term goals, but KPIs are also used to quantify the impact of a disruption on a system by comparing a performance indicator in a disrupted and an undisrupted scenario, as in Aldrighetti et al. (2019); Burgos and Ivanov (2021), Schleifenheimer and Ivanov (2024). Among others, some performance indicators refer to a cumulative value only, such as lost profit or lost sales. For long-lasting disruptions, there is the need for KPIs that track the time-dependent response and evolution of performance, not just the final aggregate value. This interest in the time-dependent aspect of SCR is already highlighted in the literature (Ivanov, 2022a, 2024c). Measuring characteristics related to this time-dependent domain can help to understand the mechanisms underlying resilience and, in short, how to better prepare for disruptive events in an efficient way (Aldrighetti et al., 2023, 2024). On the other hand, to describe the properties of a SC, researchers proposed indicators from network science (NS) deriving managerial and theoretical recommendations (Allesina et al., 2010; Basole and Bellamy, 2014; Li et al., 2020). These indicators consider the graph representation of the SC, considering nodes (such as DCs) and edges (such as the flows between different nodes). However, the NS approach has yet to incorporate some relevant SC logics, such as product hierarchy and inventory policies. The question that underlies our study concerns the relationship between NS indicators (that can be computed before the disruption occurs), and performance measured by KPIs that can only be computed after the disruption event, and it is as follows:

RQ: *Which indicators from network science can help predict supply chain performance during a disruption?*

In fact, Ivanov (2024c) described resilience by dividing it into a "performance deviation-based view" and an "adaptation-based view": the first is more related to resilience as an emergence activity and is in short described as "resilience as a quantity", the second as "resilience as a quality", meaning as

10.1016/j.ifacol.2024.09.108

the ability of a system to overcome disruption in general (see also viability (Ivanov, 2022b; Gruchmann et al., 2024, Ivanov 2024a)). The basic idea of our work is to put into correspondence NS indicators that only describe the network of the SC with the measured performance deviations in disrupted scenarios. We do this through a real-world case study from a SC of mechanical components in Europe, where also dynamic elements such as demand fluctuations and disruptions come into play. By doing so, we want to propose a method to start investigating which of the NS indicators resist the noise introduced by real data and the time-dependent behavior of the impact of disruptions. In fact, network indicators mainly deal with so-called static elements (Huatuco et al., 2021), representing only a part of reality (see section 2). The method includes the evaluation of different SCDs under a variety of disruption scenarios. Then, the time-dependent characteristics of the performance are put into correspondence with NS indicators. In literature, the term supply network (SN) is used sometimes as synonym of SC, others to refer to intertwined and complex SCs (Echefaj et al. 2024, Ivanov 2024b). In this paper, we will use the "SC" abbreviation.

The study is organized as follows: section 2 reviews the relevant literature, section 3 presents the methodology and the case study, section 4 is for the results, and section 5 is for the conclusions and future research directions.

2. LITERATURE REVIEW

2.1 Static and dynamic elements

To clarify our approach, we begin by noting a distinction between static and dynamic elements in SCs (Sivadasan et al., 1999; Huatuco et al., 2021). Static elements are the ones that are not time dependent, such as the number and location of customers and DCs, or the product portfolio's variety. Dynamic elements are, for example, fluctuation in demand and delivery times. The indicators from NS for SC deal with so-called static elements (Huatuco et al., 2021), which describe, for example, the redundancy of facilities or the number of edges between nodes of the graph representing the SC. Martignago et al. (2023) stress that indicators like these have been used to measure different aspects in SC, such as the complexity of managing SCs (Allesina et al., 2010), visibility, risks, and resilience (Basole and Bellamy, 2014; Li et al., 2020). These indicators are mainly related to strategic choices, which in SCs are made with a time horizon of some years. By contrast, tactical and operational decisions respond to short-term changes and fluctuations in dynamic elements on the scale of days, weeks, and months, such as seasonal demand or delivery requirements. Indicators that aim at giving insights for SCR are of little value if their contribution is questioned by a relatively short disruption or by the variability of demand present in a real case study: this is also why Sokolov et al. (2016) used a multi-criteria approach to select SCDs considering both static and dynamic elements.

