Model-based Risk Analysis of Supply Chains for Supporting Resilience

Zohoori, B.

DOI
10.4233/uuid:436fc248-4efb-4081-8a65-a4836c7e49e3

Publication date
2024

Document Version
Final published version

Citation (APA)
Zohoori, B. (2024). *Model-based Risk Analysis of Supply Chains for Supporting Resilience*. [Dissertation (TU Delft), Delft University of Technology]. https://doi.org/10.4233/uuid:436fc248-4efb-4081-8a65-a4836c7e49e3

Model-based Risk Analysis of Supply Chains for Supporting Resilience

Bahareh Zohoori

Delft University of Technology

Model-based Risk Analysis of Supply Chains for Supporting Resilience

Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology
by the authority of the Rector Magnificus, Prof.dr.ir. T.H.J.J. van der Hagen,
chair of the Board for Doctorates
to be defended publicly on
Thursday 3 October 2024 at 10:00 o'clock

by

Bahareh ZOHOORI
Master of Engineering in Industrial Engineering,
Universiti Teknologi Malaysia (UTM), Malaysia
born in Shiraz, Iran

This dissertation has been approved by the promotors.

Composition of the doctoral committee:

Rector Magnificus	chairperson
Prof.dr.ir. A. Verbraeck	Delft University of Technology, promotor
Prof.dr.ir. J. H. Kwakkel	Delft University of Technology, promotor

Independent members:

Prof.dr. A.G. de Kok	Eindhoven University of Technology
Prof.dr. B. Behdani	University of South-Eastern Norway
Prof.dr. R.A. Zuidwijk	Erasmus University Rotterdam
Prof.dr. M.E. Warnier	Delft University of Technology
Prof.dr. M. Comes	Delft University of Technology

This work is part of the research programme Complexity in high-tech manufacturing with project number 439.16.121, which is financed by the Dutch Research Council (NWO).

TRAIL Thesis Series No. T2024/7, the Netherlands Research School TRAIL
TRAIL
P.O. Box 5017
2600 GA Delft
The Netherlands
E-mail: info@rsTRAIL.nl

ISBN: 978-90-5584-346-6

Printed in the Netherlands

To my parents

To Masoud

To Radmehr

Preface

Learning enjoyment is a great motivation for me to go forward in my life. That's why I decided to continue pursuing my studies and start my PhD journey after several years of working as an industrial engineer. I still remember my excitement when I was officially registered as a PhD candidate at TU Delft graduate school. At that moment, I didn't know that PhD is not only a journey of successful and positive experiences but also a long journey full of challenges and difficulties.

Surviving in the PhD journey is not possible without great support networks. I am very thankful to have two of the nicest people as my promotors. Alexander and Jan, Thank you! Only your guidance and support made this research possible. Alexander - the first days of working with you, I realized that I had found my dream supervisor. Your kind support and professional mentorship helped me to overcome several research and personal challenges that I had during my PhD journey. You raised my research confidence by always being open and patient about any relevant and irrelevant research ideas that I had. Your scientific knowledge together with your comprehensive view of the supply chain in practice, helped me to overcome the lack of finding a real-world case for implementing my research. No matter how busy you were, you were always there for me. You were more than a supervisor to me. You were a friend during these years. Jan - it was my honor to be a student of a research scholar like you. During the first months of having you as my supervisor, I tried to find a common research language when talking with you because I was an industrial engineer and you were the DMDU guy. I still remember the first meeting with you as my supervisor when I told you I was afraid of you because I don't know you, and you laughed and said, "ok, what do you want to know?". Everything I learned from you made me a better researcher. You gave me the gift of *decision making under deep uncertainty* that I'm always thankful for.

I am also thankful for the colleagues and friends I had at the policy analysis group that made working at TPM joyful. I will always miss the lunch times we had together at TPM cafeteria. I

learned so many things about Netherlands and Dutch people there. Anique and Maria, you two gamers were great officemates. We could have much more fun being officemates if Covid had never happened. Bramka, thank you for always helping me in answering my questions about exploratory modeling. Also, I am grateful to the secretaries of policy analysis group and TRAIL research school, Monique, Marlise, Vera, Conchita and Esther for their constant help and support.

I thank the NWO for funding my research. I appreciate the support of my colleagues in our project consortium Ton de Kok, Willem van Jaarsveld, Mirjam Meijer, Dennis Schol, Bert Zwart and Maria Vlasiou. It was a great opportunity for me to attend the meetings held by European supply chain forum (eSCF) in Eindhoven and be involved in the discussion of supply chain decision makers of top High-Tech companies in Europe. Those discussions inspired me in developing my simulation model.

I would also like to thank my Iranian friends who made living in the Netherlands joyful for me. Najmeh, Haniyeh, Hemila, Fatetemeh, and Reihaneh, we spent almost all the weekends together with our families. Our friendship will last forever. Khale Simin and Batul, you were like family to me in the Netherlands. You were taking care of me when Radmehr was born during Covid. Thanks for everything.

Finally, I would like to thank my beloved family. Mom and Dad, without you, I would not be where I am today. Imagining your proud face for having a successful daughter made me try harder and never give up. My Parents-in-law, thank you for understanding me during these years. I was busy studying from the first moment we met. My lovely Radmehr, you have been my inspiration for the past three years. I am sorry for the times that I was not around because I had to do research. Dear Azra, thank you for taking care of Radmehr when I was not around. Finally, my dear Masoud, I would not have been able to complete the PhD without your utmost care all these years. We have faced many challenges during the past few years but have overcome them and successfully completed both of our PhDs. You were always by my side, and I cannot express enough gratitude for your wonderful and heartfelt support. Thank you for your encouragement and love throughout the years.

Bahareh Zohoori
Abu Dhabi, May 2024

Content

1 Introduction

1.1 Background

A Supply chain (SC), or logistic network, is a network of connected and interdependent actors involved in different activities to fulfill customer demand. A typical supply chain might include suppliers of raw materials or components, manufacturers, distributors, retailers, and customers, all linked to each other by upstream and downstream flows of products, services, funds, and information (Chopra & Meindl, 2015; Christopher, 2011; Mentzer, Keebler, Nix, Smith, & Zacharia, 2001; Simchi-Levi, Kaminsky, & Simchi-Levi, 1999). Supply chain management (SCM) involves integrating actors and coordinating material, information, and financial flows to improve the competitiveness of the whole supply chain (Stadtler, Kilger, & Meyr, 2002). While the expansion and complexity of modern supply chains have driven several advances in supply chain management in recent decades, they have also introduced risks and made supply chains more vulnerable to disruptions. Critical advances in supply chains and their associated risks can be summarized as follows:

Just-in-time: The concept of Just-in-time (JIT) was introduced first by Toyota to have competitive advantages through waste elimination, inventory reduction, and efficiency improvement. In a JIT strategy, the materials and products will be available only when they are needed. This results in a minimum inventory level, consequently increasing the supply chain's vulnerability to unexpected events. Thus inventory reduction strategies, such as JIT, would be efficient only if they are established with an acceptable level of resilience to disruption (Cedillo-Campos, 2014; Jiang, Rigobon, & Rigobon, 2022; Ye, Suleiman, & Huo, 2022).

Reduction of suppliers: There has been a growing trend of reducing the number of suppliers during recent decades because of advantages such as reduction of transaction and administrative costs, benefits of economies of scale, making stronger relationships with suppliers, and developing or sharing technologies (Behdani, 2013; Choi & Krause, 2006). Despite several benefits that supplier reduction strategy brings to an industry, it might also result in more severe supply chain disruptions due to the failure of a supplier that is the only source of supply for a particular component (Cajal-Grossi, Del Prete, & Macchiavello, 2023; Remko, 2020).

Outsourcing: Outsourcing is defined as the strategy of receiving semi-finished or finished products or services from outside of the company, such as third-party specialists, instead of producing these products or delivering these services internally (Dolgui & Proth, 2013). A company might outsource functions such as distribution, manufacturing, accounting, and information systems (Christopher, 2011). The main reason behind an outsourcing strategy is to focus on business core competencies. The core competency refers to activities or skills through which the company achieves long-term competitive advantages in the market (Tompkins, Simonson, Tompkins, & Upchurch, 2005). The risks associated with outsourcing include loss of control due to the expansion of network boundaries as well as increasing the complexity of the supply network in terms of increasing links and nodes, which bring their own risk of failures (Kazancoglu et al., 2023; Pellicelli, 2023).

Centralized distribution: Flows of products are better facilitated within geographical boundaries (e.g., the European Union) due to the lack of trade barriers and tariff reductions. Therefore, companies are tempted to centralize their production and distribution facilities. Besides that, to take advantage of economies of scale, companies shift toward producing a large volume of few products in a particular plant instead of a full variety of products. The centralized facility strategies increase the disruption risks as a result of long-distance transportation as well as lack of flexibility and redundancy (Christopher, 2011; Parast & Oke, 2022; Rezapour, Farahani, Dullaert, & De Borger, 2014).

Globalization: Globalization of a supply chain is the act of offshoring activities related to sourcing, manufacturing, and assembly (Stecke & Kumar, 2009). The motivation for a supply chain to use offshoring can be access to domestically unavailable or cheaper resources, technical expertise, and access to new markets (Behdani, 2013). As the globalization strategy expands to new geographical regions, it brings a variety of risks: long lead times, heavy reliance on transportation, exchange rate fluctuations, and natural, criminal, and political risks (Shih, 2020).

While supply chain advances offer competitive advantages to the organizations involved, they also increase the vulnerability of supply chains to disruptions. Christopher and Peck (2004) define supply chain vulnerability as "an exposure to serious disturbance, arising from risks within the supply chain as well as risks external to the supply chain". Numerous examples in the literature that show unexpected adverse events provide evidence of high uncertainty and turbulence in today's business environment. In a recent example, several US and European manufacturers and retailers suffered from disruptions due to the pandemic, which suspended operations in China and resulted in supply shortages (Li, Chen, Collignon, & Ivanov, 2021). In another example, Ford was forced to close five of its production plants for several days due to the limited air traffic after the 9-11 terrorism attack. Also, because of the bankruptcy of one of Land Rover's key suppliers, the company laid off almost 1400 of its workers in 2001 (Tang, 2006). Other examples exist related to the earthquakes in China in 2008, the tsunami in Japan in 2011, earthquakes in Chile in 2011 and

2015, Typhoon Haiyan in the Philippines in 2013, and the most recent Covid-19 crises (Fahimnia, Tang, Davarzani, & Sarkis, 2015; Jabbarzadeh, Fahimnia, Sheu, & Moghadam, 2016; Klibi, Martel, & Guitouni, 2010; Rinaldi, Murino, Gebennini, Morea, & Bottani, 2022).

To be competitive in today's turbulent marketplace, besides concentrating on primary objectives such as cost minimization or service maximization, supply chains need to develop disruption management strategies to decrease both short-term and long-term negative impacts of disruptions on business performance. One of the ways industries can approach inevitable disruptions is by becoming resilient (Christopher, 2011; Jabbarzadeh et al., 2016).

Supply chain resilience is an emerging topic in supply chain risk management. Since resilience is a multi-dimensional and multi-disciplinary concept, no well-established and widely accepted definition exists. Ponomarov and Holcomb (2009) try to develop a comprehensive and integrated definition of supply chain resilience by reviewing the concept of resilience from various perspectives, including social, ecological, organizational, psychological, and economic disciplines. Based on their definition, resilience is "the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function." This definition of supply chain resilience comprises three dimensions: readiness, response, and recovery. Hohenstein et al. (2015) provide a complementary definition by defining supply chain resilience as "the ability to be prepared for unexpected risk events, responding and recovering quickly to potential disruptions to return to the original situation or grow by moving to a new, more desirable state to increase customer service, market share, and financial performance." Compared to Ponomarov and Holcomb (2009), Hohenstein et al. (2015) add 'growth,' achieving a new and improved position after recovery. The authors believe that while readiness is associated with proactive disruption management, response, recovery, and growth focus on how a disruption is handled after it has occurred.

This research applies the term "supply chain resilience" to refer to the ability of supply chains to manage disruption proactively and reactively in an efficient manner. Given this, the term "supply chain disruption management" is used interchangeably in this thesis with the term supply chain resilience. Also, the term supply chain stress-testing is used interchangeably in this thesis with the term supply chain vulnerability analysis.

Various supply chain resilience frameworks have been put forward in which principles of a resilient supply chain and drivers for achieving resilience are identified qualitatively (Blackhurst, Dunn, & Craighead, 2011; Christopher & Peck, 2004; Ponomarov & Holcomb, 2009). Also, various quantitative methods have been developed to address different aspects of supply chain resilience. These methods propose models for assessing the vulnerability of a supply chain to disruptive risk as well as evaluating mitigation and recovery policies against disruption to improve resilience (Fahimnia, Tang, Davarzani, & Sarkis, 2015; Hosseini, Ivanov, & Dolgui, 2019; Pires Ribeiro & Barbosa-Povoa, 2018).

The first step in improving supply chain resilience or, in general, supply chain risk management is to identify risks and assess them. The approaches toward assessing risk mainly depend on the availability of information about disruptive risks. These approaches assume that the probability of occurrence of a disruptive risk and its magnitude are known or can be estimated. Although probability-based approaches toward risk modeling work acceptably for typical supply chain disturbances or operational risks, they are misleading for dealing with less frequent or unknown disruptions (Heckmann, Comes, & Nickel, 2015). The main reason is that information related to rare events can hardly be obtained, and even if the information becomes available, it may not be a reliable representation of the future due to the unpredictability of these kinds of risks. Also, probability-based approaches typically give the same weight to both high frequency-low impact events and low frequency-high impact events, resulting in underestimation of the losses due to the aggregation over time horizons. Moreover, the managers ignore the disruptive risks because they believe that the probability of their occurrence is very low, so it can be neglected.

Model-based approaches for supporting supply chain resilience must be capable of assessing the vulnerability of a supply chain despite unknown or incomplete information about risk, considering the unpredictable nature of disruptive risks. In this thesis, we suggest a consequence-based approach toward risk analysis of the supply chain. Instead of focusing on identifying the root causes of risks and determining their characteristics, such as probability of occurrence and intensity, one concentrates on analyzing the negative impact of disruptions on supply chain performance. For example, no matter whether a strike or congestion in a port disturbs a water transportation activity within the supply chain, the focus is on answering the question of what will happen if that transport activity is disrupted. Similarly, the focus is not on understanding whether a flood, bankruptcy, or cyber-attack stops a supplier's functionality within the supply chain; this research tries to answer what would happen if that supplier stopped working. However, a big challenge for consequence-based risk analysis of a supply chain is that, considering the complexity of a supply chain that consists of thousands of interdependent and globally distributed actors, generating a comprehensive set of possible disruptive events is hard. Also, developing effective disruption management strategies under many possible disruption scenarios is another challenge that is important for improving resilience.

The way in which a disruptive event propagates through a supply chain network depends on the structure of the supply chain. Therefore, the vulnerability of a supply chain is directly related to its structure. Considering the structure of the supply chain network in resilience practices and analyzing supply chain disruption at the network level is crucial. To compare the resilience of different supply chain network structures, researchers frequently adopt a graph theoretical perspective and focus on the topology of the supply chain. From this perspective, different network structures imply different configurations of nodes (facilities) and links (transport links). Supply chain resilience can be assessed by exposing nodes and links to disruptions. However, conceptualizing different supply chain networks based only on different configurations of nodes and links disregards key operational characteristics that may affect supply chain functioning and, thus, resilience. This research investigates the strength of several supply chain structures, which differ in several operational characteristics, including product structure, sourcing strategy, and production strategy. Although these functional characteristics play an essential role in research on supply chain design, research on the impact of these three operational characteristics on the resilience of different supply chain structures remained uninvestigated.

A successful supply chain resilience practice depends on reliable stress-testing of the supply chain. Reliable stress-testing of a supply chain depends on the availability of information about the supply chain structure where relations among different supply chain actors are clear. However, the complexity and globalization of today's supply chains make it difficult for decision makers to access data and information, especially from actors more than a few tiers upstream or downstream. Also, as a dynamic system, a supply chain changes structure and configuration over time. Here, there is a need for an approach to stress-test a supply chain to improve its resilience that can deal with a lack of information about the structure of the supply chain.

1.2 Research question

With the aim of supporting the resilience of a supply chain in a complex, unpredictable, and turbulent business environment, the following research question is defined as the main question to be addressed in this research:

What is an adequate approach for model-based risk analysis of a supply chain to support its resilience?

To answer the above question, three sub-questions are formulated as follows:

1. ***How can consequence-based risk analysis overcome the challenges of conventional risk analysis approaches for improving supply chain resilience?*** This research question investigates how consequence-based risk analysis can treat the challenges of the unpredictability of disruptive risks, the complexity of a supply chain, and the robustness of disruption management strategies in model-based approaches for supporting supply chain resilience. To this end, we treat supply chain disruption management as a problem of decision making under deep uncertainty (DMDU) to benefit from approaches developed in this domain, specifically robust decision making.
2. ***What operational aspects affect the resilience of a supply chain structure?***
   This research question aims at incorporating operational aspects of a supply chain in structural vulnerability analysis of the supply chain. To this end, various supply chain network structures, which differ in three operational aspects, including product structure, sourcing strategy, and production strategy, are stress-tested and compared to find key operational characteristics that affect the resilience of a supply chain structure.
3. ***How to do model-based stress testing of a supply chain despite a lack of precise information about the supply chain structure?***
   This research question aims at addressing uncertainties related to supply chain structure in resilience practices. To this end, we adopt an ensemble modeling approach, which implies that instead of relying on one single supply chain structure, one can generate multiple structures for a supply chain using stochastic parameters and draw conclusions from a range of possible outcomes.

1.3 Research approach

Literature review: To conduct our research, we start with a review of current model-based approaches for supporting supply chain resilience to reflect on the limitations of the existing literature. The results from the literature review highlight the need for the consequence-based risk analysis approach, which is the underpinning approach in conducting risk analysis in this research. This approach addresses the challenges of the unavailability of risk information in resilience practices, which is the case in the problems associated with all three sub-questions of this research. See Chapter 2 for the details of the literature review.

Simulation modeling: To measure the impact of potential disruptions on supply chain performance and to evaluate resilience strategies, we model the behavior of supply chains using simulation. Several researchers highlight that in situations where supply chains consist of a complex network of actors and activities and in situations where multiple resilience strategies are to be evaluated, simulation is the most promising approach due to its flexibility for exploring a variety of what-if scenarios (Schmitt & Singh, 2009). Among several simulation formalisms, we adopt discrete event simulation (DES), a widely used and promising approach for simulating supply chains (Oliveira, Lima, & Montevechi, 2016). A DES model consists of entities interacting in a process-based system environment where entities queue for services or compete for resources (Brailsford, 2013). In a DES model, the behavior of a system is described as a sequence of events where the state of the system changes when an event occurs at a particular instant in time (Robinson, 2004). The supply chain simulation model developed in this research is used to conduct experiments to address all three sub-questions in this thesis. The details of the simulation model are given in Chapter 3.

Exploratory modeling: To answer the research questions of this research, several experiments are designed. To perform and analyze the experiments, we adopt the exploratory modeling approach. Exploratory modeling is a model-based methodology that uses computational experiments to analyze complex and uncertain systems (Bankes, 1993; Kwakkel & Pruyt, 2013). Exploratory modeling involves exploring a comprehensive set of scenarios that cover uncertainties about input variables and models for various outcomes of interest and possible solutions (Kwakkel, Walker, & Marchau, 2010) to get insights into systematic system behavior patterns across the scenarios. The approach has been successfully applied in different contexts ranging from transportation management to climate adaptation (Halim, Kwakkel, & Tavasszy, 2016). Exploratory modeling is applied to address all three sub-questions in this thesis.

1.4 Outline of the thesis

Figure 1 shows an overview of the thesis. In Chapter 2, we elaborate on the need to shift from cause-based risk analysis to consequence-based risk analysis of a supply chain, with supporting arguments from the literature review. The concept of consequence-based risk analysis underpins the approaches for addressing the research questions of this thesis. In Chapter 3, we describe the simulation model developed for conducting the experiments related to this research. Chapter 4 addresses research question 1 by proposing an approach for designing resilient supply chains using consequence-based risk analysis and robust decision making. In Chapter 5, we address research question 2 by exploring the relation between supply chain resilience and network topologies with different operational aspects. In Chapter 6, we address research question 3 by proposing an approach for supporting supply chain ensemble modeling as a model-based decision-support tool toward supply chain resilience. The last chapter closes the thesis with conclusions and recommendations for research and practice.

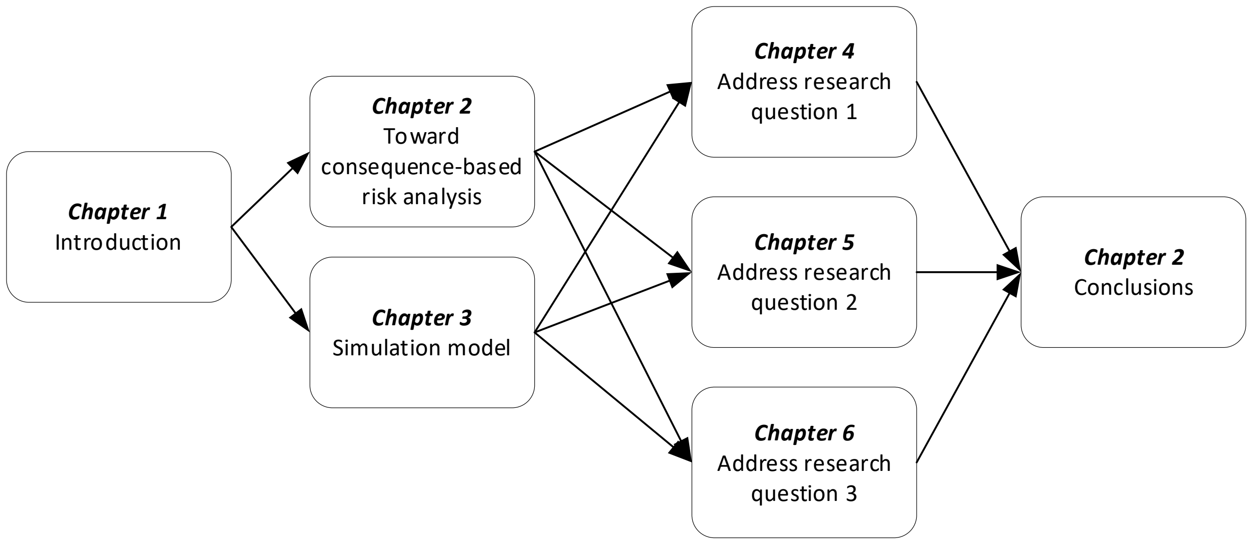


Figure 1. Overview of the thesis.

References

Bankes, S. (1993). Exploratory Modeling for Policy Analysis. *Operations Research*, *41*(3), 435–449. https://doi.org/10.1287/opre.41.3.435

Behdani, B. (2013). *Handling Disruptions in Supply Chains: An Integrated Framework and an Agent-based Model (PhD thesis)*. Delft University of Technology.

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An Empirically Derived Framework of Global Supply Resiliency. *Journal of Business Logistics*, *32*(4), 374–391.

Brailsford, S. (2013). Discrete-event simulation is alive and kicking ! *Journal of Simulation*, *8*(1), 1–8. https://doi.org/10.1057/jos.2013.13

Cajal-Grossi, J., Del Prete, D., & Macchiavello, R. (2023). Supply chain disruptions and sourcing strategies. *International Journal of Industrial Organization*, *90*(July), 103004. https://doi.org/10.1016/j.ijindorg.2023.103004

Cedillo-Campos, M. G. (2014). Supply chain clustering : The next logistics frontier ? In *International Congress on Logistics & Supply Chain*.

Choi, T. Y., & Krause, D. R. (2006). The supply base and its complexity: Implications for transaction costs, risks, responsiveness, and innovation. *Journal of Operations Management*, *24*(5), 637–652. https://doi.org/10.1016/j.jom.2005.07.002

Chopra, S., & Meindl, P. (2015). *Supply Chain Management: Strategy, Planning, and Operation*. *Supply Chain Management: Strategy, Planning, and Operation* (Sixth). Pearson.

Christopher, M. (2011). *Logistics & Supply Chain Management* (Fourth). Edinburgh Gate: Pearson Education Limited. https://doi.org/10.1007/s12146-007-0019-8

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *International Journal of*

Logistics Management, *15*(2), 1–13. https://doi.org/10.1080/13675560600717763

Dolgui, A., & Proth, J. M. (2013). Outsourcing: Definitions and analysis. *International Journal of Production Research*, *51*(23–24), 6769–6777. https://doi.org/10.1080/00207543.2013.855338

Fahimnia, B., Tang, C. S., Davarzani, H., & Sarkis, J. (2015a). Quantitative models for managing supply chain risks: A review. *European Journal of Operational Research*, *247*(1), 1–15. https://doi.org/10.1016/j.ejor.2015.04.034

Halim, R. A., Kwakkel, J. H., & Tavasszy, L. A. (2016). A scenario discovery study of the impact of uncertainties in the global container transport system on European ports. *Futures*, *81*, 148–160. https://doi.org/10.1016/j.futures.2015.09.004

Heckmann, I., Comes, T., & Nickel, S. (2015). A critical review on supply chain risk - Definition, measure and modeling. *Omega (United Kingdom)*, *52*, 119–132. https://doi.org/10.1016/j.omega.2014.10.004

Hohenstein, N.-O., Edda, F., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience: a systematic review and paths for further investigation. *International Journal of Physical Distribution & Logistics Management*.

Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, *125*(December 2018), 285–307. https://doi.org/10.1016/j.tre.2019.03.001

Jabbarzadeh, A., Fahimnia, B., Sheu, J. B., & Moghadam, H. S. (2016). Designing a supply chain resilient to major disruptions and supply/demand interruptions. *Transportation Research Part B: Methodological*, *94*, 121–149. https://doi.org/10.1016/j.trb.2016.09.004

Jiang, B., Rigobon, D., & Rigobon, R. (2022). *From Just-in-Time, to Just-in-Case, to Just-in-Worst-Case: Simple Models of a Global Supply Chain under Uncertain Aggregate Shocks*. *IMF Economic Review* (Vol. 70). Palgrave Macmillan UK. https://doi.org/10.1057/s41308-021-00148-2

Kazancoglu, Y., Lafci, C., Berberoglu, Y., Upadhyay, A., Rocha-Lona, L., & Kumar, V. (2023). The effects of globalization on supply chain resilience: outsourcing techniques as interventionism, protectionism, and regionalization strategies. *Operations Management Research*. https://doi.org/10.1007/s12063-023-00429-1

Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: A critical review. *European Journal of Operational Research*, *203*(2), 283–293. https://doi.org/10.1016/j.ejor.2009.06.011

Kwakkel, J. H., & Pruyt, E. (2013). Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. *Technological Forecasting and Social Change*, *80*(3), 419–431. https://doi.org/10.1016/j.techfore.2012.10.005

Kwakkel, J. H., Walker, W. E., & Marchau, V. A. W. J. (2010). Classifying and communicating uncertainties in model-based policy analysis. *International Journal of Technology, Policy and Management*, *10*(4), 299. https://doi.org/10.1504/IJTPM.2010.036918

Li, Y., Chen, K., Collignon, S., & Ivanov, D. (2021). Ripple effect in the supply chain network: Forward and backward disruption propagation, network health and firm vulnerability. *European Journal of Operational Research*, *291*(3), 1117–1131. https://doi.org/10.1016/j.ejor.2020.09.053

Mentzer, J. T., Keebler, J. S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining supply chain management. *Journal of Business Logistics*, *22*(2), 1–25.

Oliveira, J. B., Lima, R. S., & Montevechi, J. A. B. (2016). Perspectives and relationships in Supply Chain Simulation: A systematic literature review. *Simulation Modelling Practice and Theory*, *62*, 166–191. https://doi.org/10.1016/j.simpat.2016.02.001

Parast, M. M., & Oke, A. (2022). To focus or not: investigating the viability of the "focused factory" concept in firms facing service disruptions. *International Journal of Operations and Production Management*, *42*(5), 661–686. https://doi.org/10.1108/IJOPM-10-2021-0636

Pellicelli, M. (2023). Gaining Flexibility by Rethinking Offshore Outsourcing for Managing Complexity and Disruption †. *Engineering Proceedings*, *39*(1), 1–6. https://doi.org/10.3390/engproc2023039037

Pires Ribeiro, J., & Barbosa-Povoa, A. (2018). Supply Chain Resilience: Definitions and quantitative modelling approaches – A literature review. *Computers and Industrial Engineering*, *115*(May 2017), 109–122. https://doi.org/10.1016/j.cie.2017.11.006

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, *20*(1), 124–143. https://doi.org/10.1108/09574090910954873

Rezapour, S., Farahani, R. Z., Dullaert, W., & De Borger, B. (2014). Designing a new supply chain for competition against an existing supply chain. *Transportation Research Part E: Logistics and Transportation Review*, *67*, 124–140. https://doi.org/10.1016/j.tre.2014.04.005

Rinaldi, M., Murino, T., Gebennini, E., Morea, D., & Bottani, E. (2022). A literature review on quantitative models for supply chain risk management: Can they be applied to pandemic disruptions? *Computers and Industrial Engineering*, *170*(June), 108329. https://doi.org/10.1016/j.cie.2022.108329

Robinson, S. (2004). *Simulation : The Practice of Model Development and Use*. England: John Wiley& Sons Ltd.

Schmitt, A. J., & Singh, M. (2009). Quantifying supply chain disruption risk using Monte Carlo and discrete-event simulation. In *Winter Simulation Conference (WSC), Proceedings of the 2009* (pp. 1237–1248). https://doi.org/10.1109/WSC.2009.5429561

Shih, W. (2020). Is it time to rethink globalized supply chains? *MIT Sloan Management Review*, *61*(4).

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (1999). *Designing and managing the supply chain: Concepts, strategies, and cases* (First). New York: McGraw-Hill.

Stadtler, H., Kilger, C., & Meyr, H. (2002). *Supply Chain Management and Advanced Planning* (Fifth). Springer Texts in Business and Economics.

Stecke, K. E., & Kumar, S. (2009). Sources of supply chain disruptions, factors that breed vulnerability, and mitigating strategies. *Journal of Marketing Channels*, *16*(3), 193–226. https://doi.org/10.1080/10466690902932551

Tang, C. (2006). Robust strategies for mitigating supply chain disruptions. *International Journal of Logistics*, *9*(1), 33–45. https://doi.org/10.1080/13675560500405584

Tompkins, J. A., Simonson, S. W., Tompkins, B. W., & Upchurch, B. (2005). *Logistics and Manufacturing Outsourcing: Harness Your Core Competencies*. Tompkins press.

Van Hoek, R. (2020). Research opportunities for a more resilient post-COVID-19 supply chain – closing the gap between research findings and industry practice. *International Journal of Operations and Production Management*, *40*(4), 341–355. https://doi.org/10.1108/IJOPM-03-2020-0165

Ye, Y., Suleiman, M. A., & Huo, B. (2022). Impact of just-in-time (JIT) on supply chain disruption risk: the moderating role of supply chain centralization. *Industrial Management and Data Systems*, *122*(7), 1665–1685. https://doi.org/10.1108/IMDS-09-2021-0552

2 Toward consequence-based disruption management of the supply chain

In this chapter, we discuss the importance of moving from cause-based to consequence-based risk analysis in supply chains, supported by evidence from the literature review. The principle of consequence-based risk analysis forms the foundation for addressing three research questions explained in section 1.2.

2.1 Introduction to supply chain disruption and resilience

Supply chains today are more complex than ever before. Various trends such as globalization, outsourcing, lean manufacturing, single-sourcing strategy, and short product life cycles add to the complexity of today's supply chains (Diabat, Govindan, & Panicker, 2012; Finch, 2004; Prater, 2005; Rinaldi, Murino, Gebennini, Morea, & Bottani, 2022; Tukamuhabwa, Stevenson, Busby, & Zorzini, 2015)J. Blackhurst, Craighead, Elkins, & Handfield, 2005; M.s Christopher, Mena, Khan, & Yurt, 2011; Kamalahmadi & Parast, 2016; Stecke & Kumar, 2009; C. S. Tang, 2006; Wagner & Bode, 2006; Zhao, Kumar, Harrison, & Yen, 2011; Zhao et al., 2011). Although supply chain advances bring competitive advantages to the involved organizations, they also make supply chains more vulnerable to disruptions. The complexity of a supply chain can lead to significant disruptions in its performance when an unexpected adverse event, natural or man-made, happens.

The vulnerabilities of complex supply chains can be explained in relation to the concept of embedded supply chains which implies that a supply chain is highly interconnected with broader economic, social, environmental, and technological systems instead of operating independently (Carter & Rogers, 2008). From this perspective, vulnerabilities are potential risks that can disturb the supply chain operations due to the involvement of the supply chain in various external systems, such as economic, social, and environmental systems. The supply chain vulnerabilities in relation to the complexities of an embedded supply chain can be explained as follows:

- Economic factors: embedded supply chains are influenced by trends and fluctuations in the global economy, such as changes in trade policies, tariffs, and exchange rates or downturns of the economy, which result in demand and supply fluctuations (Escaith, Lindenberg, & Miroudot, 2010).
- Social factors: social factors, such as labor practices and ethical standards can contribute to vulnerabilities of an embedded supply chain. For example, social unrest, poor working conditions, or violations of ethical norms can lead to operational disruptions (Ding et al., 2023).
- Environmental factors: climate change, natural disasters, and sustainability regulations, have a significant influence on embedded supply chains. For example, extreme weather can damage infrastructure, delay shipments, or increase costs, making the supply chain more fragile (Seuring & Müller, 2008).
- Geopolitical factors: Political instability, trade wars, and changes in government policies can disrupt operations, alter trade routes, and impose new regulatory requirements. These geopolitical factors can lead to sudden and unpredictable disruptions (Bednarski et al., 2024).
- Technological factors: As supply chains become more digitized, they also become more vulnerable to cybersecurity threats and technological failures (Ho et al., 2022).

There are several examples of supply chain disruption over the last decades. One example is the 2011 tsunami in Japan, which disrupted Japanese suppliers of Toyota, General Motors, and silicon wafer industries (Hosseini, Ivanov, & Dolgui, 2019; Tordecilla, Juan, Montoya-Torres, Quintero-Araujo, & Panadero, 2021). In another example, Ford’s supply chain was disrupted after the September 11, 2001, terrorist attacks because of the shutting down of US air transport (Sheffi & Rice Jr., 2005). A recent example is the COVID-19 pandemic, which resulted in the suspension of many operations globally from and to China. (Aldrighetti, Battini, Ivanov, & Zennaro, 2021). Other examples of supply chain disruptions are Hurricane Mitch and the Taiwan earthquake in 1999, explosions at a container warehouse of toxic chemicals at the Port of Tianjin, China in 2015, and Hurricane Harvey in 2017 (Niels Bugert & Lasch, 2018).

In the supply chain risk management literature, researchers distinguish between disruption risks and operational risks. While disruption risk refers to a low-probability but high-impact type of risk, such as natural disasters, operational risk is associated with a high-probability but low-impact kind of risk, such as uncertainty in demand, supply, and capacity (Bier, Lange, & Glock, 2020; Dolgui, Ivanov, & Rozhkov, 2020). Although disruptive risks occur less frequently than operational risks, they can quickly spread and propagate through the entire supply chain network. This phenomenon is called the ripple effect (Dmitry Ivanov & Dolgui, 2019; Dmitry Ivanov, Sokolov, & Dolgui, 2014; Liberatore, Scaparra, & Daskin, 2012). The ripple effect of disruptive risks has significant negative impacts on supply chain performance, including increasing cost and loss of profit, delay in delivery, loss of market share, and reputation (Aldrighetti et al., 2021; Bier et al., 2020; J. Blackhurst et al., 2005; Hendricks & Singhal, 2003; D Ivanov, Tsipoulanidis, & Schönberger, 2017; Vanany, Zailani, & Pujawan, 2009; Yildiz, Yoon, Talluri, & Ho, 2016).

Studies show that despite the concerns about the increase of supply chain disruptive risks and their negative consequences (Chopra & Sodhi, 2004; Fahimnia, Tang, Davarzani, & Sarkis, 2015; Sheffi

& Rice Jr., 2005; Sodhi & Christopher, 2012), only few companies consider disruption management actively, and most of the companies do apparently not believe in disruption management practices, and only react to disruption once it happens (Kamalahmadi & Parast, 2016; Sáenz & Revilla, 2014). Fiksel et al. (2015) relate the belief of the ineffectiveness of disruption management practices to the fact that conventional risk management practices rely on the availability of statistical information about risk; however, disruptive risks are unpredictable, so there may be no reliable information about them to use for developing effective disruption management strategies. However, having a disruption management strategy can bring competitive advantages to a supply chain and even improve its market share and reputation (Golan, Jernegan, & Linkov, 2020; Kwak, Seo, & Mason, 2018). Nokia and Ericsson's disruption case of 2000 is a good example of the importance of a disruption management strategy for companies. Fire at a semiconductor plant of a supplier of both Nokia and Ericsson resulted in the damage of millions of microchips. Nokia was able to handle the situation by changing the design of its chips and making use of backup suppliers. The company even made a profit from the disruption. Ericsson, however, took no action by waiting for the supplier to recover from the disruption and, therefore, lost a considerable amount of money from the situation (Niels Bugert & Lasch, 2018; Lee, 2004; Tang, 2006).

To manage disruptive risk, supply chains must become resilient (Sheffi, 2005). Resilience is defined as the capability of the supply chain to resist disruptions and quickly return to normal or to a better status (Jennifer Blackhurst, Dunn, & Craighead, 2011; Hosseini & Ivanov, 2019; Pettit, Croxton, & Fiksel, 2019; Tukamuhabwa et al., 2015). To achieve resilience, supply chains can use proactive and/or reactive strategies (Aldrighetti et al., 2021; Tomlin, 2006). The proactive resilience strategies are concerned with increasing resistance and robustness against disruption (Klibi, Martel, & Guitouni, 2010; Lin & Wang, 2011). Examples of proactive resilience strategies are redundancy practices that take action before disruption, such as buffer capacities, backup suppliers, and contingency inventory for mitigating risk (Dmitry Ivanov & Dolgui, 2019). In contrast, reactive resilience strategies aim to modify supply chain processes and structures in response to disruptions. (Knemeyer, Zinn, & Eroglu, 2009; Paul, Sarker, & Essam, 2014). Reactive strategies are mainly achieved through flexibility and adaptation (Dolgui, Ivanov, & Sokolov, 2020; Y. Li, Chen, Collignon, & Ivanov, 2021).

The resilience of a supply chain is closely related to its vulnerability. Carvalho et al. (2012) define vulnerability as the incapacity of a supply chain network to react to disruption. Therefore, reducing the vulnerability of a supply chain directly increases its resilience. Vulnerability assessment of a supply chain is the basis of the resilience practices. Sheffi and Rice (2005) argue that vulnerability assessment tries to answer questions like “what can go wrong? What is the likelihood of that happening? What are the consequences if it does happen?”.

Supply chain resilience has recently gained extensive attention among both researchers and practitioners. The supply chain resilience literature can be classified into two categories: qualitative-based studies and quantitative-based studies. The first category focuses on identifying principles of a resilient supply chain as well as drivers for achieving resilience from a qualitative point of view. An example of research in this category is Christopher & Peck (2004), the most cited paper in this category, which defines the principles of a resilient supply chain as supply chain reengineering, agility, collaboration, and supply chain risk management culture. Several other qualitative supply chain resilience frameworks have been put forward (Jennifer Blackhurst et al., 2011; W. Christopher, Johnny, & Robert, 2007; Pettit, Fiksel, & Croxton, 2010; Ponomarov &

Holcomb, 2009; Wieland & Marcus Wallenburg, 2013). Hohenstein et al. (2015) provide a synthesis of supply chain resilience frameworks in terms of proactive (pre-disruption) and reactive (post-disruption) strategies. Kamalahmadi and Parast (2016) provide a literature review on definitions of supply chain resilience, principles, and strategies.

The second category focuses on developing quantitative methods to address different aspects of supply chain resilience. The studies in this category deal with proposing decision support models for assessing the vulnerability of a supply chain to disruptive risk as well as evaluating mitigation and recovery policies against disruption for improving resilience. An example is Datta et al. (2007) who try to improve the resilience of a multi-product, multi-national supply chain by developing an agent-based model of a supply chain to investigate the effect of various strategies for promoting resilience, including decentralized informational structure, flexible decision rules, regular monitoring of key performance indicators, and information sharing with other supply chain partners. The authors find that flexibility in all the elements of the supply network, demand-led adaptive production planning, and sequencing and distributing materials based on a combination of push and pull strategies are the key strategies to improve resilience.

Researchers use various methods to address the problem of supply chain resilience quantitatively. Hosseini et al. (2019) divide these methods into five categories including mathematical and optimization modeling, structural equations modeling, Bayesian networks, simulation techniques, and multi-criteria decision making. The authors also identify five main categories of solution techniques for solving model-based approaches toward supply chain resilience, including exact methods for solving optimization models, exact solver commercial software such as GAMS, CPLEX, Lingo, meta-heuristic algorithms, Multi-criteria decision making such as AHP, ANP, and VIKOR, and Fuzzy logic and grey set theory. In another classification, Bier et al. (2020) identify two categories of risk modeling methods in quantitative-based approaches toward supply chain disruption management: Direct methods and proxy methods. The direct methods assess the impact of risk by analyzing the probability distribution of disruptive events through the supply chain network. In this category, several scholars adapt approaches from the risk management discipline, including Value-at-Risk analysis (Madadi, Kurz, Taaffe, Sharp, & Mason, 2014; Mizgier, 2017; Mizgier, Wagner, & Jüttner, 2015), the Z-score analysis (Basole & Bellamy, 2014; Basole, Bellamy, Park, & Putrevu, 2016), the ANOVA method (Kauppi, Longoni, Caniato, & Kuula, 2016) and the HAZOP method (Adhitya, Srinivasan, & Karimi, 2009). Several scholars also adopt simulation-based approaches for risk modeling of a supply chain, including discrete event simulation (Reyes Levalle & Nof, 2015; Y. Wang & Xiao, 2016), Monte-Carlo simulations (Levitin, Gertsbakh, & Shpungin, 2013; R. Li, Dong, Jin, & Kang, 2017; Mizgier, 2017; Mizgier et al., 2015), Bayesian networks (Garvey, Carnovale, & Yeniyurt, 2015; Ojha, Ghadge, Tiwari, & Bititci, 2018), agent-based simulations (Basole & Bellamy, 2014; Priya Datta, Christopher, & Allen, 2007b; Reyes Levalle & Nof, 2015), dynamic simulations (Adhitya et al., 2009; Xiao, Cao, Sun, & Zhou, 2016), and Petri nets (J. W. Wang, Ip, Muddada, Huang, & Zhang, 2013). In the categorization of Bier et al. (2020), proxy methods are the methods that consider risk assessment and structural aspects of the supply chain. The authors highlight that the majority of the methods in this category rely on graph modeling of the supply chain network to benefit from metrics from graph theory and social network analysis, such as degree centrality, betweenness centrality, and closeness centrality (Yan, Choi, Kim, & Yang, 2015).

2.2 Approaches for modeling uncertainty associated with disruptive risk

Modeling uncertainty associated with disruptive risk is at the heart of quantitative-based approaches for supporting supply chain resilience. The central aspect of uncertainty modeling in most research domains, including supply chain disruption management, is the availability of information. However, this is difficult in complex systems where different types of uncertainty are present (Heckmann, Comes, & Nickel, 2015). In such systems, uncertainty modeling is a complex aspect of risk management practices. Scholars argue that decision processes are dependent on three conditions: certainty, risk, and uncertainty (Rosenhead, Elton, Gupta, & Rosenhead, 1972). In this definition, certainty refers to a situation where all decision-related parameters and variables are deterministic and known, and the relation between information as input and the decision as output is clear. Risk and uncertainty, on the other hand, refer to situations where there is a lack of decision-related information due to reasons such as a lack of time and resources to collect and process information or the complexity of the system under study. Heckmann et al. (2015) argue that decision-making under risk relies on probability distributions, which define the relation between input and output. However, decision making under uncertainty deals with a lack of information about the probability distribution of the model parameters. Heckmann et al. (2015) argue that supply chain risk management concerns decision-making under risk and under uncertainty depending on the availability of information and different uncertainty models used to describe each situation. Owen and Daskin (1998) categorize supply chain uncertainty modeling approaches into probabilistic-based approaches and scenario planning approaches. Probabilistic approaches consider the probability distribution of uncertain parameters. These approaches mainly rely on historical data to determine or estimate the probability of uncertain risk parameters. Examples of work in this category include Baghalian et al. (2013), Cui et al. (2010) and Fang et al. (2013). Aldrighetti et al. (2021) argue that, in the literature on supply chain resilience, the most used approach for defining disruption probability is the scenario approach. In such an approach, the stochastic parameters are modeled as a set of discrete scenarios with their associated probability of occurrence. For example, Klibi and Martel (2012) and Snoeck et al. (2019) model disruptions as meta-events with generic impacts which are called multi-hazards. In their approach, facilities have different incident profiles regarding impact and time to recovery. For mapping potential threats, the authors partition the geographic territory of the supply chain operations into a set of hazard zones, each with a corresponding exposure level. Finally, multihazard scenarios occur independently, and probability distributions are generated from the expert opinion, historical data, and the literature. This probability modeling formulation permitted a wide variety of expected disruption costs (EDC) to be included, such as damage costs, backlog costs, recovery/restoration costs, procurement cost penalties, and transportation cost penalties.

In another work, Salimi and Vahdani (2018) used a spatial statistic model to approximate supply chain failure probabilities. The authors create their model by averaging the probability of a disaster event (from historical data) and a spatial dependency. In another example, to design a resilient supply chain network Fattahi and Govindan (2018) and Fattahi et al. (2017) generate random scenarios of a disruption in storage capacity in each period by assuming a Bernoulli distribution for disruption probability. As the complexity of the problem under study increases, researchers apply more advanced probability formulation methods. Decision-tree and probabilistic graphical models are two techniques adopted by several scholars for probability formulation. An example is the work by Kamalahmadi and Parast (2017), who develop a scenario-based mathematical program where the authors use decision-tree analysis to determine the probability distribution of disruption scenarios dependent on supplier failures and regional disruptions. In another work, Hosseini et al. (2019) used a Bayesian network to calculate the probability of supplier disruption due to various random disruption risks such as earthquakes, floods, hurricanes, and labor strikes. Their analysis considers the dependency between the suppliers and the disruptive events.

The scenario planning approach refers to the method of modeling uncertainty by identifying a number of plausible future scenarios to determine efficient strategies under all scenarios (Owen & Daskin (1998). Several scholars have adopted scenario planning to address supply chain resilience. For example, Breuer et al. (2013) develop an agent-based simulation model to assess the impact of thirty scenarios of disruptive events on the sensitive logistic nodes of a supply chain. The authors attempt to build scenario-specific strategies to maintain the flow of goods after disruption. Simchi-Levi et al. (2015) developed a methodology for stress-testing critical supply chain entities to design strategic, tactical, and operational decisions. The authors use the risk-exposure index, time-to-recovery, and time-to-survive metrics for designing a robust supply chain. Thekdi and Santos (2016) introduce a performance metric for characterizing resilience, and by applying a scenario approach, they assess economic sensitivity to sudden-onset disruptions such as labor strikes, terrorist attacks, and hurricanes.

2.3 Limitations of the current disruption modeling approaches

Reviewing the literature highlights several concerns and gaps in common approaches for modeling uncertainty related to disruptive risks. This section elaborates on these gaps.

Many of the current approaches in the literature of disruption modeling assume that the probability of disruptive risks is known or can reliably be estimated. Although probability-based approaches toward risk modeling work acceptable for typical supply chain disturbances or operational risks, it would be misleading to use them for dealing with less frequent or unknown disruptions (Heckmann et al., 2015). Aldrighetti et al. (2021) argue that probability estimation of disruptive events might not be a reliable approach because data related to rare events can hardly be obtained, and even if the data becomes available, it may not be a reliable representative of the future. Disruptions happen unpredictably with various natures, frequency of occurrence, and intensity, so it is almost impossible to characterize them based on historical data (Dolgui, Ivanov, & Sokolov, 2018; He, Alavifard, Ivanov, & Jahani, 2019; Torabi, Baghersad, & Mansouri, 2015). Chan and Kroese (2011) argue that even minor errors in the probability estimation of disruption can impact the analysis result significantly. Besides concerns regarding probability estimation of disruptive risks, probability-based approaches normally give the same weight to both high frequency-low impact events and low frequency- high impact events, resulting in underestimation of the losses due to the aggregation over time horizons (Klibi et al., 2010). As a result, disruptive risks are ignored by managers because they believe that the probability of their occurrence is very low, so they can be neglected (Johnson & Nagarur, 2012). Another reason for neglecting low-frequency, high-impact events is that managers are often fully engaged with daily operational issues with short term impacts within their supply chains, which leads to a focus on high-frequency, low-impact events over the more significant but less frequent risks (Akkermans & Van Wassenhove, 2018).

Additionally, in supply chains, the focus is often on past risk events, and the importance of risk management is typically recognized only when a major disruption occurs (Urata & Pel, 2018).

There are also several limitations associated with scenario planning approaches toward disruption modeling. In most current scenario planning approaches, a specific limited set of disruptive scenarios is selected to represent future risks related to a supply chain. However, such a narrow view of the future is misleading since, in reality, the number of plausible future scenarios is infinite, and potential extreme events for which no information and experience exist should not be ignored (Golan et al., 2020; Klibi et al., 2010; Olivares-Aguila & Vital-Soto, 2021; Tordecilla et al., 2021). Gao et al. (2019) highlight that disruption scenarios with a higher degree of unknowns must be included in resilience practices. Another gap in scenario-based approaches relates to the fact that most of the studies treat risks independently of each other and ignore scenarios of risks that can affect several entities in the network at the same time, known as compound risk (Basole & Bellamy, 2014; Bier et al., 2020; N Bugert & Lasch, 2018; Klibi & Martel, 2012; Klibi et al., 2010; Zobel & Khansa, 2014). Considering only the impact of an individual disruption is misleading because the combination of unexpected events may have diverse and complicated effects that should be considered in designing a resilient system (Raymond et al., 2020). An example of compound risk is the tsunami earthquake in Japan, which disrupted manufacturers in the region and blacked out transportation links to Japan. A recent example is the COVID-19 pandemic, which affected many global supply chain entities (Golan et al., 2020).

The final gap relates to the fact that in most approaches, a single mathematical or simulation model of a supply chain is developed to model the impact of the selected disruptive scenarios on a few performance measures of interest. There are two concerns regarding this approach. First, in complex supply chains with many interdependent actors, there might be a lack of information to build a single reliable model for representing the supply chain under study. Second, there might be situations where different decision makers cannot decide or do not have any clear opinion about their outcomes of interest on which the impact of the disruptive risk should be assessed, and therefore, including one or two predefined supply chain performance metrics would be misleading.