2.2 Indicators from network science

Network science (NS) has been used for analyzing connections among numerous elements within complex networks in a wide variety of fields, from computer science, to biology, to social networks (Barabási, 2016). NS has been utilized in SC to investigate complex networks in uncertain times (Kim et al., 2015; Li et al., 2020). A network is determined by nodes and edges: nodes can be entities such as suppliers, manufacturers, and customers, but also products, while edges can represent material flow, information flow, or organizational relations (Bier et al., 2020). Researchers have utilized NS to explore the interconnected relationships and flows between these SCs entities: both node-level metrics (e.g., degree, betweenness, and eigenvector centrality) and network-level metrics (e.g., clustering coefficient) can be employed to study the network (Li et al., 2020). Sokolov et al. (2016) tried to interpret the meaning of common graph indicators when applied to SCs: they used an analytic hierarchy process method to evaluate different SCDs with multi-criteria approach. These criteria include both static indicators from NS theory (e.g. robustness, resilience, and efficiency) and dynamic measurements coming from simulation (e.g. transportation costs and service level). For them, these latest measurements allow them to consider the dynamic nature of uncertainties and disruptions. It is worth highlighting that they started by giving a managerial interpretation in SC of network indicators used in other fields (e.g. energy grids). This is why they quantified resilience as "the minimal number of nodes and arcs, the unavailability of which makes the graph non-connected". Ivanov (2019) provided another indicator on resilience, by correlating entropy with more alternative ways to reach customers, and thus with higher level of SC recoverability. Basole and Bellamy (2014) moved from indicators to a more holistic view of the graphs, putting into correspondence resilience measures with network types such as small-world or scale-free networks. Li et al. (2020) noted that real networks are sometimes hard to be associated to a specific network type. Thus, they used network indicators such as degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, and eccentricity to describe general networks, and put these indicators in correspondence with some performance of the SC coming from simulations when some nodes are infected and the infection, representing risk, propagates through the SC. The performances they observed were the recovery time, the minimum size of the largest connected component, and the minimum number of healthy nodes. They then validated the results through two industrial case studies of SC networks.

2.3 Performance in disruption times

The measurement of resilience is a wide and discussed topic. For a detailed analysis, we refer to Ribeiro and Barbosa-Povoa (2018) and Hosseini et al. (2019). For the scope of this paper, we focus on the work of Habibi et al. (2023): they proposed to describe different facets of SC performance using metrics labeled M1 to M6. Among those facets, four represent timespans and two performance losses. They put M1 and M2 into correspondence with reliability and preparedness, respectively, thus both with absorptive capacity. M3, M4, and M5 are put in association with responsiveness, persistence, and resourcefulness, thus with adaptive capacity, and, finally, M6 with recovery time, thus with restorative capacity. Those ideas are summarized in Fig. 1. This figure also integrates Time-To-Survive as proposed by Simchi-Levi et al. (2015) (see M1) into the six-phases analysis of supply chain performance, because the impacts of disruption in practice usually takes time to be recognized. Our work draws from the above literature in methodology to find, for the first time, a correlation between NS indicators and SC performance (measured with KPIs) with a focus on time-dependent development of SC performance.

3. CASE AND METHOD

The considered SC deals with mechanical components produced by a company in the North of Italy. Over a 1-year span, 194 customers scattered across Europe placed 71,907 orders in total, representing a demand of 484,325 items across the 30 available products in the considered portfolio. Two locations are set as open (factory and central distribution center, CDC, which are in Northern Italy and very close one to each other), while 5 other locations (in Spain, Netherlands, Belgium, Poland, and Bulgaria) are set as possible DCs. Thus, in this phase, the SCD problem is a facility location problem with a choice of facilities among a discrete set of candidates, in line with the nature of the NS indicators that we use. Different SCD alternatives are obtained by considering the inclusion or exclusion of some DCs. The network is optimized with a commercial solver (anyLogistix™ version 2.15 – network optimization). The six selected SCDs are among the ten best-performing ones in terms of SL and profitability when disruptions do not happen. We selected six SCDs to consider the effect of four different structures and to consider differences in results between similar structures. In the last tier, the 194 customers are grouped by the DC that serves them.

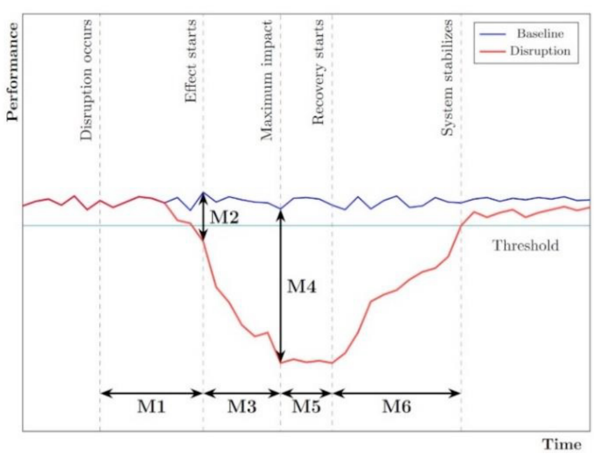

Figure 1. M1 to M6 facets of performance during disruption (adapted from (Habibi et al., 2023)).

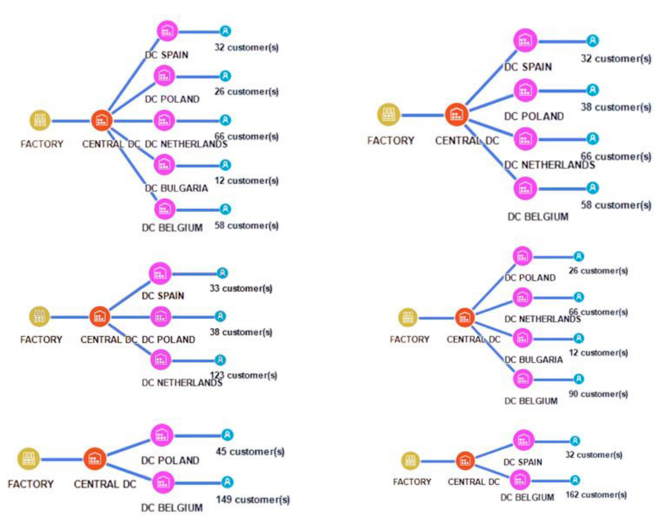

Figure 2. The six supply chain designs selected.

3.1 General method

We summarize the steps of the procedure we followed in our work, dividing it into three parts for easier comprehension. We recall that we use the term "KPI" when measuring the performance of SCs, and we use the term "indicator" to refer to a NS metric that describes the properties of a SC.

Part 1: Data collection, selection of SCDs, calculation of indicators

(1) Collect data from company
(2) Identify potential DCs locations
(3) Generate different SCDs based on different combinations of opened DCs: this is done through the optimization section of anyLogistix™
(4) SCDs selection (strategic choice)
(5) Compute indicators for each SCD (only static elements are considered up to this step)

Part 2: Tactical choices, simulation in normal times, simulation in disruption times

(1) Choose inventory policies and set hypotheses
(2) First simulation phase: dynamic elements are considered here, so to assess the SCD performance with time-dependent events such as orders and shipping times
(3) Second simulation phase: integrate the previous step with disruptions, to test their impact on SCDs' performance.

Part 3: KPIs collection and result analysis

(1) Collect KPIs
(2) Evaluate the correlation between NS indicators and KPIs

3.2 Details on the case study

Most of the steps of the procedure are self-explaining, thus in this paragraph we focus on the ones deserving more clarification.