2.4 Consequence-based risk analysis

The limitations of current supply chain disruption modeling approaches are primarily rooted in the unpredictable nature of disruptive risks, making an estimation of cause, frequency of occurrence, and magnitude of disruptive risks difficult. Thus, there is a need for methods to improve supply chain resilience despite the lack of data and information regarding disruptive events.

This research aims to contribute to the literature on supply chain disruption management in the presence of information ambiguity by proposing the consequence-based supply chain risk analysis concept. Our proposed approach focuses on the consequences of plausible disruptions at elements along the supply chain rather than on the root cause of the disruption. In contrast with conventional risk modeling approaches, which deal with identifying the root causes of a risk and determining its characteristics, such as its probability of occurrence and intensity, our approach concentrates on analyzing the consequence of potential risks associated with a supply chain regardless of the root cause. For example, no matter whether a strike or congestion in a port disturbs a water transportation activity within the supply chain, the focus is on answering the question of what will happen if that transport activity is disrupted. Similarly, the focus is not on understanding whether a flood, a bankruptcy, or a cyber-attack stops a supplier's functionality within the supply chain; instead, we try to answer what would happen if that supplier stopped working. The proposed approach overcomes the need to estimate the probability of a risk, which is challenging for disruptive risks. This approach results in effective disruption management because resilience strategies are developed regardless of whatever happens in the future. Our approach contributes to identifying vulnerable elements of the supply chain that are not detectable by human reasoning, such as suppliers higher upstream in the supply chain network.

Among the few papers that consider a consequence-based approach toward risk modeling, Simchi-Levi et al. (2015) develop a mathematical model of a supply chain to quantify the financial and operational impact of potential failures at each supplier facility regardless of the cause of failure. The authors argue that their approach identifies the critical but low-cost suppliers that managers overlook since they tend to focus typically on the suppliers with high expenditures. In another work, Ghavamifar et al. (2018) assess the impact of disruption scenarios such as disruptions at distribution centers, disruption in transportation links between the manufacturing plants and distribution centers, and between the resellers and distribution centers. The authors consider both partial and complete disruption scenarios.

Recent supply chain disruption cases due to surprise events such as epidemic outbreaks and geopolitical tensions shed light on the need for more research on consequence-based risk analysis because the approach could contribute to the proactive improvement of resilience independent of what might happen. A significant challenge in consequence-based risk analysis toward disruption management, specifically in complex supply chains, is the need to investigate a wide range of risk consequences associated with thousands of interdependent, dynamic, and globally distributed supply chain elements. In such a supply chain, some vulnerability sources might have remained uninvestigated due to the limited data availability, especially from actors more than a few tiers upstream or downstream. Also, reliable consequence-based risk analysis needs consideration of not only imaginable scenarios of risk consequences but also an exploration of not-yet-experienced and implausible scenarios for risk consequences. Here, consequence-based risk analysis needs to be conducted through a scenario structuring approach that ensures a systematic process for consideration of many scenarios of disruption, including unexpected events. Consequence-based risk analysis for improving a supply chain's resilience will be an efficient approach if it is conducted collaboratively to allow consideration of the views of different supply chain stakeholders on uncertainties and outcomes of interest. Rather than anticipating what will happen in the future, consequence-based risk analysis tries to increase awareness about supply chain vulnerabilities and the effectiveness of different disruption mitigation strategies by exploring potential failures and their consequences within the supply chain. Conducting a comprehensive and systematic exploration and communicating interpretable results with supply chain stakeholders is another challenge of consequence-based risk analysis. This research adopts the emerging decision support paradigm called decision making under deep uncertainty (DMDU) to address these challenges. This paradigm emerged in the context of climate change adaptation in response to limits to predictability. A foundational idea in this paradigm is to apply models for exploring rather than predicting the future, referred to as exploratory modeling. DMDU is concerned with dealing with decision problems that involve deep uncertainty and complexity, the two aspects of the issue of consequence-based risk analysis of a complex supply chain. Deep uncertainty refers to the situation where decision makers do not agree or do not know the explicit relations between the inputs and outputs of a system or its boundaries. Moreover, it reflects the situation where outcomes of interest, their importance to the system under study, and the probability distribution of the uncertain parameters are not clearly defined (Lempert, Popper, & Bankes, 2003). It also refers to situations where decisions are made in interaction with the system over time (Haasnoot, Kwakkel, Walker, & ter Maat, 2013). This research investigates the applicability of DMDU approaches in addressing supply chain resilience problems.

References

Adhitya, A., Srinivasan, R., & Karimi, I. A. (2009). Supply Chain Risk Identification Using a HAZOP-Based Approach. *AIChE Journal*, *59*(4), 215–228. https://doi.org/10.1002/aic

Aldrighetti, R., Battini, D., Ivanov, D., & 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*(March), 108103. https://doi.org/10.1016/j.ijpe.2021.108103

Akkermans, H., & Van Wassenhove, L. N. (2018). Supply chain tsunamis: research on low-probability, high-impact disruptions. *Journal of Supply Chain Management*, *54*(1), 64-76.

Baghalian, A., Rezapour, S., & 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. https://doi.org/10.1016/j.ejor.2012.12.017

Basole, R. C., & Bellamy, M. A. (2014). Visual analysis of supply network risks: Insights from the electronics industry. *Decision Support Systems*, *67*, 109–120. https://doi.org/10.1016/j.dss.2014.08.008

Basole, R. C., Bellamy, M. A., Park, H., & Putrevu, J. (2016). Computational Analysis and Visualization of Global Supply Network Risks. *IEEE Transactions on Industrial Informatics*, *12*(3), 1206–1213. https://doi.org/10.1109/TII.2016.2549268

Bednarski, L., Roscoe, S., Blome, C., & Schleper, M. C. (2024). Geopolitical disruptions in global supply chains: a state-of-the-art literature review. *Production Planning & Control*, 1-27.

Bier, T., Lange, A., & 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. https://doi.org/10.1080/00207543.2019.1687954

Blackhurst, J., Craighead, C. W., Elkins, D., & Handfield, R. B. (2005). An empirically derived agenda of critical research issues for managing supply-chain disruptions. *International Journal of Production Research*, *43*(19), 4067–4081. https://doi.org/10.1080/00207540500151549

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An Empirically Derived Framework of Global Supply Resiliency. *Journal of Business Logistics*, *32*(4), 374–391.

Breuer, C., Siestrup, G., Haasis, H.-D., & Wildebrand, H. (2013). Collaborative risk management in sensitive logistics nodes. *Team Performance Management: An International Journal*, *19*(7/8), 331–351. https://doi.org/10.1108/TPM-11-2012-0036

Bugert, N, & Lasch, R. (2018). Supply chain disruption models: A critical review. *Logistics*

Research, *11*(1), 1–35. https://doi.org/10.23773/2018_5

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: moving toward new theory. *International journal of physical distribution & logistics management*, *38*(5), 360-387.

Carvalho, H., Barroso, A. P., MacHado, V. H., Azevedo, S., & Cruz-Machado, V. (2012). Supply chain redesign for resilience using simulation. *Computers and Industrial Engineering*, *62*(1), 329–341. https://doi.org/10.1016/j.cie.2011.10.003

Chan, J. C. C., & Kroese, D. P. (2011). Rare-event probability estimation with conditional Monte Carlo. *Annals of Operations Research*, *189*(1), 43–61. https://doi.org/10.1007/s10479-009-0539-y

Chopra, S., & Sodhi, M. S. (2004). Managing risk to avoid supply-chain breakdown. *MIT Sloan Management Review*, *46*(46109), 53–61. https://doi.org/10.1108/IJOPM-10-2012-0449

Christopher, M., Mena, C., Khan, O., & Yurt, O. (2011). Approaches to managing global sourcing risk. *Supply Chain Management: An International Journal*, *16*(2), 67–81. https://doi.org/10.1108/13598541111115338

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *International Journal of Logistics Management*, *15*(2), 1–13. https://doi.org/10.1080/13675560600717763

Christopher, W., Johnny, M., & Robert, B. (2007). The Severity of Supply Chain Disruptions : Design Characteristics and Mitigation Capabiliti. *Decision Sciences*, *38(1)*(1), 131–156. https://doi.org/10.1111/j.1540-5915.2007.00151.x

Cui, T., Ouyang, Y., & Shen, Z. J. M. (2010). Reliable facility location design under the risk of disruptions. *Operations Research*, *58*(4 Part 1), 998–1011. https://doi.org/10.1287/opre.1090.0801

Diabat, A., Govindan, K., & Panicker, V. V. (2012). Supply chain risk management and its mitigation in a food industry. *International Journal of Production Research*, *50*(11), 3039–3050. https://doi.org/10.1080/00207543.2011.588619

Ding, H., Hu, Y., Jiang, H., Wu, J., & Zhang, Y. (2023). Social embeddedness and supply chains: Doing business with friends versus making friends in business. *Production and Operations Management*, *32*(7), 2154-2172.

Dolgui, A., Ivanov, D., & Rozhkov, M. (2020). Does the ripple effect influence the bullwhip effect? An integrated analysis of structural and operational dynamics in the supply chain†. *International Journal of Production Research*, *58*(5), 1285–1301. https://doi.org/10.1080/00207543.2019.1627438

Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: an analysis and recent literature. *International Journal of Production Research*, *56*(1–2), 414–430. https://doi.org/10.1080/00207543.2017.1387680

Dolgui, A., Ivanov, D., & Sokolov, B. (2020). Reconfigurable supply chain: the X-network. *International Journal of Production Research*, *58*(13), 4138–4163. https://doi.org/10.1080/00207543.2020.1774679

Escaith, H., Lindenberg, N., & Miroudot, S. (2010). International supply chains and trade elasticity in times of global crisis. *World Trade Organization* (Economic Research and Statistics Division) Staff Working Paper ERSD-2010-08.

Fahimnia, B., Tang, C. S., Davarzani, H., & Sarkis, J. (2015). Quantitative models for managing supply chain risks: A review. *European Journal of Operational Research*, *247*(1), 1–15. https://doi.org/10.1016/j.ejor.2015.04.034

Fang, J., Zhao, L., Fransoo, J. C., & Van Woensel, T. (2013). Sourcing strategies in supply risk management: An approximate dynamic programming approach. *Computers and Operations Research, 40*(5), 1371–1382. https://doi.org/10.1016/j.cor.2012.08.016

Fattahi, M., & Govindan, K. (2018). A multi-stage stochastic program for the sustainable design of biofuel supply chain networks under biomass supply uncertainty and disruption risk: A real-life case study. *Transportation Research Part E: Logistics and Transportation Review*, *118*(February), 534–567. https://doi.org/10.1016/j.tre.2018.08.008

Fattahi, M., Govindan, K., & Keyvanshokooh, E. (2017). Responsive and resilient supply chain network design under operational and disruption risks with delivery lead-time sensitive customers. *Transportation Research Part E: Logistics and Transportation Review*, *101*, 176–200. https://doi.org/10.1016/j.tre.2017.02.004

Fiksel, J., Polyviou, M., Croxton, K. L., & Pettit, T. J. (2015). From risk to resilience: Learning to deal with disruption. *MIT Sloan Management Review, 56*(2), 79–86.

Finch, P. (2004). Supply chain risk management. *Supply Chain Management*, *9*(2), 183–196. https://doi.org/10.1108/13598540410527079

Gao, S. Y., Simchi-Levi, D., Teo, C. P., & Yan, Z. (2019). Disruption risk mitigation in supply chains: The risk exposure index revisited. *Operations Research*, *67*(3), 831–852. https://doi.org/10.1287/opre.2018.1776

Garvey, M. D., Carnovale, S., & Yeniyurt, S. (2015). An analytical framework for supply network risk propagation: A Bayesian network approach. *European Journal of Operational Research*, *243*(2), 618–627. https://doi.org/10.1016/j.ejor.2014.10.034

Ghavamifar, A., Makui, A., & Taleizadeh, A. A. (2018). Designing a resilient competitive supply chain network under disruption risks: A real-world application. *Transportation Research Part E: Logistics and Transportation Review*, *115*(February), 87–109. https://doi.org/10.1016/j.tre.2018.04.014

Golan, M. S., Jernegan, L. H., & Linkov, I. (2020). Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the COVID-19 pandemic. *Environment Systems and Decisions*, *40*(2), 222–243. https://doi.org/10.1007/s10669-020-09777-w

Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. *Global Environmental Change, 23*(2), 485–498. https://doi.org/10.1016/j.gloenvcha.2012.12.006

Hasani, A., & Khosrojerdi, A. (2016). Robust global supply chain network design under disruption and uncertainty considering resilience strategies: A parallel memetic algorithm for a real-life case study. *Transportation Research Part E: Logistics and Transportation Review*, *87*, 20–52. https://doi.org/10.1016/j.tre.2015.12.009

He, J., Alavifard, F., Ivanov, D., & Jahani, H. (2019). A real-option approach to mitigate disruption risk in the supply chain. *Omega (United Kingdom)*, *88*, 133–149. https://doi.org/10.1016/j.omega.2018.08.008

Heckmann, I., Comes, T., & Nickel, S. (2015). A critical review on supply chain risk - Definition, measure and modeling. *Omega (United Kingdom)*, *52*, 119–132. https://doi.org/10.1016/j.omega.2014.10.004

Hendricks, K. B., & Singhal, V. R. (2003). The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management*, *21*(5), 501–522. https://doi.org/10.1016/j.jom.2003.02.003

Ho, W. R., Tsolakis, N., Dawes, T., Dora, M., & Kumar, M. (2022). A digital strategy development framework for supply chains. *IEEE Transactions on Engineering Management*, *70*(7), 2493-2506.

Hohenstein, N. O., Feise, E., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience: A systematic review and paths for further investigation. *International Journal of Physical Distribution and Logistics Management*, *45*(2005), 90–117. https://doi.org/10.1108/IJPDLM-05-2013-0128

Hosseini, S., & Ivanov, D. (2019). A new resilience measure for supply networks with the ripple effect considerations: a Bayesian network approach. *Annals of Operations Research*, *319*(1), 581–607. https://doi.org/10.1007/s10479-019-03350-8

Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, *125*(December 2018), 285–307. https://doi.org/10.1016/j.tre.2019.03.001

Hosseini, S., Morshedlou, N., Ivanov, D., Sarder, M. D., Barker, K., & Khaled, A. Al. (2019). Resilient supplier selection and optimal order allocation under disruption risks. *International Journal of Production Economics*, *213*(March), 124–137. https://doi.org/10.1016/j.ijpe.2019.03.018

Ivanov, D., Tsipoulanidis, A., & Schönberger, J. (2017). *Global Supply Chain and Operations Management: A Decision-Oriented*.

Ivanov, D., & Dolgui, A. (2019). Low-Certainty-Need (LCN) supply chains: a new perspective in managing disruption risks and resilience. *International Journal of Production Research*, *57*(15–16), 5119–5136. https://doi.org/10.1080/00207543.2018.1521025

Ivanov, D., Sokolov, B., & Dolgui, A. (2014). The Ripple effect in supply chains: Trade-off “efficiency-flexibility- resilience” in disruption management. *International Journal of Production Research*, *52*(7), 2154–2172. https://doi.org/10.1080/00207543.2013.858836

Johnson, A. R., & Nagarur, N. (2012). A discussion on supply chain robustness and resiliency. In *Industrial and Systems Engineering Research Conference* (pp. 3414–3423). Retrieved from http://www.scopus.com/inward/record.url?eid=2-s2.0-84900309915&partnerID=40&md5=77684e59170865d90363ae120566aa3f

Kamalahmadi, M., & Parast, M. M. (2016). A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. *International Journal of Production Economics*, *171*, 116–133. https://doi.org/10.1016/j.ijpe.2015.10.023

Kamalahmadi, M., & Parast, M. M. (2017). An assessment of supply chain disruption mitigation strategies. *International Journal of Production Economics*, *184*(December 2016), 210–230. https://doi.org/10.1016/j.ijpe.2016.12.011

Kauppi, K., Longoni, A., Caniato, F., & Kuula, M. (2016). Managing country disruption risks and improving operational performance: risk management along integrated supply chains. *International Journal of Production Economics*, *182*(October), 484–495. https://doi.org/10.1016/j.ijpe.2016.10.006

Klibi, W., & Martel, A. (2012). Scenario-based Supply Chain Network risk modeling. *European Journal of Operational Research*, *223*(3), 644–658. https://doi.org/10.1016/j.ejor.2012.06.027

Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: A critical review. *European Journal of Operational Research*, *203*(2), 283–293. https://doi.org/10.1016/j.ejor.2009.06.011

Knemeyer, A. M., Zinn, W., & Eroglu, C. (2009). Proactive planning for catastrophic events in supply chains. *Journal of Operations Management*, *27*(2), 141–153. https://doi.org/10.1016/j.jom.2008.06.002

Kwak, D. W., Seo, Y. J., & Mason, R. (2018). Investigating the relationship between supply chain innovation, risk management capabilities and competitive advantage in global supply chains. *International Journal of Operations and Production Management*, *38*(1), 2–21. https://doi.org/10.1108/IJOPM-06-2015-0390

Lee, H. L. (2004). The Triple-A Supply Chain. *Harvard Business Review*, *82*(10), 102–113.

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis*. RAND Corporation. https://doi.org/10.1016/j.techfore.2003.09.006

Levitin, G., Gertsbakh, I., & Shpungin, Y. (2013). Evaluating the damage associated with intentional supply deprivation in multi-commodity network. *Reliability Engineering and System Safety*, *119*, 11–17. https://doi.org/10.1016/j.ress.2013.05.002

Li, R., Dong, Q., Jin, C., & Kang, R. (2017). A new resilience measure for supply chain networks. *Sustainability (Switzerland)*, *9*(1), 1–19. https://doi.org/10.3390/su9010144

Li, Y., Chen, K., Collignon, S., & Ivanov, D. (2021). Ripple effect in the supply chain network: Forward and backward disruption propagation, network health and firm vulnerability. *European Journal of Operational Research*, *291*(3), 1117–1131. https://doi.org/10.1016/j.ejor.2020.09.053

Liberatore, F., Scaparra, M. P., & Daskin, M. S. (2012). Hedging against disruptions with ripple effects in location analysis. *Omega*, *40*(1), 21–30. https://doi.org/10.1016/j.omega.2011.03.003

Lin, C. C., & Wang, T. H. (2011). Build-to-order supply chain network design under supply and demand uncertainties. *Transportation Research Part B: Methodological*, *45*(8), 1162–1176. https://doi.org/10.1016/j.trb.2011.02.005

Madadi, A., Kurz, M. E., Taaffe, K. M., Sharp, J. L., & Mason, S. J. (2014). Supply network design: Risk-averse or risk-neutral? *Computers and Industrial Engineering*, *78*, 55–65. https://doi.org/10.1016/j.cie.2014.09.030

Mizgier, K. J. (2017). Global sensitivity analysis and aggregation of risk in multi-product supply chain networks. *International Journal of Production Research*, *55*(1), 130–144. https://doi.org/10.1080/00207543.2016.1198504

Mizgier, K. J., Wagner, S. M., & Jüttner, M. P. (2015). Disentangling diversification in supply chain networks. *International Journal of Production Economics*, *162*, 115–124. https://doi.org/10.1016/j.ijpe.2015.01.007

Ojha, R., Ghadge, A., Tiwari, M. K., & Bititci, U. S. (2018). Bayesian network modelling for supply chain risk propagation. *International Journal of Production Research*, *56*(17), 5795–5819. https://doi.org/10.1080/00207543.2018.1467059

Olivares-Aguila, J., & Vital-Soto, A. (2021). Supply Chain Resilience Roadmaps for Major Disruptions. *Logistics*, *5*(4). https://doi.org/10.3390/logistics5040078

Owen, S. H., & Daskin, M. S. (1998). Strategic facility location: A review. *European Journal of Operational Research*, *111*(3), 423–447. https://doi.org/10.1016/S0377-2217(98)00186-6

Paul, S. K., Sarker, R., & Essam, D. (2014). Real time disruption management for a two-stage batch production-inventory system with reliability considerations. *European Journal of Operational Research*, *237*(1), 113–128. https://doi.org/10.1016/j.ejor.2014.02.005

Pettit, T. J., Croxton, K. L., & Fiksel, J. (2019). The Evolution of Resilience in Supply Chain Management: A Retrospective on Ensuring Supply Chain Resilience. *Journal of Business Logistics*, *40*(1), 56–65. https://doi.org/10.1111/jbl.12202

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring Supply Chain Resilience: Development of a Conceptual Framework. *Journal of Business Logistics*, *31*(1), 1–21. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, *20*(1), 124–143. https://doi.org/10.1108/09574090910954873

Prater, E. (2005). A framework for understanding the interaction of uncertainty and information systems on supply chains. *International Journal of Physical Distribution and Logistics Management*, *35*(7), 524–539. https://doi.org/10.1108/09600030510615833

Priya Datta, P., Christopher, M., & Allen, P. (2007). Agent-based modelling of complex production/distribution systems to improve resilience. *International Journal of Logistics Research and Applications*, *10*(3), 187–203. https://doi.org/10.1080/13675560701467144

Raymond, C., Horton, R. M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J., … White, K. (2020). Understanding and managing connected extreme events. *Nature Climate Change*, *10*(7), 611–621. https://doi.org/10.1038/s41558-020-0790-4

Reyes Levalle, R., & Nof, S. Y. (2015). Resilience by teaming in supply network formation and re-configuration. *International Journal of Production Economics*, *160*, 80–93. https://doi.org/10.1016/j.ijpe.2014.09.036

Rinaldi, M., Murino, T., Gebennini, E., Morea, D., & Bottani, E. (2022). A literature review on quantitative models for supply chain risk management: Can they be applied to pandemic disruptions? *Computers and Industrial Engineering*, *170*(June), 108329. https://doi.org/10.1016/j.cie.2022.108329

Rosenhead, J., Elton, M., Gupta, S. K., & Rosenhead, J. (1972). Robustness and Optimality as Criteria for Strategic Decisions Published by : Palgrave Macmillan Journals on behalf of the Operational Research Society Stable URL : http://www.jstor.org/stable/3007957 Robustness and Optimality as Criteria for Strategic Dec. *Operational Research Quarterly*, *23*(4), 413–431.

Sáenz, M. J., & Revilla, E. (2014). Creating more resilient supply chains. *MIT Sloan Management Review*, *55*(4), 22–24.

Salimi, F., & Vahdani, B. (2018). Designing a bio-fuel network considering links reliability and risk-pooling effect in bio-refineries. *Reliability Engineering and System Safety*, *174*(February), 96–107. https://doi.org/10.1016/j.ress.2018.02.020

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. *Journal of cleaner production*, *16*(15), 1699-1710.

Sheffi, Y. (2005). *The resilient enterprise: overcoming vulnerability for competitive advantage*. Cambridge: MIT Press Books.

Sheffi, Y., & Rice Jr., J. B. (2005). A Supply Chain View of the Resilient Enterprise. *MIT Sloan Management Review*, *47*(1), 41–48. https://doi.org/10.1007/978-0-387-79933-9

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

Snoeck, A., Udenio, M., & Fransoo, J. C. (2019). A stochastic program to evaluate disruption mitigation investments in the supply chain. *European Journal of Operational Research*, *274*(2), 516–530. https://doi.org/10.1016/j.ejor.2018.10.005

Sodhi, M. S., & Christopher, T. (2012). *Managing Supply Chain Risk* (Vol. 157). London: Springer. https://doi.org/10.1007/978-1-4614-1900-6

Stecke, K. E., & Kumar, S. (2009). Sources of supply chain disruptions, factors that breed vulnerability, and mitigating strategies. *Journal of Marketing Channels*, *16*(3), 193–226. https://doi.org/10.1080/10466690902932551

Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, *103*(2), 451–488. https://doi.org/10.1016/j.ijpe.2005.12.006

Thekdi, S. A., & Santos, J. R. (2016). Supply Chain Vulnerability Analysis Using Scenario-Based Input-Output Modeling: Application to Port Operations. *Risk Analysis*, *36*(5), 1025–1039.

https://doi.org/10.1111/risa.12473

Tomlin, B. (2006). On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management Science*, *52*(5), 639–657. https://doi.org/10.1287/mnsc.1060.0515

Torabi, S. A., Baghersad, M., & Mansouri, S. A. (2015). Resilient supplier selection and order allocation under operational and disruption risks. *Transportation Research Part E: Logistics and Transportation Review*, *79*, 22–48. https://doi.org/10.1016/j.tre.2015.03.005

Tordecilla, R. D., Juan, A. A., Montoya-Torres, J. R., Quintero-Araujo, C. L., & Panadero, J. (2021). Simulation-optimization methods for designing and assessing resilient supply chain networks under uncertainty scenarios: A review. *Simulation Modelling Practice and Theory*, *106*(August 2020), 102166. https://doi.org/10.1016/j.simpat.2020.102166

Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. *International Journal of Production Research*, *53*(18), 5592–5623. https://doi.org/10.1080/00207543.2015.1037934

Urata, J., & Pel, A. J. (2018). People's risk recognition preceding evacuation and its role in demand modeling and planning. *Risk analysis*, *38*(5), 889-905.

Vanany, I., Zailani, S., & Pujawan, N. (2009). Supply chain risk management: literature review and future research. *International Journal of Information Systems and Supply Chain Management* (IJISSCM), 2(1), 16-33.