In part 1, step 3 only considers aggregate data and does not consider dynamic elements such as fluctuations in demand, disruptions, or the stochastic nature of transport times. Step 4 leads to the choice of six SCDs that guarantee sufficient profits and SL in normal times (Fig. 2). Some of these SDCs are similar to another because we want also to investigate differences in performances when static indicators are comparable. In step 5, we use the Python NetworkX package (Hagberg et al., 2008) to compute most of the indicators, as in Li et al., (2020). In step 5, we use the following four indicators, of which we recall the meaning. Degree centrality (DEC) counts the ratio between the number of links of a node and the total number of nodes in the network. Eigenvector centrality (EVC) measures the importance of the nodes in the network considering both the number of connections and their relevance on the same score. Betweenness centrality (BC) is higher for nodes that are the most common in the shortest paths between any two given nodes. The clustering coefficient (CC)

Table 1. Correlation (r > 0.6) between performance characteristics (M1, M2, M3, M4, M6) and network indicators (eigenvector centrality (EVC), degree centrality (DEC), betweenness centrality (BC), clustering coefficient (CC))

Network indicator		Time independent performance characteristics				Time dependent performance characteristics (†)				
		M2		M4		M3		M6		
		Avg	Min	Avg	Min	Avg	Std dev	Avg	Min	Max
EVC	Avg	0.64	0.68	0.68	0.76			0.78	0.65	0.66
	Std dev	-0.64	-0.70	-0.69	-0.78			-0.80	-0.67	-0.66
	Min	**0.66**	**0.75**	0.73	**0.83**		0.60	**0.86**	**0.74**	**0.69**
DEC	Avg	0.64	0.68	0.68	0.77			0.78	0.65	0.66
	Std dev	0.63	0.64	0.78	0.78	**0.61**	**0.65**	0.78	0.63	0.63
	Min	0.64	0.68	0.68	0.77			0.78	0.65	0.66
	Max	0.61	0.62	**0.79**	0.77		0.62	0.74	0.61	
BC	Avg	0.64	0.68	0.68	0.76			0.78	0.65	0.66
	Std dev	0.63	0.65	0.78	0.78	**0.61**	0.65	0.79	0.64	0.63
	Max	0.61	0.62	0.79	0.77		0.62	0.74	0.62	
CC	Avg	0.64	0.68	0.68	0.77			0.78	0.65	0.66
	Std dev	-0.64	-0.69	-0.69	-0.77			-0.79	-0.66	-0.66
	Max	0.64	0.68	0.68	0.77			0.78	0.65	0.66
Num DCs		-0.64	-0.68	-0.68	-0.76			-0.78	-0.65	-0.66

(†) M1 did not show any relevant correlation. M5 was not collected. Bold: highest values on each column.

measures the tendency of nodes to cluster together. For proper mathematical definitions, see (Barabási, 2016; Li et al., 2020).

In part 2, step 1: the variability in demand quantity and lead time adds to the overall uncertainty in forecasting the customers' orders and meeting customers' demand on time. To manage this issue, the (s,S) with safety stock inventory policy is used for each scenario. The SCDs are in fact tested in terms of service level (SL) (fulfillment rate at the warehouse) in scenarios without and with disruptions. SL is average among 5 working days: in fact, SL for a single day is of no interest if, for example, it relates to a period when there were few orders from customers served by non-disrupted DCs. A critical point in this phase is the selection of disruption scenarios to test SCD alternatives. Each SCD is tested against each DC shutdown (one at a time) considering those shutdowns equally likely. We call these "elementary disruptions".

Other considerations can be made on different likelihood of DC closure in different geographical areas, but this is outside the scope of this paper. The simulation runs from 1st December to 30th November of the following year, while the disruption occurs on 4th April: the disrupted DC shuts down completely for 45 working days and then becomes fully operational. Thus, using the terminology of Kim et al. (2015), the focus is only on node disruptions, not on arc or network disruptions. The previous considerations on failures resulted in 58 different simulations.

In part 3, step 1, we are interested in the characteristics M1 to M6 of the performance, as in Fig. 1. To this purpose, we define a drop in SL above 5% compared to the non-disrupted scenario as a threshold below which we consider that the effects of the disruption are enough relevant. The same threshold is also used to consider the system fully recovered. Compared to the situation described by Habibi et al. (2023), we cannot define the M5 characteristic of the performance, because it is never visible a clear plateau where the effects of the disruption are constant. Therefore, M5 is not present in the results section.

3.3 Notes on indicators and on data collection

In Part 1, step 5, for every indicator that could be computed for every node, we collect the average value across the network, the maximum, the minimum, and the standard deviation. In part 3, step 1, for every SCD we have as many disrupted scenarios as the total number of DCs. For each KPI and their characteristic such as M1 to M6, we collect the average value across these scenarios, the maximum, the minimum, and the standard deviation.

4. RESULTS

In this study, we analyze the impact of an "elementary disruption" on the performance of different SCDs (subsection 3.2, Part 2). More studies will be needed to assess how different disruptions affect SC performance. Table 1 summarizes the results of our study. To avoid the collinearity issue as in Li et al. (2020), we select only one indicator at a time and check the impact of its variation on the performance metric under exam by calculating the coefficient of correlation r. We note that, in general, changing the network structure impacts more indicators simultaneously. Thus, considerations on the SCDs should be made by looking globally at the problem. First, we compare these indicators with the total number of DCs (Num DCs): Num DCs correlates ($|r| \geq 0.6$) with some of the statistical characteristics of M2, M4, M6. This is intuitive since a disruption on a SCD with fewer DCs leads in general to more severe problems. The interesting part is that Num DCs is not the most strongly correlated to any measure and it is not correlated with M1 and M3. Table 1 summarizes in "time-independent" columns the results about M2 and M4, the performance facets that lie on the vertical axis of figure 1, by reporting which indicators they correlate the most with. Results show that the maximum impact (ave(M4), min(M4)) on the SL is correlated to some indicators that represent strategic choices only. Table 1 summarizes in "time-dependent" columns the performance facets that lie on the horizontal axis of figure 1. Min(EVG) is the most strongly correlated with M2, M4, M6. The selected indicators do not help in understanding the behavior of the delay between the disruption event and when disruption effects are visible on the KPI (M1), and few indicators help in describing the relationship between the disruption event and the time of maximum impact (M3): this is because those time-dependent phenomena are deeply impacted also by other choices, such as inventory level. This shows the need to better consider even decisions at tactical level, to better understand the time-dependent performances of a SC against a disruption. In fact, the table is particularly interesting in the facets of performance with which the indicators fail to correlate: these are areas where further studies are needed. To conclude, we highlight that M1 and M3 require more study, but that even other characteristics should also be studied more closely: for example, minimizing the max(M4) means protecting the system against a worst-case scenario, but no indicator was correlated with max(M4).

5. CONCLUSION AND FUTURE RESEARCH

The objective of this study is to investigate the application of indicators from the theoretical network level to some disruption scenarios of a real case study. It is evident that the network level cannot comprehend in detail the complexity of the many parameters that characterize a SC – even less one subject to disruptions. The goal of this case study is to assess if the network level properties resist the noise introduced by real-life data (e.g. fluctuations in demand), real-life tactical choices (e.g. inventory policies), and disruptions (a 45-days shutdown of a DC), or if these overtake the relevance of the network structure and the indicators coming from it.