Wagner, S. M., & Bode, C. (2006). An empirical investigation into supply chain vulnerability. *Journal of Purchasing and Supply Management*, *12*(6 SPEC. ISS.), 301–312. https://doi.org/10.1016/j.pursup.2007.01.004

Wang, J. W., Ip, W. H., Muddada, R. R., Huang, J. L., & Zhang, W. J. (2013). On Petri net implementation of proactive resilient holistic supply chain networks. *International Journal of Advanced Manufacturing Technology*, *69*(1–4), 427–437. https://doi.org/10.1007/s00170-013-5022-x

Wang, Y., & Xiao, R. (2016). An ant colony based resilience approach to cascading failures in cluster supply network. *Physica A: Statistical Mechanics and Its Applications*, *462*, 150–166. https://doi.org/10.1016/j.physa.2016.06.058

Wieland, A., & Marcus Wallenburg, C. (2013). The influence of relational competencies on supply chain resilience: a relational view. *International Journal of Physical Distribution & Logistics Management*, *43*(4), 300–320. https://doi.org/10.1108/IJPDLM-08-2012-0243

Xiao, Z., Cao, B., Sun, J., & Zhou, G. (2016). Culture of the stability in an eco-industrial system centered on complex network theory. *Journal of Cleaner Production*, *113*, 730–742. https://doi.org/10.1016/j.jclepro.2015.11.096

Yan, T., Choi, T. Y., Kim, Y., & Yang, Y. (2015). A Theory of the Nexus Supplier: A Critical Supplier From A Network Perspective. *Journal of Supply Chain Management*, *51*(1), 52–66. https://doi.org/10.1111/jscm.12070

Yildiz, H., Yoon, J., Talluri, S., & Ho, W. (2016). Reliable Supply Chain Network Design.

Decision Sciences, *47*(4), 661–698. https://doi.org/10.1111/deci.12160

Zhao, K., Kumar, A., Harrison, T. P., & Yen, J. (2011). Analyzing the resilience of complex supply network topologies against random and targeted disruptions. *IEEE Systems Journal*, *5*(1), 28–39. https://doi.org/10.1109/JSYST.2010.2100192

Zobel, C. W., & Khansa, L. (2014). Characterizing multi-event disaster resilience. *Computers and Operations Research*, *42*, 83–94. https://doi.org/10.1016/j.cor.2011.09.024

3 Simulation model

The concept of consequence-based risk analysis underpins the approaches for addressing the research questions in this thesis. Consequence-based risk analysis is a model-based approach that uses a simulation model to analyze, predict, and manage risk in the supply chain. This chapter elaborates on the supply chain simulation model developed for performing experiments related to each research question. The main objective of the simulation model is to assess the impact of disruption scenarios on supply chain performance and evaluate the efficiency of various resilience practices. In the rest of this section, the details of the simulation model are explained.

3.1 Modular modeling approach

A modular and parametrized modeling approach is adopted in this research to develop the simulation model. In this approach, pre-built model components are designed so that different simulation models can be generated automatically from various configurations of model components. The approach uses parametrized simulation components so the modeler can create, run, and adjust the model without reprogramming (Goodall, Sharpe, & West, 2019; Huang, 2011). This approach reduces the modeling complexity and enables the simulation model's scalability to range from small to significant supply chain networks. For building the simulation model, Simio, a discrete-event simulation package (Houck & Whitehead, 2019) is used. The simulation model in this research consists of several building blocks for handling processes and events. These building blocks include Demand Generator, Demand Handler, Order Handler, Production Plant, Inventory Component, and Inventory End (Figure 1). Four main components of the model are generated from these building blocks: Market, Manufacturer, Supplier, and Inventory. Several supply chain models can be generated through different configurations of these four model components.

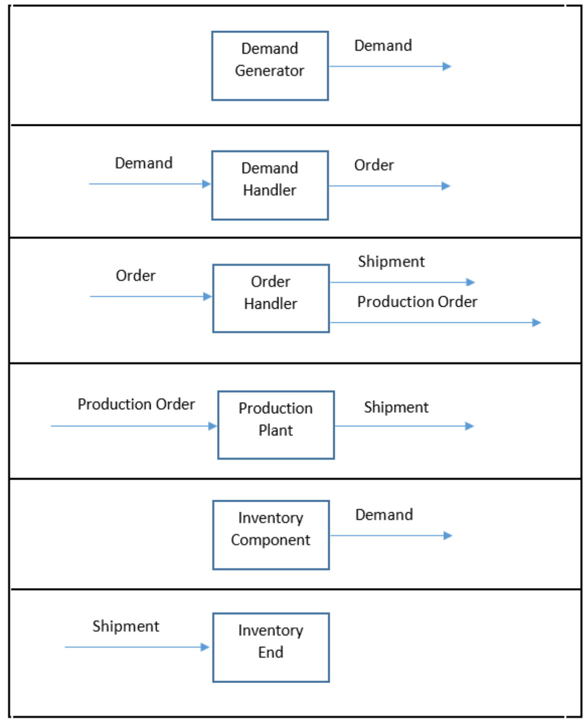


Figure 1. Building blocks of the simulation model.

3.2 Simulation model overview and logic

We try to simulate the supply chain in such a way that it mimics the complexities of a real-world supply chain. To this end, we consider the development of an assemble-to-order (ATO) supply chain in which the focal company starts assembling the final product when the actual order from the customer arrives. Figure 2 represents a sample ATO supply chain diagram that shows a possible configuration of our simulation model. The supply chain consists of two markets: an ATO manufacturer as the focal company, two make-to-order (MTO) suppliers, one make-to-stock (MTS) supplier in the first tier, and two MTO suppliers and five MTS suppliers in the second tier. Supply chain processes start with receiving the order from the focal company from the market. The focal company places the order for sub-assembly components with MTO suppliers and begins production with the inventory of components from its MTS suppliers. When the MTO supplier receives the order from the focal company, it also places the order for the required components to its MTO sub-suppliers. It starts production with the inventory of components from its MTS sub-supplier. Other suppliers within the supply chain also follow the same procedures. The manufacturer and suppliers keep an inventory of components as well as an inventory of end products. When the focal company receives the required components from the MTO suppliers, it finalizes the production procedure and sends the shipment to the final customer.

It should be noted that inventories from MTS suppliers are managed based on the product demand forecast. This supply chain model can be expanded in terms of the number of markets, tiers, and suppliers. The rest of this section explains the model components in more detail and discusses several assumptions underlying the simulation model.

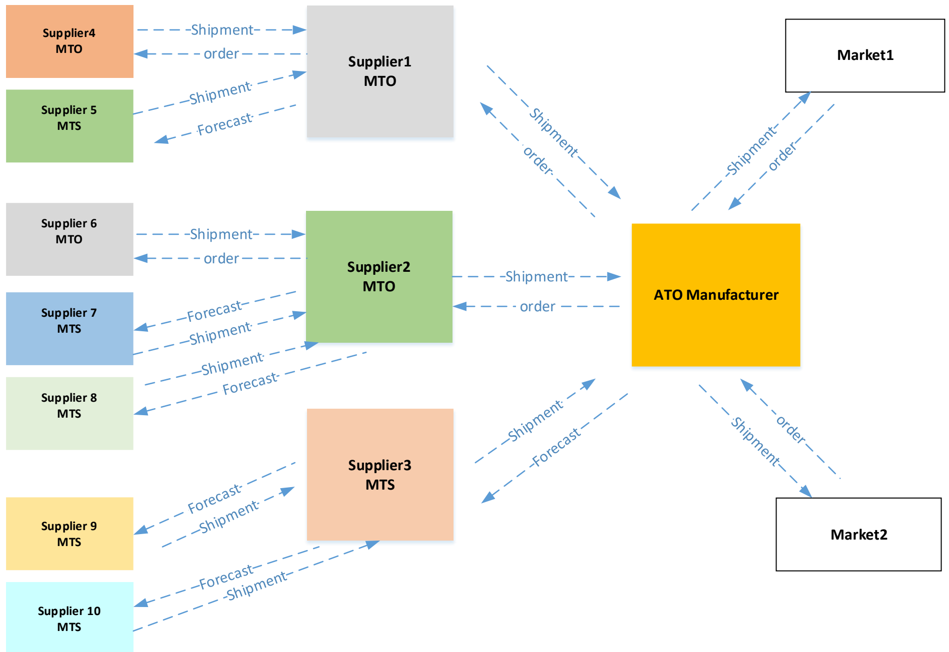


Figure 2. Schematic of a sample supply chain.

3.2.1 Model components

The simulation model consists of four main components as described below:

Market component: The Market component in the simulation model represents the market in which the demand for the final product (end item) is generated. The component consists of two building blocks: demand generator and demand handler. The demand generator generates demand within defined time intervals. Demand uncertainty is captured through stochastic interarrivals of demand in the demand generator. The generated demand is then passed to the demand handler. The demand handler creates an order from the demand and passes it to the ATO manufacturer for further processing. A supply chain can consist of several markets. In our model, we assume two types of markets: nearby and faraway. The nearby market is close to the location of the focal company, and the faraway market is far beyond the focal company's geographic boundaries. For example, for a focal company located in Europe, customers within Europe are considered as the nearby market, and customers within Asia as a faraway market.

Manufacturer component: The Manufacturer component represents the focal company within the supply chain, which produces the final product (end item) for the last customer. The manufacturer adapts the assemble-to-order (ATO) production strategy and starts assembling the final product (end item) after receiving the actual order from the Market. The manufacturer has three building blocks: order handler, production plants, and demand handler. The order handler receives orders from the market and determines order information such as order ID, order amount, selling price, expected production time, expected transportation time, etc. The order handler then creates a production order from the market order and gives it to the production plant. Before starting production procedures, the production plant checks inventories of the needed components (items) based on the bill of materials. The bill of materials is a list of components required to produce final product (end item). Inventories of the required components (items) are received from suppliers with make-to-stock (MTS) or make-to-order (MTO) manufacturing strategies. Inventories of MTS suppliers are handled through the MRP system in which, at the beginning of each production period, the needed inventory of components (items) is calculated and ordered to associated suppliers. However, for MTO components' suppliers, the focal company puts an order to the supplier only when the actual order arrives. The demand handler takes care of this procedure. The demand handler calculates the needed inventory of the components (items) based on the bill of materials and then sends it to the associated MTO suppliers. When all the components (items) for producing customer orders (end item) are ready, the production plant starts producing the final product (end item). The uncertainty related to the production time is addressed by defining a stochastic process time per unit. The manufactured product (end item) is shipped to the associated customer through an order handler. The focal company can have two types of suppliers: nearby and faraway. The nearby supplier is close to the location of the focal company, and the faraway supplier is far beyond the focal company's geographic boundaries.

Supplier component: The supplier component represents suppliers who produce components (items) for focal companies or other suppliers within the supply chain. Suppliers are spread through different tiers of the supply chain. A supplier can produce for one or more customers within a supply chain. In the case of producing for more than one customer, the supplier is called a shared supplier. Suppliers are producing based on MTS or MTO strategies. The MTS supplier uses past sales data to forecast the demand and determines how much stock to produce for the next production period. Incoming orders are fulfilled from the inventory of end products of the MTS supplier. The MTS supplier keeps inventories of the required components (items) for production from MTS sub-suppliers based on its MRP system. On the other hand, the MTO supplier starts producing when the actual order arrives from the customer. The MTO supplier keeps inventories of the required components (items) for production from both MTS and/or MTO sub-suppliers. The supplier uses an MRP system to order components (items) from MTS sub-suppliers. However, the supplier places the order for components (items) with MTO sub-suppliers when the actual order arrives. The supplier component in the simulation model consists of three building blocks: an order handler which handles the orders from customers, the production plant which takes care of producing products, and the demand handler that handles demand request for the required components to the related sub-suppliers and synchronize the replenishment orders. A supplier can have two types of sub-suppliers: nearby and faraway. The nearby sub-supplier is near the location of the supplier, and the faraway sub-supplier is far beyond the supplier's geographic boundaries.

Inventory component

The inventory component represents the location in which inventories of end products (end item) or components (items) are kept. Both focal company and suppliers within the supply chain carry inventories of end products and components in their location. The produced end products are sent to the inventory of the end product before shipping to the final customer. The shipments from suppliers of the components are sent to the inventory of components in the customer's location. The inventory of end products keeps track of products produced by the production plant. Inventory of components keeps track of ordered components to the suppliers.

3.2.2 Handling transportation

In the simulation model, transportation of the shipments is handled by the order handler inside the ATO manufacturer or suppliers. When produced products arrive in the inventory of the end product, the inventory sends a message to the order handler. The order handler then sends the shipment to the final customer within the transportation time of the order. Two types of transportation time are considered in the simulation model. Short transportation time is the transport time for sending shipment to a nearby customer and long transportation time is the transport time for sending the shipment to a faraway customer. This way, we model the geographical dispersion between supply chain entities. Uncertainty related to transportation time is captured by defining a triangular probability distribution for the transportation time within the model.

3.2.3 Data tables

All the inputs to the model are read from several data tables, which are imported from Excel sheets. These tables are generated automatically from a network generator, which will be explained later in this chapter. The input tables and their attributes are shown in Appendix A. An output table is also defined in the model where the information about all the orders to the focal company and all suppliers within the supply chain are recorded. The attributes of the order table are shown in Appendix B. This table is used for calculating the forecasted demand, average lead times, total revenue, etc.

3.2.4 Performance metrics

In our simulation model, the following performance metrics are calculated:

- Market lead time: Time between placing an order and receiving the corresponding shipment. This performance metric measures the efficiency and responsiveness of the supply chain. Shorter market lead times show improved performance in terms of fulfillment of the order and, as a result, satisfaction of the final customer.
- Total cost: Summation of the production cost, purchasing cost, and transportation cost. This performance metric allows tradeoffs between cost and effectiveness of the supply chain.
- Total revenue: Sales volume times selling price. This performance metric reflects the overall profitability of the supply chain in terms of revenue generation.
- Time to detect disruption: Time between the start of the adverse event and recognizing the first impact on supply chain performance. This performance metric plays an important role in assessing and improving the resilience of the supply chain, where the quick detection of disruption is crucial for minimizing the adverse effects of disruptions.
- Total recovery time: Time between the detection of the disruption and the return to business as usual. This performance metric evaluates the resilience and recovery capabilities of the supply chain. Shorter recovery times indicate a more resilient supply chain capable of returning to normal operations after a disruption.

Among the performance metrics, market lead time, total cost, and total revenue give insights into the supply chain's normal operations which provides a baseline for performance that is essential for comparing against performance during disruptions. However, time to detect disruption and total recovery time give insights into the performance of the supply chain under a disruptive situation. Each of these metrics provides valuable insights into different aspects of supply chain performance, both under normal conditions and during disruptions, making them highly relevant to our research on improving supply chain resilience.

3.2.5 Modeling a disruptive risk

We model disruption scenarios to assess potential disruptions' impact on supply chain performance. To this end, we define seven model properties representing the attributes of disruption as follows:

- *Disrupted tier:* a variable representing the tier of supply chain in which the disruption happens.
- *Disrupted* region: a variable representing the geographical region in which the disruption happens.
- *Disrupted component*: a variable representing the type of component (product) of which the availability is disrupted.
- *Disrupted element*: a variable representing the type of facility that is disrupted.
- *Disruption duration*: a variable representing the duration of a disruption.
- *Post-disruption capacity:* a variable representing the remaining capacity of the disrupted element after disruption. It is a variable for representing the intensity of a disruption. After a disruption, the remaining capacity of the disrupted element can vary between zero to a hundred percent depending on the severity of the disruptive event.
- *Recovery rate of disrupted capacity:* a deeply uncertain variable representing the time it will take for the disrupted element to recover fully after implementing a post-disruption contingency plan. It is a variable for representing the intensity of a disruption and it is independent of the managerial choice for mitigating disruptions. This variable is considered deeply uncertain because it depends on several factors that are out of control of a decision maker such as scarcity of the backup capacity that might be constrained due to the disruption as well; or long waiting time for availability of the backup capacity due to the existence of a queue for accessing the backup capacity. For example, imagine the disruption of a production plant due to a fire accident in a factory. It may take a few weeks to several months for the factory, depending on the severity of the fire, to rebuild or repair the production plant and get it back to normal. This is different from the recovery time of the supply chain as a performance metric, which refers to the time it takes for a disrupted supply chain to deliver products to end customers within a normal (no disruption) lead time.

Different configurations of different values of the above disruption variable result in various disruption scenarios. The values of the disruption properties are given to the model as an input. Then, the model triggers the associated disruption scenario at the defined time of disruption.

3.2.6 Mitigation strategies

We model the mitigation strategy of the supply chain against disruption using a model property called mitigation. In our model, a supply chain can have four strategies against disruption:

- *Expensive-Fast:* this represents a mitigation strategy with high cost of implementation but a short time to availability. An example of such a mitigation strategy is the usage of strategic stock where a firm keeps inventory of strategic products and products that could become a bottleneck. Although such a strategy involves extra cost, it enables a quick replacement of the disrupted capacity in case of a disruption.

- *Cheap-Slow:* this represents a mitigation strategy with a low cost of implementation but a longer time to availability. An example of such a mitigation strategy could be the implementation of a backup strategy where a firm has backup suppliers for its critical components that enable the firm to switch to alternative sources in case of disruption. Since the backup supplier is activated only when the primary supplier disrupts, it may involve less cost to the firm in comparison with the strategic stock policy. It may, however, take longer for the backup capacity to become available in comparison to the strategic stock policy.
- *Medium:* this represents a mitigation strategy with an average cost of implementation and an average time to availability. The “average” refers to a value that represents a midpoint between the low and high extremes of both cost and time. The cost associated with the Medium strategy is calculated as the midpoint between the low cost of the Cheap-Slow strategy and the high cost of the Expensive-Fast strategy. The time associated with the Medium strategy is determined as the midpoint between the longest and shortest times to availability .An example of such a mitigation strategy is to use a mix of investing in strategic stock and a backup supplier strategy. In this strategy, the firm makes a tradeoff between cost of the mitigation measures and time to availability of the mitigation measures.
- *Acceptance:* we also explored a scenario in which no mitigation strategy such as strategic stock or backup is used by the firm to replace disrupted capacity. In the acceptance strategy, a firm waits for the disrupted capacity to become available again. In this strategy, the company does not invest anything in resilience, and it is a good reference strategy to compare the other strategies with.

3.2.7 Model Validation

To ensure that our simulation model works as expected, we conducted sensitivity analysis and scenario testing in different stages of the model development. We built a toy model of a stylized supply chain to check the robustness of our model to changes in the input parameters. We tested the correct working of the stylized model across several scenarios, including extreme scenarios. This allowed us to refine the model and improve its validity iteratively.

3.3 Running experiments

For the experiments in this dissertation, we run the model for 220 weeks, in which the model reaches a steady state. We consider a warm-up period of 16 weeks. It should be mentioned that these values are adjustable based on the requirements of an experiment. We assume a disruptive event is triggered at week 44. We consider five replications for each scenario to address stochasticity related to the uncertain model parameters such as demand, process time, and transportation time. Our research considers an exploratory modeling approach toward generating disruption scenarios. This approach explores a large ensemble of plausible disruption scenarios rather than focusing on a few (Bankes, 1993; Kwakkel & Pruyt, 2013). To conduct exploratory modeling, we use the Exploratory Modeling and Analysis (EMA) workbench (Kwakkel, 2017).

The EMA workbench is an open-source Python library that supports exploratory modeling by the generation and execution of a series of computational experiments as well as the visualization and analysis of the results of the computational experiments. We connect the EMA workbench to our Simio-based simulation library by developing a Simio-EMA interface. We sample over several values of disruption attributes (explained before), including disrupted tier, disrupted geographical region, disrupted component, disrupted supplier, disruption duration, post-disruption capacity, and recovery rate of disrupted component using Latin Hypercube sampling to generate thousands of disruption scenarios. Table 1 shows the possible ranges of disruption attributes we consider for this research.

Table 1. Disruption attributes and their possible value ranges

Deep uncertainties	Possibility
Region	Nearby - Faraway- Both nearby and faraway
Tier	Each tier separately- All tiers
Component	Shared/Not shared among several suppliers
Disrupted element	Production plant-Transportation link-Inventory
Disruption duration	Long-Medium-Short
Post-disruption capacity	Large-Medium-small
Recovery rate	Fast-Medium-Slow

3.4 Network generator

We use a Python-based network generator to generate input data for the simulation model and connect it to our Simio-based simulation library. The network generator is capable of generating a variety of supply chain networks using several supply chain characteristics, including the number of tiers, percentage of assembled components in each tier, number of suppliers of a supplier in each tier, number of shared suppliers in each tier, percentage of faraway vs. nearby suppliers in each tier and percentage of MTO vs. MTS suppliers in each tier. Combining different values of these network-related variables results in the generation of various supply chain network topologies. The supply chain networks can be randomly generated by sampling across different values of the network-related variables or by giving the generator predefined values of network variables. The generator then automatically creates components of the simulation model and input data tables for the simulation model based on the supply chain network topology. An example of a network generated by the network generator is shown in Figure 3.

The simulation model and python code for the network generator are available at *https://github.com/bzohoori/Bahareh_Model.git.*

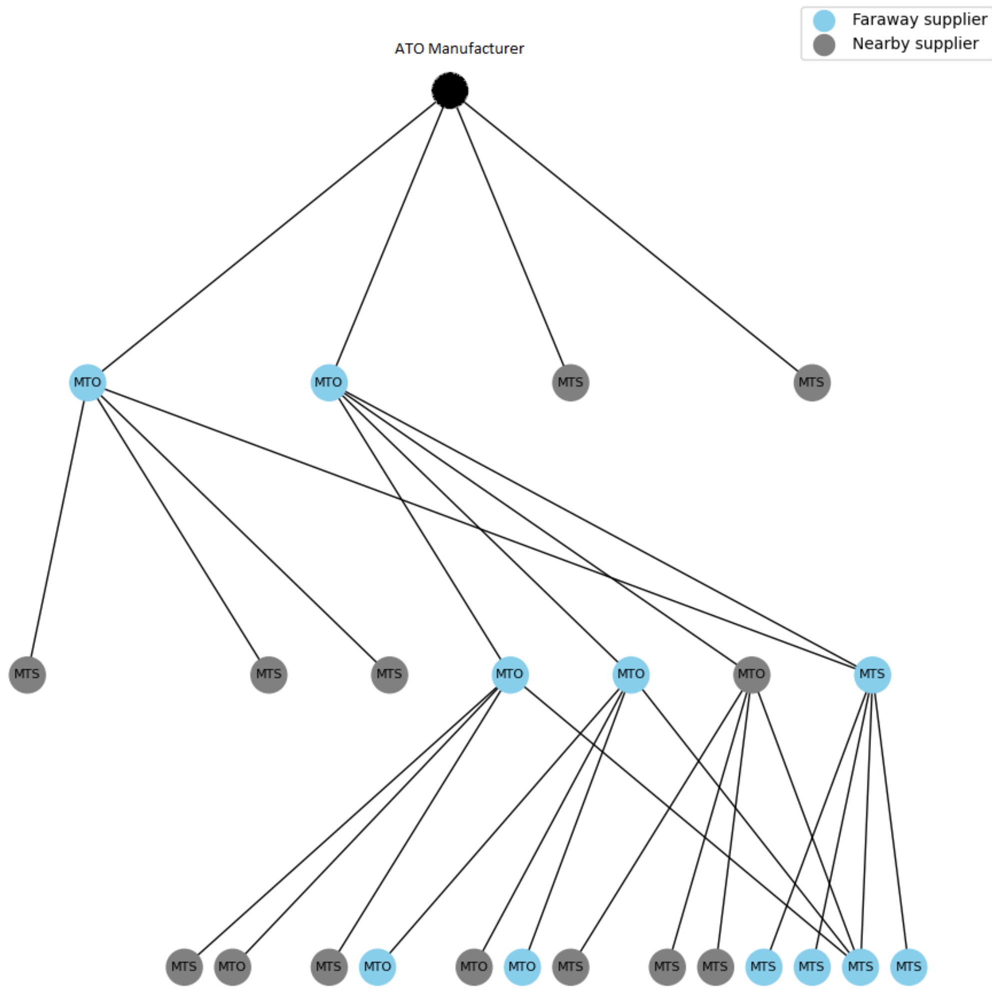
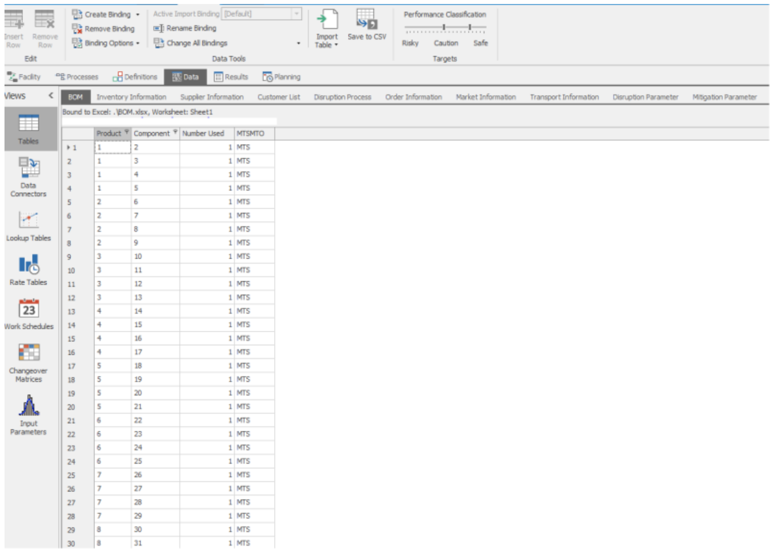


Figure 3. Example of a 3-tier supply chain network configuration created by the network generator.