The simulations lead to some preliminary insights on the use of these indicators, as described in section 4. Clearly, the results are significantly constrained by the case and cannot be generalized. However, this study aims to highlight the value of this type of research and to suggest a methodology for it. Indicators that continue to accurately represent the SC when transitioning from static design (network optimization) to dynamic testing (simulation) could be utilized in the early phases of SCD to enhance resilience. Proactive indicators as the ones coming from network science cannot describe all the complexity of a disruption: in real life, as soon as a disruption happens, companies urge to find remedies to treat the symptoms and to fix the situation. This is why it is crucial to understand which elements of the SC are correlated to which measurements of the time-related performance (such as M1 and M3). The longer those spans of time, the longer the time for proactive planning, time-to-adapt, and adaptation (using the terminology proposed by Ivanov, 2024c). The limitations of this case study suggest next steps for research. This study is limited in the variety of disruptions; analogous study on arc or network disruptions may be proposed, with different duration and propagation. Moreover, the usefulness of the proposed indicators may vary from industry to industry: some indicators and their aggregations could be categorized as useful for SCs of fast-moving goods SCs, while others for sectors with very different characteristics in terms of lead times, mean time to recover from disruptions, cost of lost sales, or again regarding high SL requirement (as in pharmaceutical sector). Also, testing case studies with different recovery policies will allow for many considerations and insights. For example, in opposition to what is explained in this paper, we also run simulations allowing “dynamic sourcing” instead of “fixed sourcing”, where “dynamic sourcing” represents the ability to meet a customer’s demand from a second DC if the most convenient cannot provide the required product. This introduces additional complexity to the analysis of the results, as maintaining a high SL in disrupted scenarios can lead to significantly increased transportation costs and, therefore, reduced profits. These simulations highlighted the critical role of the number and locations of backup suppliers in SCR: this opens the way to research on more indicators that consider the metrics also of the disrupted networks.

REFERENCES

Aldrighetti, R., Battini, D., and Ivanov, D. (2023). Efficient resilience portfolio design in the supply chain with consideration of preparedness and recovery investments. *Omega*, 102841.

Aldrighetti, R., Battini, D., Ivanov, D., and Zennaro, I. (2021). Costs of resilience and disruptions in supply chain network design models: A review and future research directions. *International Journal of Production Economics*, 235, 108103.

Aldrighetti, R., Calzavara, M., Martignago, M., Zennaro, I., Battini, D., and Ivanov, D. (2024). A methodological framework for the design of efficient resilience in supply networks. *International Journal of Production Research*, 271–290.

Aldrighetti, R., Zennaro, I., Finco, S., and Battini, D. (2019). Healthcare supply chain simulation with disruption considerations: A case study from northern Italy. *Global Journal of Flexible Systems Management*, 20(Suppl 1), 81–102.

Allesina, S., Azzi, A., Battini, D., and Regattieri, A. (2010). Performance measurement in supply chains: new network analysis and entropic indexes. *International Journal of Production Research*, 48(8), 2297–2321.

Baghalian, A., Rezapour, S., and Farahani, R.Z. (2013). Robust supply chain network design with service level against disruptions and demand uncertainties: A real- life case. *European journal of operational research*, 227(1), 199–215.

Barabási, A. (2016). *Network Science*. Cambridge University Press, Cambridge.

Basole, R.C. and Bellamy, M.A. (2014). Supply network structure, visibility, and risk diffusion: A computational approach. *Decision Sciences*, 45(4), 753-789.

Bier, T., Lange, A., and Glock, C.H. (2020). Methods for mitigating disruptions in complex supply chain structures: a systematic literature review. *International Journal of Production Research*, 58(6), 1835–1856.

Burgos, D. and Ivanov, D. (2021). Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. *Transportation Research Part E: Logistics and Transportation Review*, 152, 102412.

Echefaj, K., Charkaoui, A., Cherrafi, A., Ivanov, D. (2024). Design of resilient and viable sourcing strategies in intertwined circular supply networks. *Annals of Operations Research.*

Gruchmann, T., Stadtfeld, G. M., Thürer, M., & Ivanov, D. (2024). Supply chain resilience as a system quality: survey-based evidence from multiple industries. *International Journal of Physical Distribution & Logistics Management*, 54(1), 92-117.

Habibi, F., Chakrabortty, R.K., and Abbasi, A. (2023). Evaluating supply chain network resilience considering disruption propagation. *Computers & Industrial Engineering*, 183, 109531.