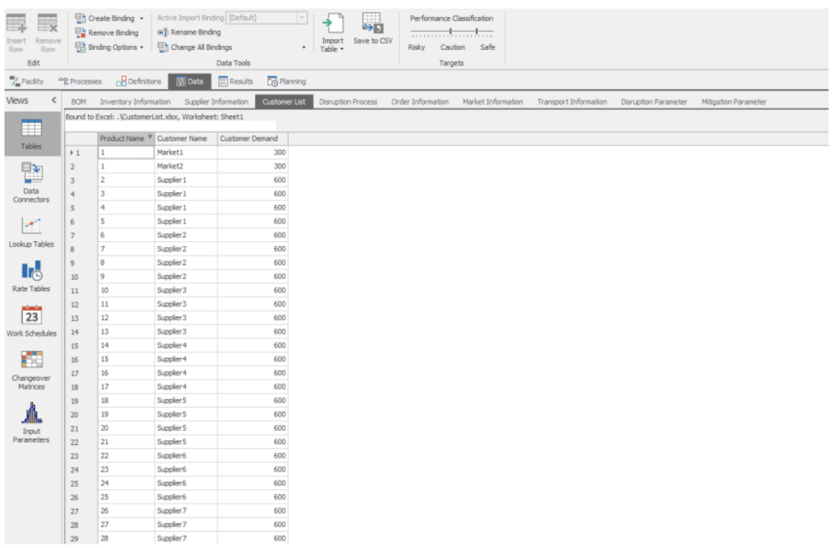
Appendices

Appendix A. Simulation model input tables



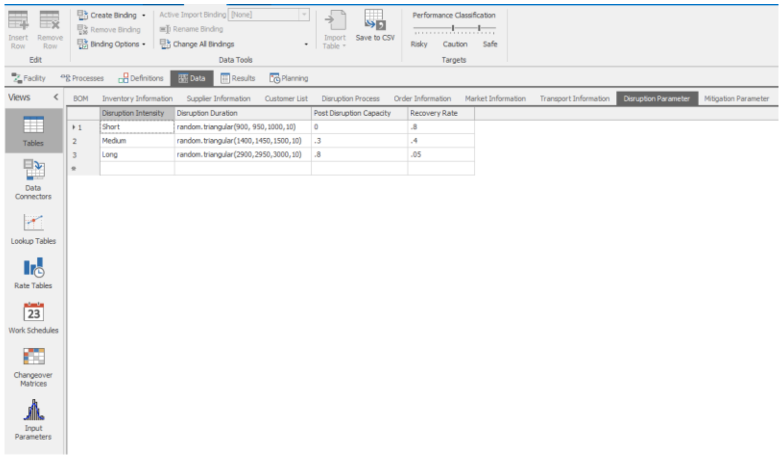
Bound to Excel: .\BOM.xlsx, Worksheet: Sheet1

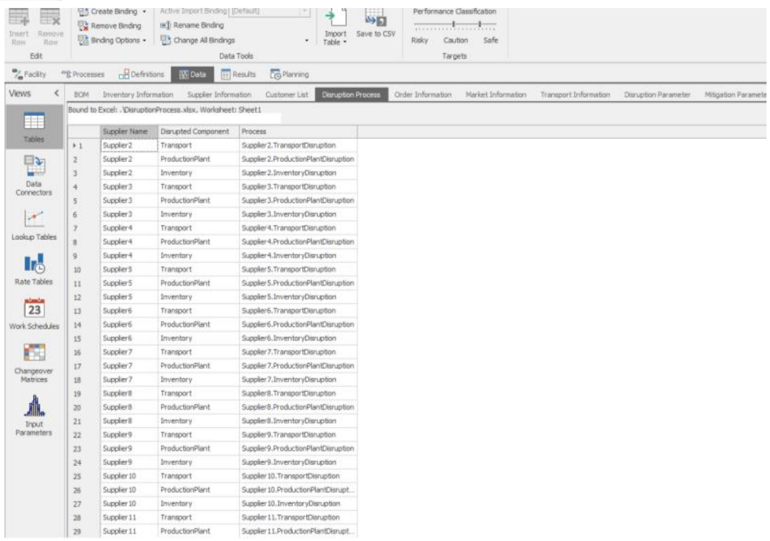
	Product	Component	Number Used	MTSMTO
1	1	2	1	MTS
2	1	3	1	MTS
3	1	4	1	MTS
4	1	5	1	MTS
5	2	6	1	MTS
6	2	7	1	MTS
7	2	8	1	MTS
8	2	9	1	MTS
9	3	10	1	MTS
10	3	11	1	MTS
11	3	12	1	MTS
12	3	13	1	MTS
13	4	14	1	MTS
14	4	15	1	MTS
15	4	16	1	MTS
16	4	17	1	MTS
17	5	18	1	MTS
18	5	19	1	MTS
19	5	20	1	MTS
20	5	21	1	MTS
21	6	22	1	MTS
22	6	23	1	MTS
23	6	24	1	MTS
24	6	25	1	MTS
25	7	26	1	MTS
26	7	27	1	MTS
27	7	28	1	MTS
28	7	29	1	MTS
29	8	30	1	MTS
30	8	31	1	MTS

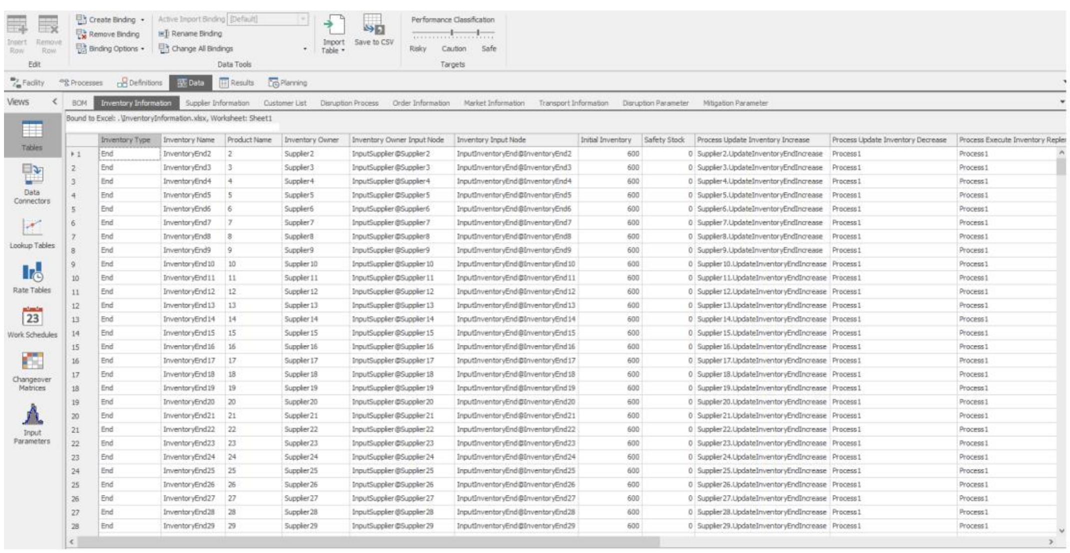


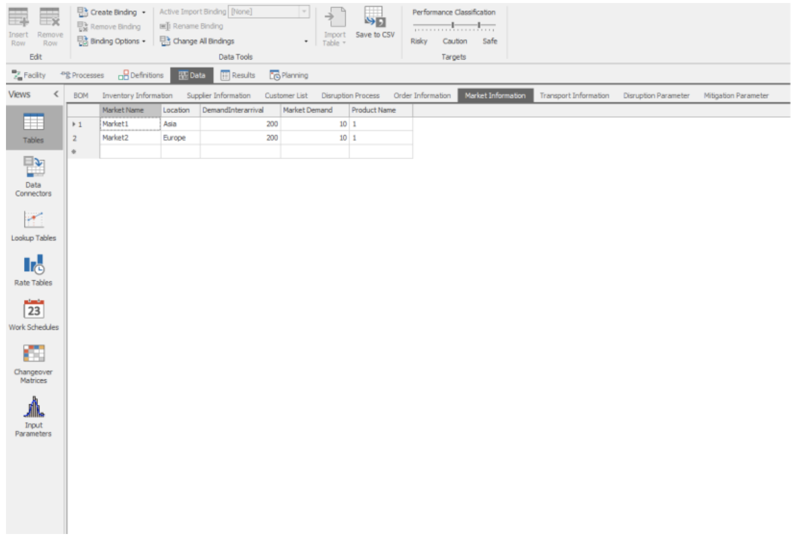
Bound to Excel: .\CustomerList.xlsx, Worksheet: Sheet1

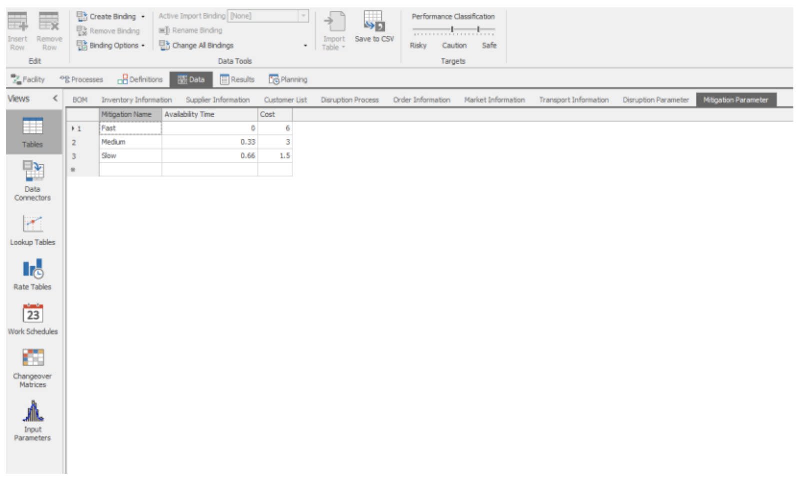
	Product Name	Customer Name	Customer Demand
1	1	Market1	300
2	1	Market2	300
3	2	Supplier1	600
4	3	Supplier1	600
5	4	Supplier1	600
6	5	Supplier1	600
7	6	Supplier2	600
8	7	Supplier2	600
9	8	Supplier2	600
10	9	Supplier2	600
11	10	Supplier3	600
12	11	Supplier3	600
13	12	Supplier3	600
14	13	Supplier3	600
15	14	Supplier4	600
16	15	Supplier4	600
17	16	Supplier4	600
18	17	Supplier4	600
19	18	Supplier5	600
20	19	Supplier5	600
21	20	Supplier5	600
22	21	Supplier5	600
23	22	Supplier6	600
24	23	Supplier6	600
25	24	Supplier6	600
26	25	Supplier6	600
27	26	Supplier7	600
28	27	Supplier7	600
29	28	Supplier7	600

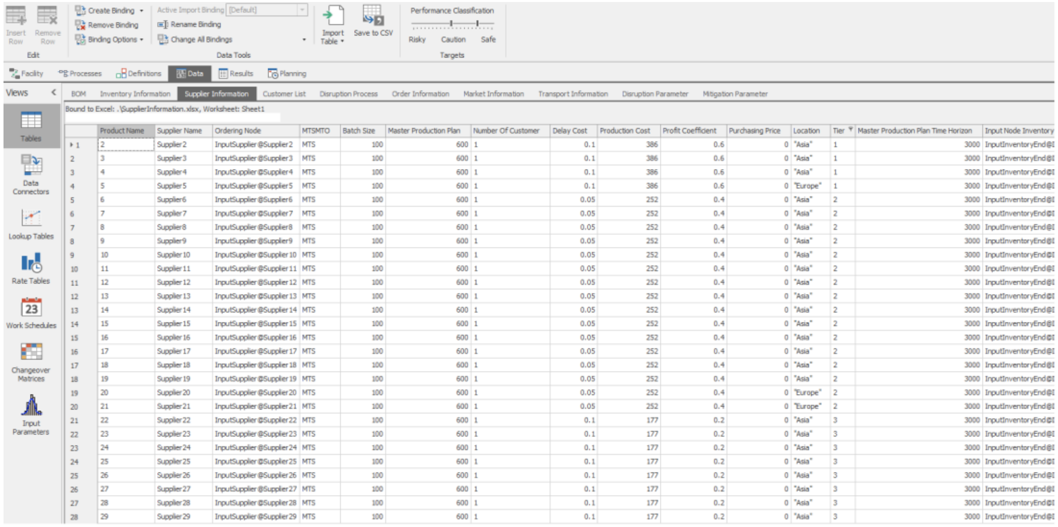

Disruption Intensity | Disruption Duration | Post Disruption Capacity | Recovery Rate
1 Short | random.triangular(900, 950,1000,10) | 0 | .8
2 Medium | random.triangular(1400,1450,1500,10) | .3 | .4
3 Long | random.triangular(2900,2950,3000,10) | .8 | .05


Bound to Excel: .\DisruptionProcess.xlsx, Worksheet: Sheet1
Supplier Name | Disrupted Component | Process
1 Supplier2 | Transport | Supplier2.TransportDisruption
2 Supplier2 | ProductionPlant | Supplier2.ProductionPlantDisruption
3 Supplier2 | Inventory | Supplier2.InventoryDisruption
4 Supplier3 | Transport | Supplier3.TransportDisruption
5 Supplier3 | ProductionPlant | Supplier3.ProductionPlantDisruption
6 Supplier3 | Inventory | Supplier3.InventoryDisruption
7 Supplier4 | Transport | Supplier4.TransportDisruption
8 Supplier4 | ProductionPlant | Supplier4.ProductionPlantDisruption
9 Supplier4 | Inventory | Supplier4.InventoryDisruption
10 Supplier5 | Transport | Supplier5.TransportDisruption
11 Supplier5 | ProductionPlant | Supplier5.ProductionPlantDisruption
12 Supplier5 | Inventory | Supplier5.InventoryDisruption
13 Supplier6 | Transport | Supplier6.TransportDisruption
14 Supplier6 | ProductionPlant | Supplier6.ProductionPlantDisruption
15 Supplier6 | Inventory | Supplier6.InventoryDisruption
16 Supplier7 | Transport | Supplier7.TransportDisruption
17 Supplier7 | ProductionPlant | Supplier7.ProductionPlantDisruption
18 Supplier7 | Inventory | Supplier7.InventoryDisruption
19 Supplier8 | Transport | Supplier8.TransportDisruption
20 Supplier8 | ProductionPlant | Supplier8.ProductionPlantDisruption
21 Supplier8 | Inventory | Supplier8.InventoryDisruption
22 Supplier9 | Transport | Supplier9.TransportDisruption
23 Supplier9 | ProductionPlant | Supplier9.ProductionPlantDisruption
24 Supplier9 | Inventory | Supplier9.InventoryDisruption
25 Supplier10 | Transport | Supplier10.TransportDisruption
26 Supplier10 | ProductionPlant | Supplier10.ProductionPlantDisrupt...
27 Supplier10 | Inventory | Supplier10.InventoryDisruption
28 Supplier11 | Transport | Supplier11.TransportDisruption
29 Supplier11 | ProductionPlant | Supplier11.ProductionPlantDisrupt...

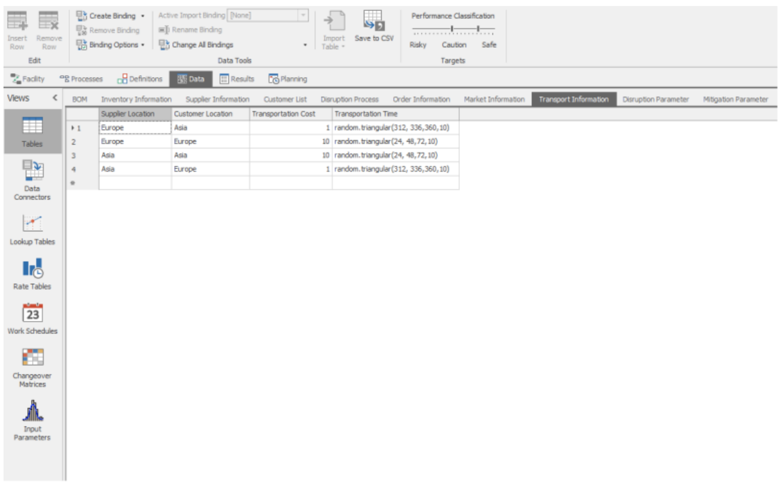

Bound to Excel: .\InventoryInformation.xlsx, Worksheet: Sheet1
Inventory Type | Inventory Name | Product Name | Inventory Owner | Inventory Owner Input Node | Inventory Input Node | Initial Inventory | Safety Stock | Process Update Inventory Increase | Process Update Inventory Decrease


Insert Row
Remove Row
Edit
Create Binding
Remove Binding
Binding Options
Active Import Binding [None]
Rename Binding
Change All Bindings
Data Tools
Import Table
Save to CSV
Performance Classification
Risky
Caution
Safe
Targets
Facility
Processes
Definitions
Data
Results
Planning
Views
BOM
Inventory Information
Supplier Information
Customer List
Disruption Process
Order Information
Market Information
Transport Information
Disruption Parameter
Mitigation Parameter
Market Name | Location | DemandInterarrival | Market Demand | Product Name
1 | Market1 | Asia | 200 | 10 | 1
2 | Market2 | Europe | 200 | 10 | 1
Tables
Data Connectors
Lookup Tables
Rate Tables
23
Work Schedules
Changeover Matrices
Input Parameters


Insert Row
Remove Row
Edit
Create Binding
Remove Binding
Binding Options
Active Import Binding [None]
Rename Binding
Change All Bindings
Data Tools
Import Table
Save to CSV
Performance Classification
Risky
Caution
Safe
Targets
Facility
Processes
Definitions
Data
Results
Planning
Views
BOM
Inventory Information
Supplier Information
Customer List
Disruption Process
Order Information
Market Information
Transport Information
Disruption Parameter
Mitigation Parameter
Mitigation Name | Availability Time | Cost
1 | Fast | 0 | 6
2 | Medium | 0.33 | 3
3 | Slow | 0.66 | 1.5
Tables
Data Connectors
Lookup Tables
Rate Tables
23
Work Schedules
Changeover Matrices
Input Parameters

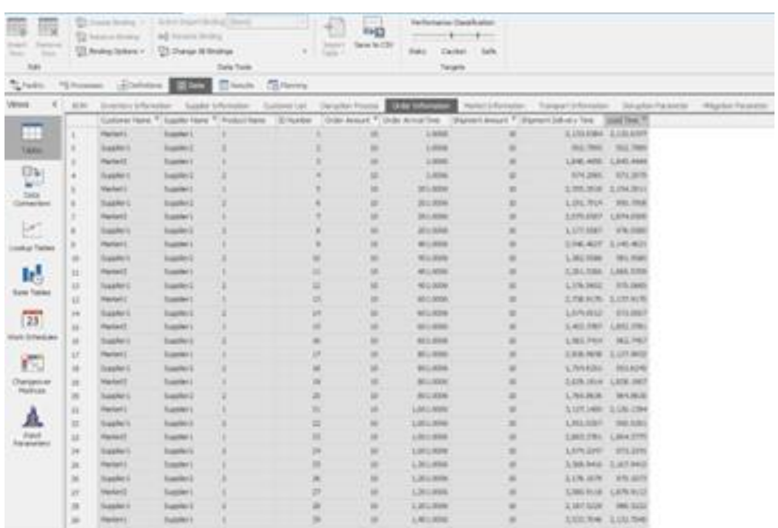


	Product Name	Supplier Name	Ordering Node	MTSMTO	Batch Size	Master Production Plan	Number Of Customer	Delay Cost	Production Cost	Profit Coefficient	Purchasing Price	Location	Tier	Master Production Plan Time Horizon	Input Node Inventory
1	2	Supplier2	InputSupplier@Supplier2	MTS	100	600	1	0.1	386	0.6	0	"Asia"	1	3000	InputInventoryEnd@I
2	3	Supplier3	InputSupplier@Supplier3	MTS	100	600	1	0.1	386	0.6	0	"Asia"	1	3000	InputInventoryEnd@I
3	4	Supplier4	InputSupplier@Supplier4	MTS	100	600	1	0.1	386	0.6	0	"Asia"	1	3000	InputInventoryEnd@I
4	5	Supplier5	InputSupplier@Supplier5	MTS	100	600	1	0.1	386	0.6	0	"Europe"	1	3000	InputInventoryEnd@I
5	6	Supplier6	InputSupplier@Supplier6	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
6	7	Supplier7	InputSupplier@Supplier7	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
7	8	Supplier8	InputSupplier@Supplier8	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
8	9	Supplier9	InputSupplier@Supplier9	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
9	10	Supplier10	InputSupplier@Supplier10	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
10	11	Supplier11	InputSupplier@Supplier11	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
11	12	Supplier12	InputSupplier@Supplier12	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
12	13	Supplier13	InputSupplier@Supplier13	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
13	14	Supplier14	InputSupplier@Supplier14	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
14	15	Supplier15	InputSupplier@Supplier15	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
15	16	Supplier16	InputSupplier@Supplier16	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
16	17	Supplier17	InputSupplier@Supplier17	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
17	18	Supplier18	InputSupplier@Supplier18	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
18	19	Supplier19	InputSupplier@Supplier19	MTS	100	600	1	0.05	252	0.4	0	"Asia"	2	3000	InputInventoryEnd@I
19	20	Supplier20	InputSupplier@Supplier20	MTS	100	600	1	0.05	252	0.4	0	"Europe"	2	3000	InputInventoryEnd@I
20	21	Supplier21	InputSupplier@Supplier21	MTS	100	600	1	0.05	252	0.4	0	"Europe"	2	3000	InputInventoryEnd@I
21	22	Supplier22	InputSupplier@Supplier22	MTS	100	600	1	0.1	177	0.2	0	"Asia"	3	3000	InputInventoryEnd@I
22	23	Supplier23	InputSupplier@Supplier23	MTS	100	600	1	0.1	177	0.2	0	"Asia"	3	3000	InputInventoryEnd@I
23	24	Supplier24	InputSupplier@Supplier24	MTS	100	600	1	0.1	177	0.2	0	"Asia"	3	3000	InputInventoryEnd@I
24	25	Supplier25	InputSupplier@Supplier25	MTS	100	600	1	0.1	177	0.2	0	"Asia"	3	3000	InputInventoryEnd@I
25	26	Supplier26	InputSupplier@Supplier26	MTS	100	600	1	0.1	177	0.2	0	"Asia"	3	3000	InputInventoryEnd@I
26	27	Supplier27	InputSupplier@Supplier27	MTS	100	600	1	0.1	177	0.2	0	"Asia"	3	3000	InputInventoryEnd@I
27	28	Supplier28	InputSupplier@Supplier28	MTS	100	600	1	0.1	177	0.2	0	"Asia"	3	3000	InputInventoryEnd@I
28	29	Supplier29	InputSupplier@Supplier29	MTS	100	600	1	0.1	177	0.2	0	"Asia"	3	3000	InputInventoryEnd@I



	Supplier Location	Customer Location	Transportation Cost	Transportation Time
1	Europe	Asia	1	random.triangular(312, 336, 360, 10)
2	Europe	Europe	10	random.triangular(24, 48, 72, 10)
3	Asia	Asia	10	random.triangular(24, 48, 72, 10)
4	Asia	Europe	1	random.triangular(312, 336, 360, 10)

Appendix B. Simulation model output table



Reference

Bankes, S. (1993). Exploratory Modeling for Policy Analysis. *Operations Research*, *41*(3), 435–449. https://doi.org/10.1287/opre.41.3.435

Goodall, P., Sharpe, R., & West, A. (2019). A data-driven simulation to support remanufacturing operations. *Computers in Industry*, *105*, 48–60. https://doi.org/10.1016/j.compind.2018.11.001

Houck, D., & Whitehead, C. (2019). Introduction to Simio. *Proceedings - Winter Simulation Conference*, *2019-Decem*, 3802–3811. https://doi.org/10.1109/WSC40007.2019.9004692

Huang, Y., Seck, M. D., & Verbraeck, A. (2011). From data to simulation models: component-based model generation with a data-driven approach. I*n Proceedings of the 2011 Winter Simulation Conference* (WSC) (pp. 3719-3729). IEEE.

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling and Software*, *96*, 239–250. https://doi.org/10.1016/j.envsoft.2017.06.054

Kwakkel, J. H., & Pruyt, E. (2013). Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. *Technological Forecasting and Social Change*, *80*(3), 419–431. https://doi.org/10.1016/j.techfore.2012.10.005

4 Improving supply chain resilience using consequence-based risk analysis and robust decision making

This chapter has been based on a paper that is under review at a scientific journal.

This chapter addresses the first sub-question introduced in section 1.2. We investigate how consequence-based risk analysis can treat the challenges of the unpredictability of disruptive risks, the complexity of a supply chain, and the robustness of disruption management strategies in model-based approaches for supporting supply chain resilience. To this end, we treat supply chain disruption management as a problem of decision making under deep uncertainty (DMDU) to benefit from approaches developed in this domain, specifically robust decision making.

Abstract

In response to supply chain disruptions over the past several years, improving supply chain resilience has become an important research topic. Conventional methods for resilience improvement of a supply chain mostly rely on the estimation of the risks that could impact the supply chain, with the aim of identifying the main sources of vulnerabilities in need of resilience practices. However, a major limitation of the conventional approaches for resilience improvement of a supply chain is the limited predictability of potential disruptive risks in terms of their probability of occurrence and their magnitude. Therefore, consequence-based risk analysis is suggested as an alternative in this paper. In consequence-based risk analysis, rather than relying on knowing the likelihood of occurrence and magnitude of the impact of potential risk events, one explores the effects of plausible scenarios of risk consequences on supply chain performance, independent of the root cause, to find vulnerabilities within the supply chain in need of resilience practices. In such an analysis, a risk consequence is characterized by several parameters that are deeply uncertain, and a combination of different values of those parameters generates various scenarios for disruptions that can be explored by supply chain decision makers. A major challenge in consequence-based risk analysis of a supply chain is the generation of a comprehensive set of disruption scenarios and their exploration, particularly in the case of complex supply chains consisting of thousands of interdependent and globally distributed actors. Also, to effectively manage disruptions when using consequence-based risk analysis, it is crucial to identify resilience practices that are effective in as many future scenarios as possible. To address these challenges, we draw on the paradigm of decision making under deep uncertainty (DMDU). This paradigm emerged in the context of climate change adaptation in response to limits to predictability. A foundational idea in this paradigm is to apply models for exploring rather than for predicting the future. Robust decision making (RDM) is one of the approaches in DMDU that focuses on identifying planning strategies that result in satisfactory outcomes across a large set of scenarios regarding the future. RDM uses large-scale computational experimentation for analyzing complex and uncertain systems. We investigate the potential of using RDM for supporting consequence-based risk analysis for complex supply chains using a stylized assemble-to-order supply chain. We conclude that our approach can support effective decision making for evaluating the resilience of a complex supply chain by systematic and data-driven exploration among a wide range of disruption assumptions that otherwise might have remained uninvestigated by human reasoning. Our approach can contribute to enhancing supply chain resilience by identifying and managing sources of vulnerabilities that are hard to detect, such as vulnerabilities beyond the first or second tier of the supply chain network. The proposed approach helps to assess the robustness of different disruption management responses to these vulnerabilities, which is crucial for an effective investment in supply chain resilience.

Keywords: Supply chain disruption, Resilience, Consequence-based risk analysis, Decision making under deep uncertainty, Robust decision making, Exploratory modeling

4.1 Introduction

A multitude of events in the past years have resulted in major supply chain disruptions in many different industries. Craighead et al. (2007) define supply chain disruption as "unplanned and unanticipated events that disrupt the normal flow of goods and materials within a supply chain and, as a consequence, expose firms within the supply chain to risks". In a recent example of supply chain disruption, several US and European manufacturers and retailers were disrupted due to the Covid-19 pandemic that suspended operations in China, resulting in supply shortages (Li, Chen, Collignon, & Ivanov, 2021). Other examples are for instance the closure of five production plants by Ford for several days due to the limited air traffic after the 9-11 terrorism attacks and a fire in a semiconductor supplier's plant of Ericsson that resulted in a loss of 400 million euros in 2000 (Tang, 2006). There are many other cases of adverse events that resulted in supply chain disruptions such as earthquakes in China in 2008, the tsunami in Japan in 2011, earthquakes in Chile in 2011 and 2015, Typhoon Haiyan in the Philippines in 2013, and the COVID-19 pandemic and geopolitical tensions in 2020-2022 (Fahimnia, Tang, Davarzani, & Sarkis, 2015; Jabbarzadeh, Fahimnia, Sheu, & Moghadam, 2016; Klibi, Martel, & Guitouni, 2010; Simchi-Levi & Simchi-Levi, 2020; Diaz, Cunado, & de Gracia, 2023)

The extent to which a supply chain is disrupted due to an adverse event is determined by the vulnerability of the supply chain. Wagner and Bode (2006) define supply chain vulnerability as "a function of certain supply chain characteristics and that the loss a firm incurs is a result of its supply chain vulnerability to a given supply chain disruption". The level of vulnerability to adverse events differs from supply chain to supply chain. Complex supply chains, consisting of thousands of globally distributed interdependent suppliers, are more vulnerable than simple ones. In such complex supply chains, a disruption in any node or link can quickly propagate through the entire supply chain, resulting in a substantially degraded overall performance (Dolgui, Ivanov, & Sokolov, 2018; Ivanov, Sokolov, & Dolgui, 2014). Such negative impacts can be reduced by empowering the supply chain to be able to resist and recover from adverse events (Knemeyer, Zinn, & Eroglu, 2009), or in other words, to make the supply chain resilient to disruption. Resilience is a multidimensional and multidisciplinary concept. In the literature on supply chain management, the most common definition of resilience belongs to Ponomarov and Holcomb (2009) who define resilience as "the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function". The existing research for supporting supply chain resilience focuses on either (i) developing frameworks for identifying key drivers of supply chain resilience and developing strategic guidelines to achieve them (Blackhurst, Dunn, & Craighead, 2011; Christopher & Peck, 2004; Craighead et al., 2007); or (ii) developing methods to support stress testing of a supply chain with the aim of identifying vulnerability sources in need of resilience practices, as well as assessing the effectiveness of different resilience practices to cope with disruptions. The focus of this research is on the latter category. The literature offers two approaches for stress testing of a supply chain aimed at improving its resilience: Probability-based approaches and scenario-based approaches. In probability-based approaches, the more conventional approach, the underpinning assumption is that the probability of occurrence and the impact of risk is known or can reliably be estimated (Simchi-Levi, Kaminsky, & Simchi-Levi, 1999). Next, damage is calculated as a function of the harmful impact of a risk event on supply chain performance and the probability of occurrence of the risk event (Heckmann, Comes, & Nickel, 2015). Several scholars applied probability-based approaches for quantifying risk associated with a supply chain (Deleris, Elkins, & Pate-Cornell, 2004; Fang, Zhao, Fransoo, & Van Woensel, 2013; Wu & Olson, 2008; Yu & Goh, 2014).

Alternatively, in scenario-based approaches toward stress testing of a supply chain, a set of scenarios that represent plausible supply chain disruptions is selected. Next, the supply chain performance is assessed under each scenario. The goal is to identify sources of vulnerability in the supply chain that have a high negative impact on supply chain performance and to develop mitigation strategies that can reduce the impact of these disruptions (Babazadeh & Razmi, 2012; Klibi & Martel, 2012; Sawik, 2013).

The literature on the methods for stress testing of a supply chain reveals several research gaps. First, probability-based approaches are fine for common supply chain disruptions and high frequency-low impact risks. However, such approaches can be highly misleading when dealing with less frequent or unknown disruptions (Heckmann et al., 2015). Probability-based approaches focus on the root causes of risk and their probability of occurrence. However, estimation of the likelihood of a natural disaster, factory fires, and many other adverse events is nearly impossible (Chopra & Sodhi, 2004; Simchi-Levi, Schmidt, & Wei, 2014). Also, probability-based approaches normally give the same weight to high frequency-low impact events and low frequency-high impact events resulting in an underestimation of losses due to the aggregation over time horizons (Klibi et al., 2010). Moreover, disruptive risks are ignored by managers because they believe that the probability of their occurrence is very low, so these risks can be neglected (Johnson & Nagarur, 2012). In contrast, scenario-based approaches are more effective if one is dealing with low frequency-high impact risks, for which identifying the root cause, frequency of occurrence, and impact of the risk is almost impossible. This type of risk is caused by rare events that, if they happen, significantly reduce supply chain performance.

A second research gap, specific to scenario-based approaches, is that usually only a limited set of scenarios is selected for representing future risks. These selected scenarios are typical disruptions that could happen in critical elements of the first or second tier in the supply chain. However, given the complexity of today's supply chains and the unpredictable nature of disruptive events, it is insufficient to rely on human reasoning for selecting possible disruption scenarios for stress testing a supply chain. Given the large number of actors in today's complex supply chains, vulnerabilities may exist further upstream or downstream (Simchi-Levi et al., 2014).

A third research gap is that only few researchers consider the impact of compound events and compound effects in addressing supply chain disruption management (Klibi & Martel, 2012; Klibi et al., 2010; Zobel & Khansa, 2014). Considering only the impact of individual disruptions is misleading because a combination of unexpected events, or an event that impacts multiple actors in the supply chain at the same time, may have diverse and complicated effects that should be considered in resilience practices (Raymond et al., 2020). For example, the 2011 tsunami in Japan disrupted all Toyota's suppliers in a specific region at the same time (Matsuo, 2015).

A fourth research gap is how to assess the robustness of strategies to cope with supply chain disruptions (Hosseini, Ivanov, & Dolgui, 2019). Identifying disruption management strategies that have satisfactory outcomes under various disruption scenarios is one of the main foundations of a resilient supply chain. However, in a situation where one is dealing with a large set of disruption scenarios, identifying robust strategies is challenging.

The aforementioned gaps lead to the following central research question for this paper: what is an appropriate approach for supporting resilience improvement in a supply chain that is capable of addressing limitations of the conventional approaches for considering intrinsic limits to the predictability of disruptive risks, complexity of a supply chain, and robustness of disruption management strategies in resilience practices? To overcome the limits to the predictability of disruptive risks, this paper suggests using consequence-based risk analysis of a supply chain. In contrast to the conventional cause-based risk analysis approaches that deal with identifying the root cause of a risk and estimating its characteristics such as the probability of occurrence and the intensity, the consequence-based risk analysis focuses on exploring plausible scenarios of consequences of risks at elements along the supply chain, no matter what would be the root cause, to get insights in the vulnerabilities within a supply chain. For example, no matter how often and for how long a flood or a bankruptcy or a cyber-attack stops the operations of a supplier within a supply chain, the consequence-based risk analysis investigates the vulnerability of the supply chain to a disruption of that supplier. Conducting a reliable consequence-based risk analysis is still challenging, specifically in complex supply chains, because it needs an investigation of a wide range of risk consequences associated with thousands of interdependent, dynamic and globally distributed elements of the supply chain. In such a supply chain, some vulnerability sources might have remained uninvestigated due to the limited data availability especially from actors more than a few tiers upstream or downstream. Also, a reliable consequence-based risk analysis needs consideration of not only imaginable scenarios of risk consequences, but also an exploration of not-yet-experienced and implausible scenarios for risk consequences. This research explores the potential of an emerging methodology called decision making under deep uncertainty (DMDU) for supporting consequence-based risk analysis of a complex supply chain towards improving its resilience. DMDU is concerned with dealing with decision problems which involve *deep uncertainty* and *complexity*; the two aspects of the problem of consequence-based risk analysis of a complex supply chain. Deep uncertainty refers to the situation where decision makers do not agree or do not know the explicit relations between the inputs and outputs of a system or its boundaries. Moreover, it reflects the situation where outcomes of interest and their importance to the system under study as well as the probability distribution of the uncertain parameters are not clearly defined (Lempert, Popper, & Bankes, 2003). It also refers to situations where decisions are made in interaction with the system over time (Haasnoot, Kwakkel, Walker, & ter Maat, 2013). Deep uncertainty methods use multiple views of the future to prioritize decisions that have satisfactory outcomes under as many scenarios as possible (Lempert et al., 2003). In contrast with the conventional decision making paradigm that deals with predicting the future and acting based on that prediction, the DMDU paradigm deals with exploring the future and adapting in response to the unforeseen future (Walker et al., 2013; Stanton & Roelich, 2021). Among several deep uncertainty methods, this paper particularly focuses on robust decision making (RDM) (Lempert & Collins, 2007; Lempert, Groves, Popper, & Bankes, 2006; Lempert et al., 2003) for performing a consequence-based risk analysis of a supply chain. We conceptualize a supply chain as consisting of nodes, where operations for processing and storage of materials take place, and links where transport operations take place. RDM enables the stress testing of a supply chain over a comprehensive set of plausible scenarios of risk consequences compromising any nodes or links individually or multiple nodes and/or links simultaneously. We account for spatio-temporal correlations among disruptions. We characterize a risk consequence by several deeply uncertain parameters and then using the RDM approach, that enables the generation of many disruption scenarios by sampling across combinations of disruption characteristics. A set of thousands of simulation runs is then analyzed using statistical analysis tools to discover systematic patterns of behavior to identify vulnerable elements in the supply chain. Finally, several disruption management plans are evaluated to identify the most robust plans for tackling these vulnerabilities. For testing our approach, we developed a stylized supply chain of an assemble-to-order (ATO) manufacturer and modeled risk events in its network. The system is represented using a scalable discrete-event simulation model that captures the complexity of a real-world supply chain.

The paper is organized as follows. In section 4.2 we explain our research method. Section 4.3 introduces the case study and presents the results of applying the method. Finally, the discussion and conclusions are presented in Section 4.4.

4.2 Research method

4.2.1 Background on robust decision making (RDM)

Several approaches have been developed to support decision making under deep uncertainty (e.g. Haasnoot et al., 2013; Kasprzyk, Nataraj, Reed, & Lempert, 2013; Kwakkel, Walker, & Marchau, 2010; Lempert et al., 2006; Walker, Rahman, & Cave, 2001). Robust decision making (RDM) has proven to be a promising approach for decision making under deep uncertainty (Lempert et al., 2006). The underpinning concept in RDM is to use computational experiments to explore a wide range of *possible* futures rather than trying to *predict* the future. In RDM one runs models hundreds or thousands of times over a wide set of scenarios that cover uncertainties in the input variables. Using statistical analysis and visualization tools, decision makers gain insight into systematic patterns of behavior of the system across the scenarios. RDM aims at identifying and evaluating robust strategies: strategies that have satisfactory outcomes across many possible states of the system and its environment. The possible solution strategies can be tested in separate sets of model runs, analyzing their individual and combined effectiveness across the set of scenarios. Solution strategies that are effective over a large number of scenarios are called 'robust'. In this regard, RDM shares similarities with the minimax approach developed by Wald (1950) and the minimax regret approach introduced by Savage (1951). RDM focuses on identifying strategies that perform well across a broad range of possible futures. it is similar to Wald's minimax approach, which aims at minimizing the worst-case loss, and Savage's minimax regret approach, which aims at minimizing the maximum regret of not choosing the best possible action. Both Wald's and Savage's approaches emphasize robustness in decision-making under uncertainty, which aligns with RDM's goal of ensuring strategies that are effective despite deep uncertainty. Compared to the Wald and Savage approaches, RDM considers a broader scope for handling uncertainty by exploring a wide range of plausible futures without requiring precise probability estimates or predefined scenarios. This approach ensures that strategies remain effective across unexpected conditions. However, Wald and Savage methods may not fully capture the complexity of deep uncertainty. While conventional decision theory deals with selecting a few scenarios upfront, RDM provides *a posteriori* decision support where decision makers can discuss scenarios that matter the most for decision making after the analysis (Bryant & Lempert, 2010; Lempert & Collins, 2007). RDM starts with decision framing in which decision makers identify objectives, uncertainties and possible strategies for the system under study. After that, computer models are used to generate a large data set of results, where each result is the outcome of running one future scenario, either for the system as-is (for analysis) or combined with one or more solution strategies (for analyzing the robustness of the strategies). Using data analysis techniques, the vulnerabilities of the existing system are identified together with the evaluation of possible intervention strategies. Then decision makers can make a tradeoff among alternative strategies to select the most robust strategy that has the most satisfactory outcomes under as many futures as possible. The RDM steps are explained in more detail with respect to consequence-based risk analysis of a supply chain in sub-section 4.2.2.

There are two categories of research in the literature on RDM. The first category focuses on the application of RDM for addressing a decision making problem under deep uncertainty. Examples are applications of RDM in flood risk management (Lempert et al., 2013a; Ramm, Watson, & White, 2018), water management (Groves & Bloom, 2013; Lempert & Groves, 2010; Rosenzweig et al., 2011), and climate change (Lempert, Schlesinger, & Bankes, 1996). The second category of research on RDM focuses on the expansion of methods for supporting RDM. As an example Kasprzyk et al. (2013) expanded RDM for multiple objectives (MORDM). In this study researchers demonstrated how global optimization with multi-objective evolutionary algorithms (MOEAs) can be used to explore tradeoffs across planning alternatives. In another study Herman & Zeff (2014) advanced the MORDM framework to address investment decisions regarding long-term and short-term water plans in four cities in a region of North Carolina, U.S..

Despite the rich applications of RDM in disciplines like water management and climate adaptation, RDM has not yet been extensively used for supply chain management. A few exceptions are Halim, Kwakkel, & Tavasszy (2016), Gruchmann et al. (2019) and Paul & Venkateswaran (2020). As an example Halim et al. (2016) used scenario discovery and worst-case discovery to investigate the effect of deep uncertain factors on the competitive position of the Port of Rotterdam.

This paper adds to the literature of supply chain risk management by adapting the RDM approach to support consequence-based risk analysis of a complex supply chain for improving its resilience, where information about risks associated with the supply chain is largely unknown or can be poorly characterized.

4.2.2 RDM framework for Consequence-based risk analysis

In order to investigate the applicability of the RDM approach for addressing the gaps in the approaches for supporting resilience improvement of a complex supply chain, this research adopts the underpinning framework of RDM. The framework uses a series of steps as shown in Figure 1. In the rest of this section, we explain how the RDM steps can be operationalized for consequence-based risk analysis for supply chains.

Step 1: Decision structuring: The first step of RDM starts with structuring the information regarding the problem under study. Here, decision makers define objectives, potential strategies for meeting objectives, and uncertainties that might affect success of possible strategies. To this end, RDM employs the XLRM framework (Lempert et al., 2003). The elements of the framework are:

*X: External factors***;** the uncertainties outside the control of decision makers. In consequence-based risk analysis of a supply chain, external factors include deeply uncertain attributes of a risk consequence within the supply chain. A risk consequence can be defined as a disruption within the supply chain network with several attributes:

- *Disrupted tier:* a deeply uncertain variable representing the tier of supply chain in which the disruption happens.
- *Disrupted* region: a deeply uncertain variable representing the geographical region in which the disruption happens.
- *Disrupted component*: a deeply uncertain variable representing the type of component (product) of which the availability is disrupted.
- *Disrupted element*: a deeply uncertain variable representing the type of facility that is disrupted.
- *Disruption duration*: a deeply uncertain variable representing the duration of a disruption.
- *Post-disruption capacity:* a deeply uncertain variable representing the remaining capacity of the disrupted element after disruption. It is a variable for representing the intensity of a disruption. After a disruption, the remaining capacity of the disrupted element can vary between zero to a hundred percent depending on the severity of the disruptive event.
- *Recovery rate of disrupted capacity:* a deeply uncertain variable representing the time it will take for the disrupted element to recover fully after implementing a post-disruption contingency plan. It is a variable for representing the intensity of a disruption and it is independent of the managerial choice for mitigating disruptions. This variable is considered deeply uncertain because it depends on several factors that are out of control of a decision maker such as scarcity of the backup capacity that might be constrained due to the disruption as well; or long waiting time for availability of the backup capacity due to the existence of a queue for accessing the backup capacity. For example, imagine the disruption of a production plant due to a fire accident in a factory. It may take a few weeks to several months for the factory, depending on the severity of the fire, to rebuild or repair the production plant and get it back to normal. This is different from the recovery time of the supply chain as a performance metric, which refers to the time it takes for a disrupted supply chain to deliver products to end customers within a normal (no disruption) lead time.

Given the possible ranges of these deeply uncertain attributes, many possible scenarios of risk consequences can be generated and explored regardless of the cause of the risk and its probability of occurrence. We explore what, where, when, how long, and how intense an element of a supply chain can be disturbed and unable to function.

L: Policy levers; the mitigation actions that the decision makers would like to explore. In consequence-based risk analysis of a supply chain, policy levers are actions for reducing the negative impacts of supply chain disruptions. Examples are flexibility-based strategies such as multiple sourcing, flexible contracting, flexible product configurations, flexible transportation, and flexible manufacturing processes, or redundancy-based strategies such as extra inventory, back up suppliers and overcapacity (Behdani, Adhitya, Lukszo, & Srinivasan, 2012).

M: Performance metrics; the outcomes that decision makers are interested in. In consequence-based risk analysis of a supply chain, outcomes of interest can be any of the supply chain performance metrics such as total market lead time, total cost, and total revenue. The outcomes of interest also can be any of the resilience-related performance metrics such as total recovery time of the supply chain or time to detect disruption.

R: Relationships; one or more models representing the dependencies among external factors. In consequence-based risk analysis of a supply chain, analytical models or simulation models can be used for measuring the impact of potential disruptions on supply chain performance, as well as evaluating disruption management strategies (Rajagopal, Prasanna Venkatesan, & Goh, 2017). Several researchers highlight that when supply chains consist of a complex network of actors and activities and in case multiple resilience strategies are to be evaluated, simulation is the most promising approach due to its flexibility for exploring a variety of what-if scenarios (Schmitt & Singh, 2009).

Step 2: Case generation: In the second step of RDM, computer models are used to generate a large database of simulation model results. Here, one systematically varies the assumptions about the uncertainties (external factors) defined in step one of RDM to generate many plausible scenarios. Each unique set of assumptions is a scenario. Thousands of scenarios are generated that are each analyzed using the simulation model or analytical model to generate a database of performance outcomes for each scenario. The choice and combination of assumptions is called the experimental design. In RDM the experimental design is established by sampling uniformly across the uncertainty space that is spanned by the combination of the external factors. In consequence-based risk analysis of a supply chain, scenarios of risk consequences are generated by defining value ranges for each of the attributes of a disruption and sampling across them. Using the simulation model, the impact of these scenarios on supply chain performance metrics, possibly including disruption management strategies, are evaluated.

Step 3: Vulnerability analysis: In the third step of RDM, statistical analysis and visualization approaches are employed to help identifying future scenarios in which the objectives of decision makers are not satisfied. To this end RDM uses scenario exploration and discovery (Bryant & Lempert, 2010). Scenario discovery is a method that helps in identifying combinations of external factors where a candidate strategy fails or succeeds. In consequence-based risk analysis of a supply chain, analyzing a large ensemble of disruption scenarios together with their associated impacts on the supply chain performance measures results in the identification of the vulnerability sources, such as suppliers or transport links, specific geographical locations, disruption durations longer than a specific time or post disruption capacities less than a specific amount. Accordingly, the performance of candidate strategies against disruptions are evaluated over a large variety of possible disruption scenarios to assess their effect on the identified vulnerabilities.

Step 4: Trade-off analysis: The information obtained from the third step of RDM helps decision makers to highlight the vulnerabilities within the system of study and to develop and evaluate alternative strategies that have satisfactory outcomes under as many future scenarios as possible, in other words, robust strategies to tackle the vulnerabilities. In consequence-based risk analysis of a supply chain, this results in identifying the disruption management strategies that have satisfactory outcomes under as many disruption scenarios as possible.

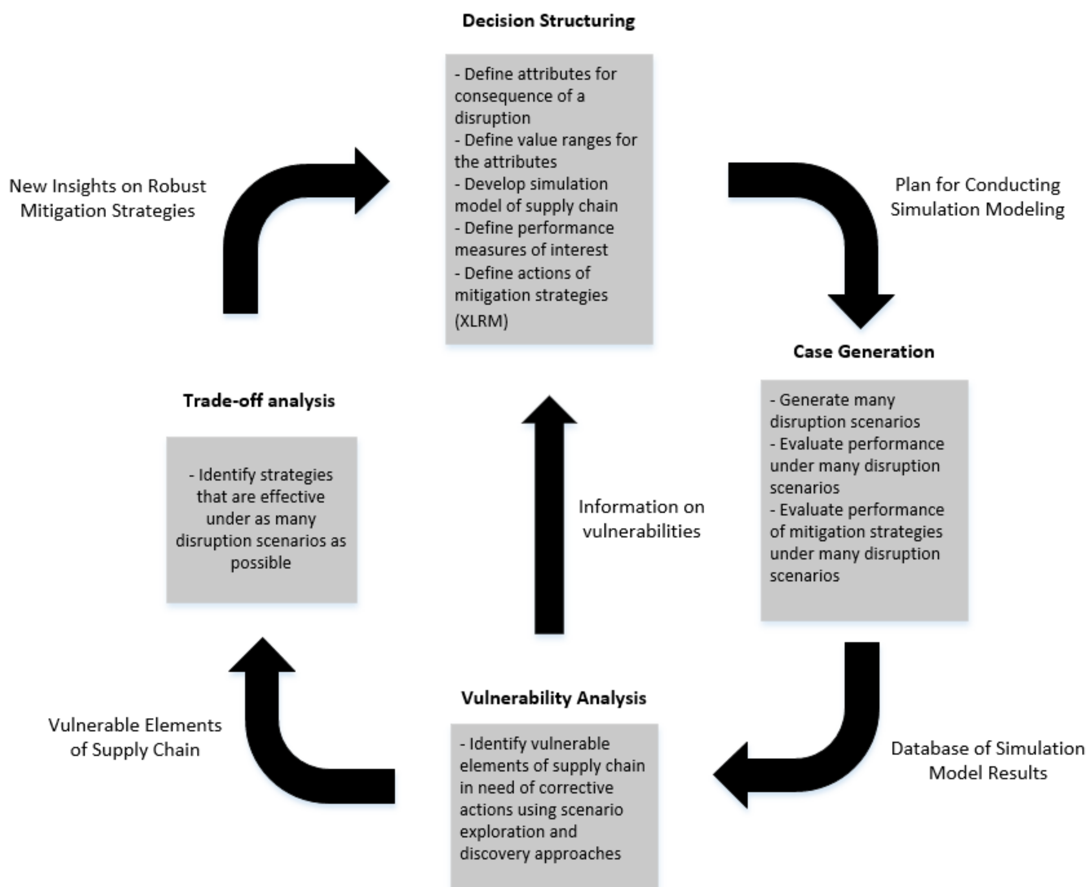


Figure 1. RDM framework for Consequence-based risk analysis (Adapted from Lempert et al. (2013)).

4.3 Case illustration and results

4.3.1 Stylized supply chain

In order to examine the applicability of the RDM approach and to demonstrate its key aspects in addressing consequence-based risk analysis of a supply chain, we developed a stylized supply chain of an assemble-to-order (ATO) manufacturer to model disruption in its network. In an ATO supply chain, the final manufacturer (the focal company that has direct contacts with end customers) assembles a final product from sub-assembly components at the moment when actual orders arrive from end customers in a market. The final manufacturer receives sub-assembly components from suppliers of different tiers who are distributed geographically. The stylized supply chain in this research is instantiated using a python-based supply chain network generator specifically developed for the purpose of this research. The network generator is capable of generating a variety of supply chain networks using supply chain characteristics such as the number of tiers, the number of suppliers in each tier, the geographical dispersion of the suppliers, the ratio between make-to-order (MTO) and make-to-stock (MTS) suppliers, and the number of shared suppliers in each tier.