Hagberg, A., Swart, P., and S Chult, D. (2008). Exploring network structure, dynamics, and function using networkx. Technical report, Los Alamos National Lab., Los Alamos, NM (US).

Hosseini, S., Ivanov, D., and Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E,* 125, 285-307.

Huatuco H., L., Smart, J., Calinescu, A., and Sivadasan, S. (2021). Complexity transfer in supplier-customer systems. *Production Planning & Control*, 32(9), pp. 747–759.

Ivanov, D. (2019). Entropy-Based Analysis and Quantification of Supply Chain Recoverability. In *International Series in Operations Research and Management Science*. Springer New York LLC, pp. 193–208.

Ivanov, D. (2021). *Introduction to Supply Chain Resilience: Management, Modelling, Technology*. Classroom Companion: Business. Springer International Publishing, Cham.

Ivanov, D. (2022a). Probability, Adaptability, and Time: Some Research-Practice Paradoxes in Supply Chain Resilience and Viability Modeling. *International Journal of Integrated Supply Management*, 15(4), 454-465.

Ivanov, D. (2022b). Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic. *Annals of Operations Research*, 319(1), 1411–1431.

Ivanov D. (2024a). Cash flow dynamics in the supply chain during and after disruptions. *Transportation Research: Part E*, 185, 103526.

Ivanov D. (2024b). Transformation of supply chain resilience research through the COVID-19 pandemic. *International Journal of Production Research, 1-22.*

Ivanov, D. (2024c). Two views of supply chain resilience. *International Journal of Production Research*, 62(11), 4031-4045.

Ivanov, D. and Dolgui, A. (2022). The shortage economy and its implications for supply chain and operations management. *International Journal of Production Research*, 60(24), 7141–7154.

Kim, Y., Chen, Y.S., and Linderman, K. (2015). Supply network disruption and resilience: A network structural perspective. *Journal of operations Management*, 33, 43-59.

Li, Y., Zobel, C.W., Seref, O., and Chatfield, D. (2020). Network characteristics and supply chain resilience under conditions of risk propagation. *International Journal of Production Economics*, 223, 107529.

Martignago, M., Calzavara, M., Katiraee, N., and Battini, D. (2023). Entropic measurement in supply chain network: past applications, current trends, and future research. In *Proceedings XXVIII Summer School "Francesco Turco".*

Queiroz, M.M., Fosso Wamba, S., and Branski, R.M. (2022). Supply chain resilience during the COVID-19: empirical evidence from an emerging economy. *Benchmarking: An International Journal*, 29(6), 1999–2018.

Ribeiro, J.P. and Barbosa-Povoa, A.P. (2018). Supply chain resilience: Definitions and quantitative modelling approaches–a literature review. *Computers & industrial engineering*, 115, 109–122.

Ribeiro, J.P. and Barbosa-Povoa, A.P. (2023). A responsiveness metric for the design and planning of resilient supply chains. *Annals of Operations Research*, 324(1-2), 1129–1181.

Schleifenheimer, M., & Ivanov, D. (2024). Pharmaceutical retail supply chain responses to the COVID-19 pandemic. *Annals of Operations Research*, 1-26.

Simchi-Levi, D., Schmidt, W., Wei, Y., Zhang, P.Y., Combs, K., Ge, Y., Gusikhin, O., Sanders, M., and Zhang, D. (2015). Identifying risks and mitigating disruptions in the automotive supply chain. *Interfaces*, 45(5), 375–390.

Sivadasan, S., Efstathiou, J., Shirazi, R., Alves, J., Frizelle, G., and Calinescu, A. (1999). Information complexity as a determining factor in the evolution of supply chains. In *Proceedings of the International Workshop on Emergent Synthesis*, 237–242. Kobe University Japan.

Sokolov, B., Ivanov, D., Dolgui, A., and Pavlov, A. (2016). Structural quantification of the ripple effect in the supply chain. *International Journal of Production Research*, 54(1), 152–169.

Tang, C.S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, 103(2), 451–488.