This research used the values of supply chain characteristics presented in Table 1. As shown in Figure 2, the stylized supply chain consists of MTO and MTS suppliers in three tiers within Asia and Europe. The ATO manufacturer, located in Europe, assembles components from suppliers in tier 1, which are located either in Europe or Asia, and sells its finished product in two separate markets in Asia and Europe. Suppliers in tier 1 and beyond assemble parts and materials they receive from their sub-suppliers. We developed the simulation model of the stylized supply chain explained in this section as the underpinning model for illustrating the key aspects of applying RDM in consequence-base risk analysis for a supply chain. The following sub-section presents the results of the case study.

Table 1. Values of supply chain characteristics for developing the stylized supply chain

Supply chain characteristics	**Value**		
Number of tiers	3		
Number of sub-suppliers of a supplier in each tier	Tier 1	Tier 2	Tier 3
	5	4	3
Percentage of assembled components in each tier	with: 80% without:20%	with: 50% without:50%	with: 80% without:20%
Percentage of MTS vs MTO suppliers in each tier	MTS:20% MTO:80%	MTS:50% MTO:50%	MTS:80% MTO:20%
Geographical dispersion of suppliers	Asia: 20% Europe: 80%	Asia:50% Europe:50%	Asia:80% Europe:20%
Number of shared suppliers in each tier	2	1	0

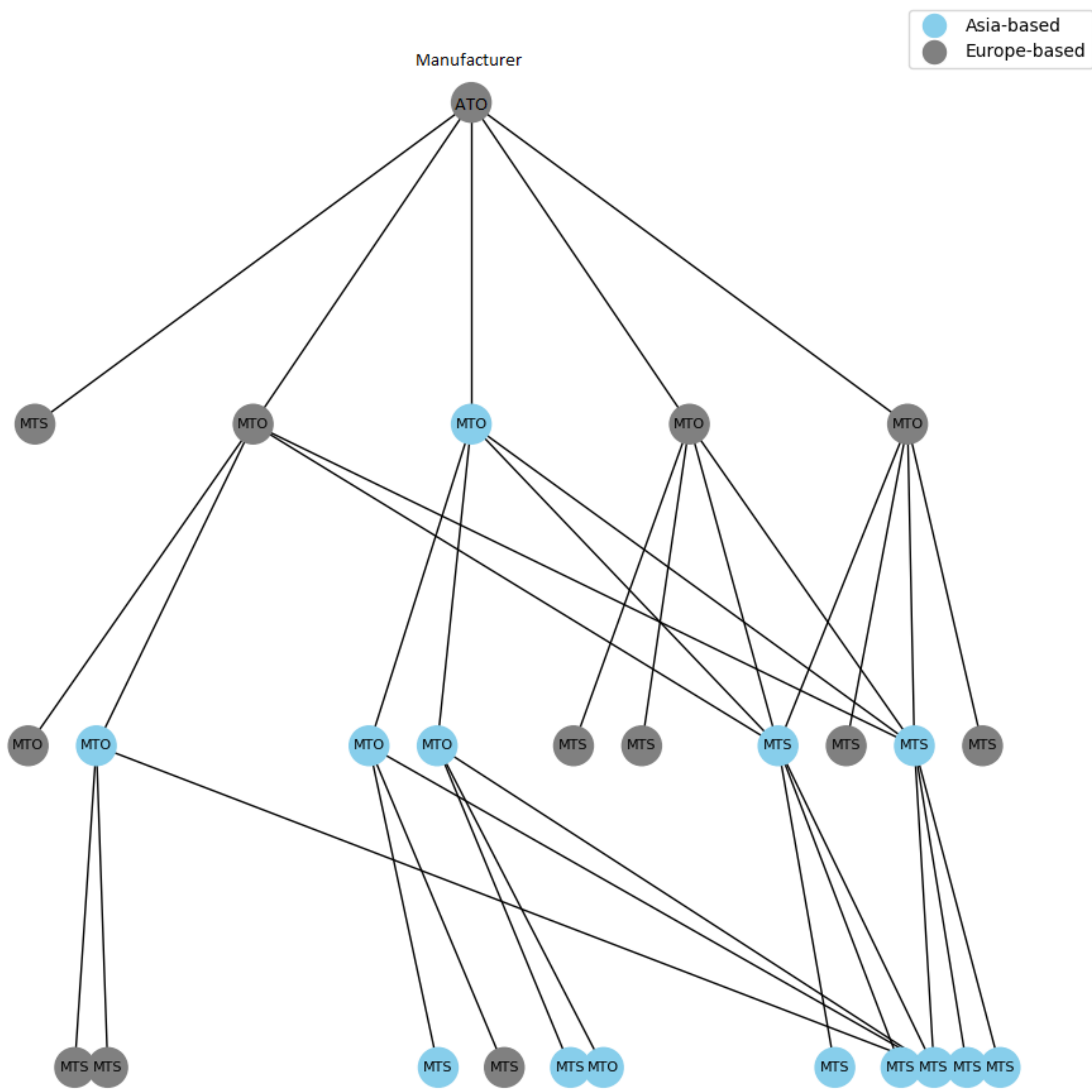


Figure 2: Network of the stylized supply chain.

4.3.2 Result

In this section we demonstrate the results of applying RDM to consequence-based risk analysis of the stylized supply chain. The subsection structure follows the steps of the RDM framework for Consequence-based risk analysis of a supply chain as shown in Figure 1.

4.3.2.1 Decision structuring (step 1)

In the first step, we identify the key elements of the XLRM framework from analyzing the stylized supply chain.

Uncertainties (X): Uncertainties related to the stylized model can be categorized into two groups. The first group includes stochastic uncertainties that typically exist in the supply chain environment, such as uncertainties related to demand, production times, and transportation times. These stochastic uncertainties are addressed through multiple runs of the discrete-event simulation model. The second group of uncertainties contains the ones related to disruptions and these are deeply uncertain parameters that should be addressed through RDM analysis. The deeply uncertain parameters here are classified in two groups: a) supplier-related parameters that identify the tier, the region, and the component (product) of the supplier who is disrupted and b) disruption-related parameters that include duration of disruption, the disrupted element, post-disruption capacity of the disrupted element, and recovery rate of the disrupted element. The definition of the deeply uncertain parameters is given in sub-section 4.2.2.

Consequence-based risk modeling, which is the underling approach for modeling disruption in this paper, is addressed by using a combination of different values of the deep uncertainties. This way many scenarios of consequences of a risk associated with a supply chain can be explored independent of the cause of the risk and its probability of occurrence. We explore what, where, when, how long and how intense an element of a supply chain cannot fulfill its function as a result of the risk consequence.

A summary of the uncertainties is provided in Figure 3. The categorical range associated with each deep uncertainty is shown in Table 2.

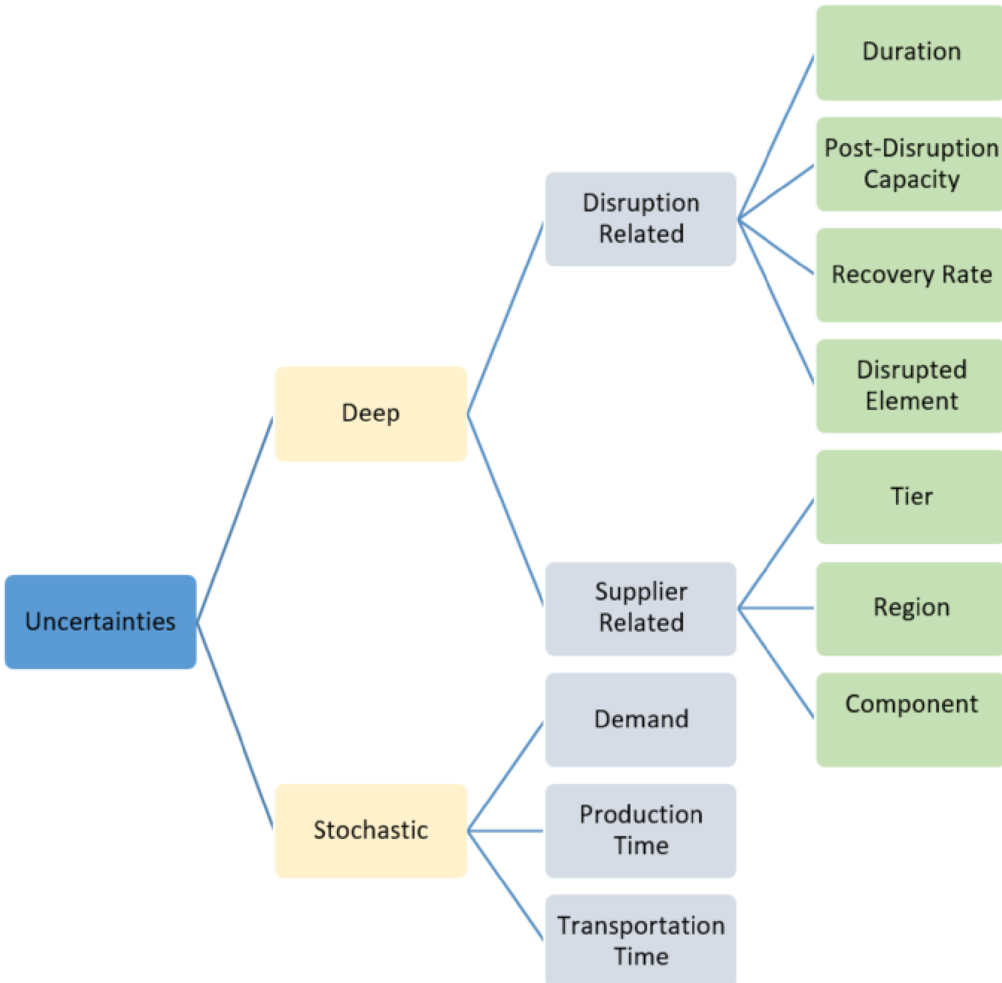


Figure 3. Categories of uncertainties.

Table 2. Deep uncertainties and their associated ranges

Deep uncertainties	Range
Disrupted region	Asia-Europe-Both Asia and Europe
Disrupted tier	1-2-3-All three tiers
Disrupted component	Shared-Not shared- Both Shared and Not shared
Disrupted element	Production plant-Transportation link-Inventory
Disruption duration	Long-Medium-Short
Post-disruption capacity	Large-Medium-Small
Recovery rate	Fast-Medium-Slow

Policy levers (L): in supply chain disruption management toward improving resilience, the policy levers include mitigation actions used by supply chain managers to cope with disruptive events. Examples are the use of multiple sourcing, flexible transportation, flexible manufacturing processes, extra inventory, back up suppliers and overcapacity. Since this paper is a methodological paper in which we aim to investigate the applicability of the RDM approach to support improving resilience, rather than focusing on detailed aspects of mitigation strategies to cope with disruptions, we define four stylized mitigation strategies to represent how RDM can be applied to explore robustness of the different mitigation strategies. For the sake of clarity, we represent a mitigation strategy using two variables: the cost of replacing the disrupted capacity, and the time to availability, which indicates the lead time of implementing the strategy. By combining different values of these two variables, we define four hypothetical mitigation strategies as follows:

- *Expensive-Fast:* this represents a mitigation strategy with high cost of implementation but a short time to availability. An example of such a mitigation strategy is the usage of strategic stock where a firm keeps inventory of strategic products and products that could become a bottleneck. Although such a strategy involves extra cost, it enables a quick replacement of the disrupted capacity in case of a disruption.
- *Cheap-Slow:* this represents a mitigation strategy with a low cost of implementation but a longer time to availability. An example of such a mitigation strategy could be the implementation of a backup strategy where a firm has backup suppliers for its critical components that enable the firm to switch to alternative sources in case of disruption. Since the backup supplier is activated only when the primary supplier disrupts, it may involve less cost to the firm in comparison with the strategic stock policy. It may, however, take longer for the backup capacity to become available in comparison to the strategic stock policy.
- *Medium:* this represents a mitigation strategy with an average cost of implementation and an average time to availability. An example of such a mitigation strategy is to use a mix of investing in strategic stock and a backup supplier strategy. In this strategy, the firm makes a tradeoff between cost of the mitigation measures and time to availability of the mitigation measures.
- *Acceptance:* we also explored a scenario in which no mitigation strategy such as strategic stock or backup is used by the firm to replace disrupted capacity. In the acceptance strategy, a firm waits for the disrupted capacity to become available again. In this strategy, the company does not invest anything in resilience, and it is a good reference strategy to compare the other strategies with.

Relationships (R): To model the relationships of an ATO supply chain as well as modeling the behavior of the supply chain under disruption together with the evaluation of mitigation strategies, we developed a discrete event simulation model. The details of the simulation model are explained in chapter 3 of this dissertation.

Performance metrics (M): to measure the impact of disruption on performance of the stylized supply chain and also evaluate the robustness of various disruption mitigation strategies, we consider several performance measures including market lead time, time to detect disruption, total recovery time, total cost, and total revenue. The definition of the performance measures is given in chapter 3 of this dissertation.

4.3.2.2 Case generation (Step 2)

The second step of RDM is the generation of a database of plausible disruption scenarios and their impact on performance measures. To this end we perform exploratory modeling: a model-based technique that can systematically explore a very large ensemble of plausible scenarios (Bankes, 1993; Kwakkel & Pruyt, 2013). To conduct exploratory modeling we use the Exploratory Modeling and Analysis (EMA) workbench (Kwakkel, 2017). The EMA workbench is an open-source Python library that supports exploratory modeling by the generation and execution of a series of computational experiments as well as the visualization and analysis of the results of the computational experiments. The EMA workbench is interfaced to the discrete event simulation model of the stylized supply chain and is used to define computational experiments to conduct with the simulation model, to analyze the results of these experiments, and to store the results. For the generation of disruption scenarios, we sampled over the 7 uncertainties explained in table 2 and we used 1000 scenarios that were drawn from the input space using Latin Hypercube sampling. We combine this with the four different strategies against disruption: *Expensive-Fast, Cheap-Slow, Medium and Acceptance*. This produces 4000 experiments in total. To address stochasticity (see sub-section 4.3.2.1), 5 replications of each experiment are run of the discrete event simulation model of the stylized supply chain using different seeds.

4.3.2.3 Vulnerability analysis (Step 3)

The exploration we performed in the previous section resulted in a data base of 4000 computational experiments that we analyzed using the EMA workbench and that will be discussed in the rest of this section.

A high-level analysis first looks at the impact of deep uncertainties on supply chain performance. To this end a feature scoring approach is used, which is a machine learning alternative to global sensitivity analysis for identifying the most influential uncertain factors on model outcomes (Geurts, Ernst, & Wehenkel, 2006). Several techniques exist to support feature scoring (Nahar et al., 2021). In this study we selected the so-called 'extra-trees algorithm', mainly because of its accuracy for non-linear regression problems (Jaxa-Rozen & Kwakkel, 2018). Figure 4 shows the results of the extra trees feature scoring for the stylized supply chain. The figure indicates which of the disruption parameters have the greatest relationship to the performance metrics. A higher number (color towards the yellow) implies a higher impact of the parameter (x-axis) on the performance metric (y-axis). The results in Figure 4 show that among disruption parameters, the disrupted element has the highest impact on supply chain total cost and supply chain total revenue. However, post-disruption capacity of the disrupted element influences market lead time the most. Also, the disrupted component has the highest impact on total recovery time of the stylized supply chain.

To get more in-depth insights on how combinations of deep uncertainties affect the outcomes of interest regarding supply chain performance under disruption, we apply Scenario discovery (Bryant & Lempert, 2010). In scenario discovery the computational experiments are analyzed subsequently with statistical machine learning algorithms to identify combinations of key factors that identify those situations where the objectives are met or are not met. For instance, in our stylized supply chain we are interested in identifying combinations of factors that cause an unacceptable supply chain performance in terms of high values for time to detect disruption. The scenario discovery method we use is the Patient Rule Induction Method (PRIM) (Friedman & Fisher, 1999). PRIM can be applied to identify combinations of values of input parameters of a model that result in similar characteristic values for an outcome of the model. To this end, PRIM looks for a set of subspaces of the input space where the values of the output variables are noticeably different from their average values. PRIM describes such subspaces with n-dimensional 'boxes' within the input space. Several alternative boxes are generated by the PRIM algorithm, which are different in terms of coverage (proportion of the total number of cases of interest), density (the fraction of the cases of interest to the total number of cases in a box), and number of restricted dimensions (limited set of dimensions of the model input space). The decision maker can select a box for interpretation of the result based on a trade-off between different values of coverage, density and restricted dimensions (Kwakkel, Auping, & Pruyt, 2013). The first step in applying PRIM is to specify the result of interest. For instance, suppose that for the stylized supply chain we are interested in the values of time to detect disruption higher than 10000 hours. Figure 5 shows the results of the PRIM analysis. Figure 5(a) shows the tradeoff between coverage, density and the number of restricted dimensions. We are interested in a scenario (i.e., a combination of factors) that captures a high proportion of the total number of cases of interest (i.e., a high coverage) while the fraction of the cases of interest to the total number of cases in that scenario is noticeable (i.e., a high density) (Bryant & Lempert, 2010). Figure 5(b) shows that with a coverage of 82% and a density of 74%, when post-disruption capacity is medium or small, simultaneous disruption of both shared and not-shared components, or a disruption of only the not-shared components can result in an unacceptable supply chain performance in terms of a high time to detect disruption.

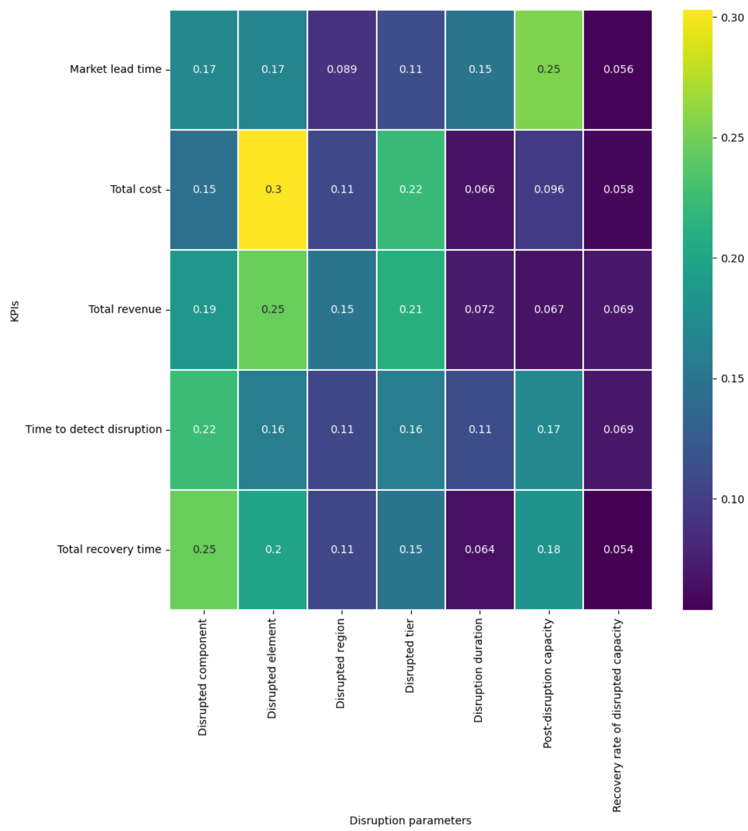
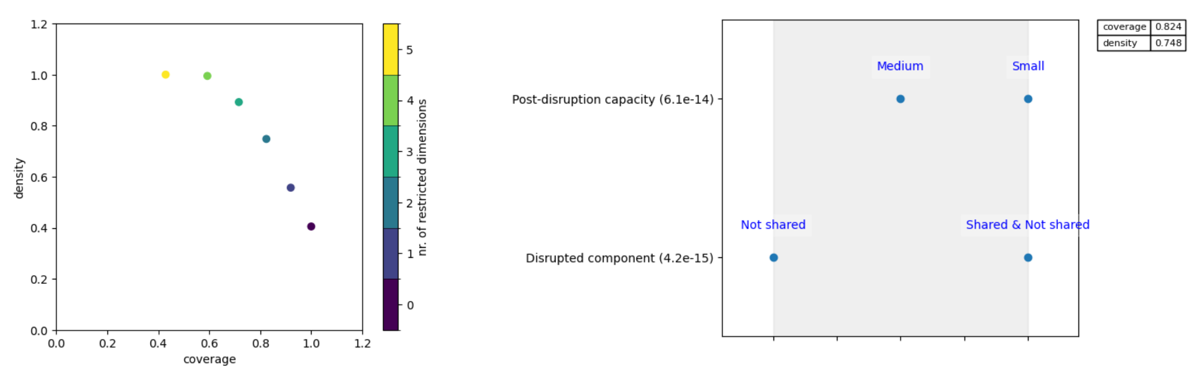


Figure 4. Results of the feature scoring analysis.



(a) (b)

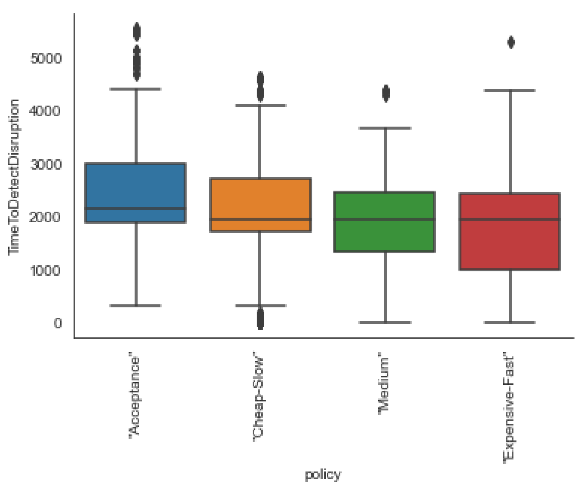
Figure 5. Result of the PRIM analysis for time to detect disruption with a trade-off between coverage and density (left) and the selected box information (right).

4.3.2.4 Trade-off analysis (Step 4):

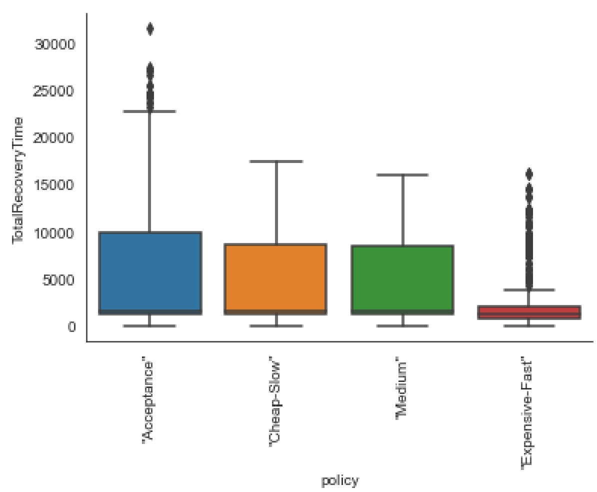
A simple tradeoff analysis on how different strategies against disruption affect the performance measures of the stylized supply chain is presented in Figure 6. As depicted in Figure 6(a), for the stylized supply chain, almost all four strategies have the same performance in terms of the time to detect disruption. Figure 6(b) shows that the total recovery time has better values under the Expensive-Fast strategy. Figure 6(c) shows that total cost has its worst value under the Expensive-Fast strategy and best value under the Cheap-Slow strategy. Market lead time and total revenue have their worst values under the Acceptance strategy (Figure 6(d) and Figure 6(e)).

We can also make a robustness tradeoff among different strategies. There are several metrics for measuring robustness (McPhail et al., 2018). For the stylized case we adopt a so-called regret-based metrics (Savage, 1951) in which the regret for a decision policy is calculated as the difference between the performance of the selected policy and the performance of the best policy under a particular scenario. In particular, we apply the maximum regret metric (J. D. Herman, Reed, Zeff, & Characklis, 2015) in which we calculate maximum regret values for all scenarios, and the robust policy is the policy with the lowest maximum regret value. Figure 7 presents the parallel coordinates plot of robustness values of the four different strategies against disruption. The favorable strategy is the one that has the lowest values of regret across all four scenarios. As it is shown in Figure 7, the Acceptance strategy has a low regret on total cost and total revenue but a high regret on the three other objectives. The Expensive-Fast strategy is the most robust strategy in terms of market lead time but it has high regret for total cost and total revenue. The Cheap-Slow and Medium strategies have high regret for market lead time and total revenue but they are robust strategies in terms of total cost. Both strategies have an average performance in terms of time to detect disruption and total recovery time.

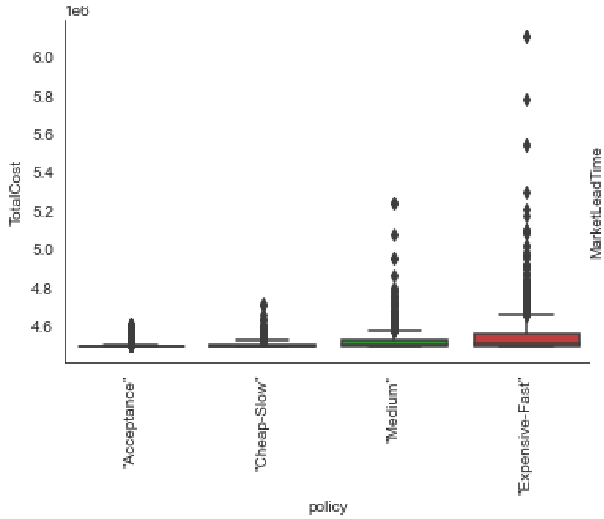
This information helps supply chain decision makers with different risk attitudes (risk averse or risk seeking) to make tradeoffs among potential risk mitigation strategies based on their preference and supply chain mission.



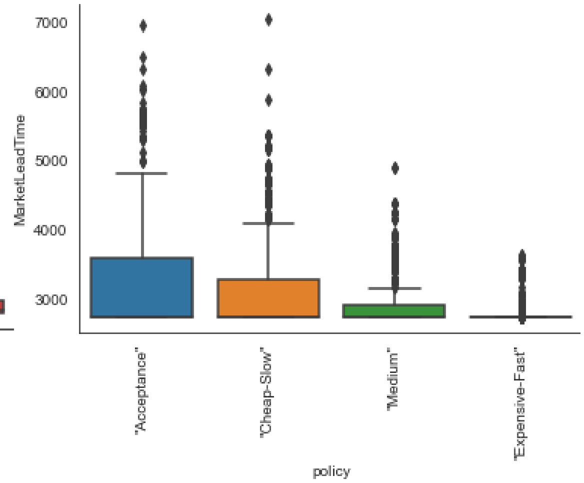
(a)



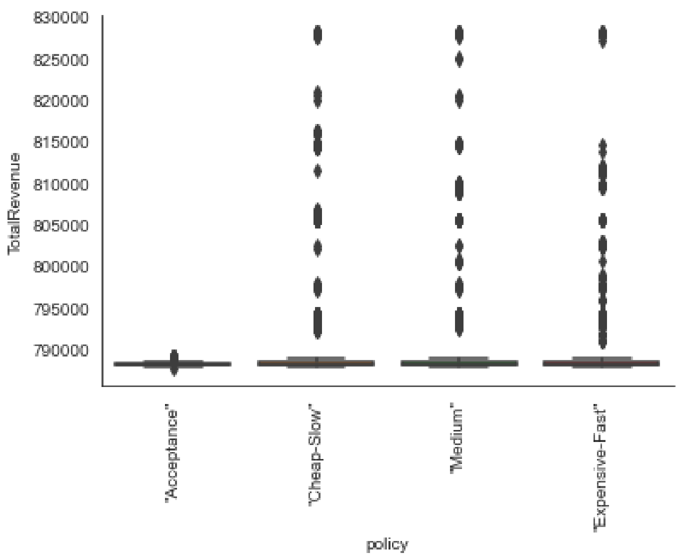
(b)



(c)



(d)



(e)

Figure 6. Box plot of KPIs values form experiments for four different strategies against disruption.

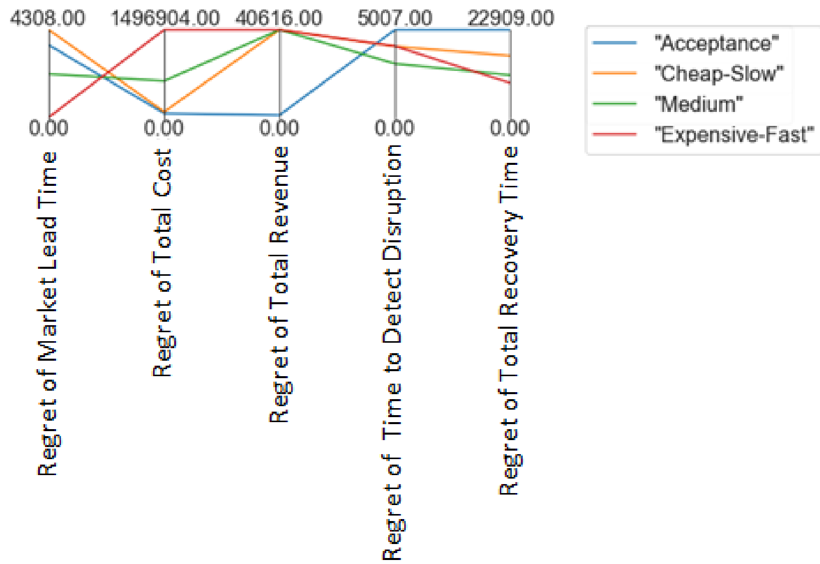


Figure 7. Parallel coordinates plot of robustness values (maximum regret metric) of four different strategies against disruption.

4.4 Discussion and conclusion

This paper provides a method for assessing and enhancing the resilience of a supply chain considering the deeply uncertain nature of disruptive risks. We propose the concept of consequence-based risk analysis in which the focus is on assessing the consequence of plausible risks at elements along the supply chain for identifying the most important vulnerabilities in need of resilience investment. In contrast with conventional risk modeling approaches that deal with identifying the root cause of a risk and determining its characteristics, such as probability of occurrence and intensity, our approach concentrates on analyzing the consequence of potential risks associated with a supply chain, regardless of the root cause of risk. For example, no matter whether a strike or a congestion in a port disturbs a water-based transportation activity within the supply chain, the focus is on answering the question of what will happen if that transport activity is disrupted.

We treat consequence-based risk analysis as a problem of decision making under deep uncertainty (DMDU) to benefit from approaches developed in this field. Specifically, we apply the robust decision making (RDM) approach, which provides supply chain decision makers with methods for identifying the most important exposures to disruption and for determining disruption mitigation strategies that have satisfactory outcomes over many plausible disruption scenarios instead of being optimal under one expected scenario of disruption, which is typical done in conventional approaches toward supply chain disruption management. In RDM, no probabilities are assigned to future disruption scenarios. Therefore, the approach overcomes the need for estimation of risk in stress testing of a supply chain and therefore the mitigation strategies are developed regardless of sub-optimal risk assessment procedures. This results in an improvement of the supply chain resilience to disruption, since all consequences of the risks are analyzed in detail and vulnerable spots on the supply chain are identified.

RDM has been applied for many years to support strategic planning problems under deep uncertainty in a variety of fields, including climate change, flood and water risk management, and economic policy. Deep uncertainty is not yet extensively considered in the supply chain risk management literature. However, with several serious supply chain disruption cases as a result of unlikely events such as a pandemic and geopolitical tensions, it is crucial to incorporate deep uncertainty in supply chain risk management practices nowadays. This research shows that approaches from the DMDU field can be applied successfully for addressing supply chain management problems that suffer from deep uncertainties.

A stylized case study was used to represent the applicability of RDM in consequence-based risk management of a supply chain. We developed a simulation model of a hypothetical ATO supply chain to mimic response of the supply chain to a variety of risk consequences as well as assessing the effect of different risk mitigation approaches. The modular and component-based approach we use for developing supply chain simulation model in this research can be used further for generation of variety of real-world supply chain models consisting of any number of actors across several tiers of the supply chain all around the word. For generating scenarios of risk consequences, we first characterize a risk consequence with several variables. Then using exploratory modeling, many scenarios of risk consequences are generated by combinations of different values of the variables. We use several data mining approaches to analyze the generated results. Analyzing the results of exploratory modeling provides decision makers with insights about the most and the least important disruption variables contributing to the vulnerability of a supply chain. For example, in our stylized supply chain, the feature scoring analysis shows that the disrupted element, disrupted component, and post-disruption capacity are the most important disruption features that should be considered in resilience practices. Also, the recovery rate of disrupted capacity and the disrupted region are the least important factors for the vulnerability of the stylized supply chain so they can be ignored in resilience practices. Supply chain decision makers can study the behavior of the important disruption factors on supply chain vulnerability in more detail and consider those factors when developing resilience strategies. On the other hand, decision makers can leave out the factors that do not contribute to the vulnerability of their supply chain.

The results of exploratory modeling also provide decision makers with insights about combinations of disruption factors that contribute to the vulnerability of a supply chain. For example, in our stylized supply chain, the PRIM analysis showed that poor supply chain performance in terms of time to detect disruption can result from disruption of not-shared components in cases where the post-disruption capacity is low. A decision maker should consider mitigating of disruptions with these profiles to avoid poor supply chain performance in terms of time to detect disruption. The same analysis can be conducted for other supply chain performance measures as well, to support resilience improvement for a supply chain.

Exploring the results of disruption scenarios and their associated impact on supply chain performance helps in identifying sources of vulnerability in the supply chain, which are not easily detectable by human reasoning. Typically, supply chain decision makers tend to focus on assessing vulnerability of the strategic suppliers, for example suppliers of the first tier. However, in complex supply chains consisting of thousands of actors that are distributed globally, hidden risks of disruption can be present anywhere within the supply chain network. Our approach enables a vulnerability assessment of more upstream suppliers and facilities, detection of critical production plants, transport links or distribution centers within a supply chain, and identifying a combination of risk factors that contribute to an unacceptable impact on supply chain performance, for instance caused by concurrent disruptions in multiple tiers, multiple locations or multiple facilities of the network. Considering compound risks in supply chain risk management practices is still limited in the current literature.

Our approach can help decision makers to make a trade-off among a variety of disruption mitigation strategies for enhance the resilience of their supply chains. Robust decision making can help in identification those disruption mitigation strategies that have satisfying outcomes under as many disruption scenarios as possible. This provides the opportunity for supply chain decision makers with conflicting objectives to help with the selection of resilience practices. To show how our approach can contribute, a simplified application of a mitigation strategy is demonstrated.

Our approach enables iterative stress testing of a supply chain by providing multiple views of the future to test several candidate mitigation strategies over many scenarios and refine the strategies in light of the result.

Of course, there are several limitations to this study. For showing how consequence-based risk analysis of a supply chain can be addressed by the RDM approach, we worked with a hypothetical stylized supply chain. Therefore the analysis of the results in this research is based on hypothetical data and it still lacks empirical evidence. The approaches and insights from this research should therefore be tested with real world data.

One possible limitation of this study is that the policy levers that define mitigation strategies for the stylized case study are selected in such a way that they avoid redesigning the supply chain structure. For example, we consider mitigation strategies such as keeping extra inventory or back-up suppliers and capacity. We do not consider strategies such as buying from competitors or building new factories.

In this research we address both deep uncertainties and stochastic uncertainties within a supply chain. Deep uncertainties are treated by exploratory modeling and stochastic uncertainties are treated by carrying out multiple runs of the discrete-event simulation model. We consider demand, production time, and transportation time as stochastic uncertainties, and region of disruption, tier of disruption, disrupted component, disrupted element, disruption duration, post-disruption capacity, and recovery rate of the disrupted element as deeply uncertain parameters for this research. Although other uncertain supply chain related variables such as cost and quality are important in risk management of a supply chain as well, we mostly focused on uncertainties related to time. Although we consider demand, production time and transportation time as stochastic uncertainties in this study, they could easily be treated as deeply uncertain parameters as well.

A final limitation is that the values of the deeply uncertain parameters and of the mitigation strategies are selected as categorical variables for this paper. A more elaborate selection of values could enhance the study and make it easier to translate the results to decision makers in a real case. All methods used can deal with continuous variables or integer variables in addition to categorical variables, so it is for sure not a limitation for the proposed method.

We demonstrated in this paper that the application of RDM is feasible for managing disruptions in complex supply chain networks and unpredictable business environments. The approach enables decision makers to quickly recognize what is important in terms of vulnerability of the network, and what corrective actions are interesting, from exploration among the large amount of information generated from many scenarios of disruption.

Our approach contributes to the literature of supply chain risk management in several aspects. First, our approach addresses the gap of conventional risk assessment approaches that are dependent on a correct estimation of risk attributes, which is hard or impossible in complex supply chains. In our method, one can explore among scenarios of consequences that a risk may have on supply chain performance instead. Second, our approach contributes to the literature of scenario-based approaches toward risk assessment of a supply chain, where, instead of considering a few scenarios of risk consequences, one can explore among many thousands of what-if scenarios that are generated by combination of uncertain risk consequences to draw decision-relevant conclusions. In addition, the MTS-MTO strategy of suppliers, multi-tier supply chain networks, shared sub-suppliers, and region-based suppliers are some relatively unexplored aspects of supply chain resilience research that we consider in our study. We also look at compound risk instead of only focusing on a single point of failures, as mostly addressed by other researchers.

Moreover, our approach is a simulation-based approach where the behavioral aspects of the supply chain are characterized in more details in comparison with similar research in the field where a mathematical or abstract model of the supply chain is used. This may pose questions on the efficiency of the proposed approach, especially in gathering the necessary information for developing the simulation model. Most of the data that is needed for developing the simulation model in this approach can be provided by the ERP system of the modeled organizations. However, obtaining information on suppliers beyond the second or third tier of the network may be hard since some suppliers are reluctant to share information.

Many of the approaches in the literature of supply chain risk management require a precise estimation of the probability and the impact of all risks to consider. In situations where risk attributes are unknown or contested, our approach can be a valuable addition to supply chain risk management enabling decision makers to obtain valuable decision-relevant insights for improving resilience of their supply chains without having to provide data that is often simply not available.

References

Babazadeh, R., & Razmi, J. (2012). A robust stochastic programming approach for agile and responsive logistics under operational and disruption risks. International Journal of Logistics Systems and Management, 13(4), 458. https://doi.org/10.1504/IJLSM.2012.050158

Bakshi, N., & Kleindorfer, P. (2009). Co-opetition and investment for supply-chain resilience. Production and Operations Management, 18(6), 583-603.

Bankes, S. (1993). Exploratory Modeling for Policy Analysis. Operations Research, 41(3), 435–449. https://doi.org/10.1287/opre.41.3.435

Behdani, B., Adhitya, A., Lukszo, Z., & Srinivasan, R. (2012). How to handle disruptions in Supply Chains – An integrated framework and a review of literature. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2114201

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An Empirically Derived Framework of Global Supply Resiliency. Journal of Business Logistics, 32(4), 374–391. https://doi.org/10.1111/j.0000-0000.2011.01032.x

Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. Technological Forecasting and Social Change, 77(1), 34–49. https://doi.org/10.1016/j.techfore.2009.08.002

Chopra, S., & Sodhi, M. S. (2004). Managing risk to avoid supply-chain breakdown. MIT Sloan Management Review, 46(46109), 53–61.

Christopher, M., & Peck, H. (2004). Building the Resilient Supply Chain. International Journal of Logistics Management, 15(2), 1–13. https://doi.org/10.1080/13675560600717763

Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007). The severity of supply chain disruptions: Design characteristics and mitigation capabilities. Decision Sciences, 38(1), 131–156. https://doi.org/10.1111/j.1540-5915.2007.00151.x

Deleris, L. A., Elkins, D., & Pate-Cornell, E. (2004). Analyzing Losses from Hazard Exposure: A Conservative Probabilistic Estimate Using Supply Chain Risk Simulation. In Proceedings of the 2004 Winter Simulation Conference (Vol. 2, pp. 323–330). https://doi.org/10.1109/WSC.2004.1371476

Diaz, E. M., Cunado, J., & de Gracia, F. P. (2023). Commodity price shocks, supply chain disruptions and US inflation. Finance Research Letters, 104495.

Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: an analysis and recent literature. International Journal of Production Research, 56(1–2), 414–430. https://doi.org/10.1080/00207543.2017.1387680

Fahimnia, B., Tang, C. S., Davarzani, H., & Sarkis, J. (2015). Quantitative models for managing supply chain risks: A review. European Journal of Operational Research, 247(1), 1–15. https://doi.org/10.1016/j.ejor.2015.04.034

Fang, J., Zhao, L., Fransoo, J. C., & Van Woensel, T. (2013). Sourcing strategies in supply risk management: An approximate dynamic programming approach. Computers and Operations Research, 40(5), 1371–1382. https://doi.org/10.1016/j.cor.2012.08.016

Friedman, J. H., & Fisher, N. I. (1999). Bump hunting in high-dimensional data. Statistics and Computing, 9(2), 123–143. https://doi.org/10.1023/A:1008894516817

Geurts, P., Ernst, D., & Wehenkel, L. (2006). Extremely randomized trees. Machine Learning, 63(1), 3–42. https://doi.org/10.1007/s10994-006-6226-1

Groves, D. G., & Bloom, E. (2013). Robust Water-Management Strategies for the California Water Plan Update 2013. RAND Corporation, Santa Monica, CA.

Gruchmann, T., Eiten, J., De La Torre, G., & Melkonyan, A. (2019). Sustainable Logistics and Transportation Systems: Integrating Optimization and Simulation Analysis to Enhance Strategic Supply Chain Decision-Making. In Innovative Logistics Services and Sustainable Lifestyles (pp. 265-279). Springer, Cham. https://doi.org/10.1007/978-3-319-98467-4_12

Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. Global Environmental Change, 23(2), 485–498. https://doi.org/10.1016/j.gloenvcha.2012.12.006

Halim, R. A., Kwakkel, J. H., & Tavasszy, L. A. (2016). A strategic model of port-hinterland freight distribution networks. Transportation Research Part E: Logistics and Transportation Review, 95, 368–384. https://doi.org/10.1016/j.tre.2016.05.014

Heckmann, I., Comes, T., & Nickel, S. (2015). A critical review on supply chain risk - Definition, measure and modeling. Omega (United Kingdom), 52, 119–132. https://doi.org/10.1016/j.omega.2014.10.004

Herman, J. D., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015). How should robustness be defined for water systems planning under change? Journal of Water Resources Planning and Management, 141(10), 04015012. https://doi.org/10.1061/(asce)wr.1943-5452.0000509

Herman, J. D., Zeff, H. B., Reed, P. M., and Characklis, G. W. (2014), Beyond optimality: Multistakeholder robustness tradeoffs for regional water portfolio planning under deep uncertainty. Water Resources Research, 50(10), 7692– 7713, https://doi.org/10.1002/2014WR015338.Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. Transportation Research Part E: Logistics and Transportation Review, 125(December 2018), 285–307. https://doi.org/10.1016/j.tre.2019.03.001

Ivanov, D., Sokolov, B., & Dolgui, A. (2014). The Ripple effect in supply chains: Trade-off "efficiency-flexibility-resilience" in disruption management. International Journal of Production Research, 52(7), 2154–2172. https://doi.org/10.1080/00207543.2013.858836

Jabbarzadeh, A., Fahimnia, B., Sheu, J. B., & Moghadam, H. S. (2016). Designing a supply chain resilient to major disruptions and supply/demand interruptions. Transportation Research Part B: Methodological, 94, 121–149. https://doi.org/10.1016/j.trb.2016.09.004

Johnson, A. R., & Nagarur, N. (2012). A discussion on supply chain robustness and resiliency. In Industrial and Systems Engineering Research Conference (pp. 3414–3423).

Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many objective robust decision making for complex environmental systems undergoing change. Environmental Modelling and Software, 42, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

Klibi, W., & Martel, A. (2012). Scenario-based Supply Chain Network risk modeling. European Journal of Operational Research, 223(3), 644–658. https://doi.org/10.1016/j.ejor.2012.06.027

Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: A critical review. European Journal of Operational Research, 203(2), 283–293. https://doi.org/10.1016/j.ejor.2009.06.011

Knemeyer, A. M., Zinn, W., & Eroglu, C. (2009). Proactive planning for catastrophic events in supply chains. Journal of Operations Management, 27(2), 141–153. https://doi.org/10.1016/j.jom.2008.06.002

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. Environmental Modelling and Software, 96, 239–250. https://doi.org/10.1016/j.envsoft.2017.06.054

Kwakkel, J. H., & Pruyt, E. (2013). Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. Technological Forecasting and Social Change, 80(3), 419–431. https://doi.org/10.1016/j.techfore.2012.10.005

Kwakkel, J. H., Walker, W. E., & Marchau, V. A. W. J. (2010). Classifying and communicating uncertainties in model-based policy analysis. International Journal of Technology, Policy and Management, 10(4), 299–315. https://doi.org/10.1504/IJTPM.2010.036918

Lempert, R. J., & Collins, M. T. (2007). Managing the risk of uncertain threshold responses: Comparison of robust, optimum, and precautionary approaches. Risk Analysis, 27(4), 1009–1026. https://doi.org/10.1111/j.1539-6924.2007.00940.x

Lempert, R. J., & Groves, D. G. (2010). Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west. Technological Forecasting and Social Change, 77(6), 960–974. https://doi.org/10.1016/j.techfore.2010.04.007

Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006). A general, analytic method for generating robust strategies and narrative scenarios. Management Science, 52(4), 514–528. https://doi.org/10.1287/mnsc.1050.0472

Lempert, R., Kalra, N., Peyraud, S., Mao, Z., Tan, S. B., Cira, D., & Lotsch, A. (2013). Ensuring robust flood risk management in Ho Chi Minh City. World Bank Policy Research Working Paper, (6465).

Lempert, R. J., Popper, S. W., Groves, D. G., Kalra, N., Fischbach, J. R., Bankes, S. C., ... & McInerney, D. J. (2013). Making good decisions without predictions: Robust decision making for planning under deep uncertainty. RAND Corporation, Santa Monica, California.

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis. RAND Corporation, Santa Monica CA. https://doi.org/10.1016/j.techfore.2003.09.006

Lempert, R. J., Schlesinger, M. E., & Bankes, S. C. (1996). When we don't know the costs or the benefits: Adaptive strategies for abating climate change. Climatic Change, 33(2), 235–274. https://doi.org/10.1007/BF00140248

Li, Y., Chen, K., Collignon, S., & Ivanov, D. (2021). Ripple effect in the supply chain network: Forward and backward disruption propagation, network health and firm vulnerability. European Journal of Operational Research, 291(3), 1117-1131.

Martel, A., & Klibi, W. (2016). Designing Value-Creating Supply Chain Networks. Springer, Cham. https://doi.org/10.1007/978-3-319-28146-9

McPhail, C., Maier, H. R., Kwakkel, J. H., Giuliani, M., Castelletti, A., & Westra, S. (2018). Robustness metrics: How are they calculated, when should they be used and why do they give different results? Earth's Future, 6(2), 169–191. https://doi.org/10.1002/2017EF000649

Nahar, N., Ara, F., Neloy, M. A. I., Biswas, A., Hossain, M. S., & Andersson, K. (2021). Feature selection based machine learning to improve prediction of Parkinson disease. In Brain Informatics: 14th International Conference, BI 2021, Virtual Event, September 17–19, 2021, Proceedings 14 (pp. 496-508). Springer International Publishing.

Paul, S., & Venkateswaran, J. (2020). Designing robust policies under deep uncertainty for mitigating epidemics. Computers and Industrial Engineering, 140(December 2019), 106221. https://doi.org/10.1016/j.cie.2019.106221

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. The international journal of logistics management, 20(1), 124-143.

Rajagopal, V., Prasanna Venkatesan, S., & Goh, M. (2017). Decision-making models for supply chain risk mitigation: A review. Computers and Industrial Engineering, 113(January), 646–682. https://doi.org/10.1016/j.cie.2017.09.043

Ramm, T. D., Watson, C. S., & White, C. J. (2018). Strategic adaptation pathway planning to manage sea-level rise and changing coastal flood risk. Environmental Science and Policy, 87(April), 92–101. https://doi.org/10.1016/j.envsci.2018.06.001

Raymond, C., Horton, R. M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J., ... & White, K. (2020). Understanding and managing connected extreme events. Nature climate change, 10(7), 611-621.

Rosenzweig, C., Solecki, W. D., Blake, R., Bowman, M., Faris, C., Gornitz, V., … Zimmerman, R. (2011). Developing coastal adaptation to climate change in the New York City infrastructure-shed: Process, approach, tools, and strategies. Climatic Change, 106(1), 93–127. https://doi.org/10.1007/s10584-010-0002-8

Savage, L. J. (1951). The Theory of Statistical Decision. Journal of the American Statistical Association, 46(253), 55–67. https://doi.org/10.1080/01621459.1951.10500768

Sawik, T. (2013). Integrated selection of suppliers and scheduling of customer orders in the presence of supply chain disruption risks. International Journal of Production Research, 51(23–24), 7006–7022. https://doi.org/10.1080/00207543.2013.852702

Schmitt, A. J., & Singh, M. (2009). Quantifying supply chain disruption risk using Monte Carlo and discrete-event simulation. In Proceedings of the 2009 Winter Simulation Conference (WSC)(pp. 1237–1248). https://doi.org/10.1109/WSC.2009.5429561

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (1999). Designing and managing the supply chain: Concepts, strategies, and cases (1st ED). New York: McGraw-Hill.

Simchi-Levi, D., Schmidt, W., & Wei, Y. (2014). From superstorms to factory fires: Managing unpredictable supply-chain disruptions. Harvard Business Review, (February), 97–101.

Simchi-Levi, D., & Simchi-Levi, E. (2020). We need a stress test for critical supply chains. Harvard Business Review, 28.

Stanton, M. C. B., & Roelich, K. (2021). Decision making under deep uncertainties: A review of the applicability of methods in practice. Technological Forecasting and Social Change, 171, 120939.

Tang, C. (2006). Robust strategies for mitigating supply chain disruptions. International Journal of Logistics, 9(1), 33–45. https://doi.org/10.1080/13675560500405584

Wagner, S. M., & Bode, C. (2006). An empirical investigation into supply chain vulnerability. Journal of purchasing and supply management, 12(6), 301-312.

Walker, W. E., Rahman, S. A., & Cave, J. (2001). Adaptive policies, policy analysis, and policy-making. European Journal of Operational Research, 128(2), 282–289. https://doi.org/10.1016/S0377-2217(00)00071-0

Walker, W. E., Marchau, V. A., & Kwakkel, J. H. (2012). Uncertainty in the framework of policy analysis. In Public policy analysis: New developments (pp. 215-261). Boston, MA: Springer US.

Wu, D., & Olson, D. L. (2008). Supply chain risk, simulation, and vendor selection. International Journal of Production Economics, 114(2), 646–655. https://doi.org/10.1016/j.ijpe.2008.02.013

Yu, M. C., & Goh, M. (2014). A multi-objective approach to supply chain visibility and risk. European Journal of Operational Research, 233(1), 125–130. https://doi.org/10.1016/j.ejor.2013.08.037

5 The relation between supply chain topology and resilience: a simulation study

This chapter has been based on a paper that is under review at a scientific journal.

This chapter addresses the second sub-question introduced in section 1.2. We investigate the effect of operational aspects of a supply chain in structural vulnerability of the supply chain. To this end, various supply chain network structures, which differ in three operational aspects, including product structure, sourcing strategy, and production strategy, are stress-tested and compared to find key operational characteristics that affect the resilience of a supply chain structure.

Abstract

Supply chain resilience is a key concern in today's fluctuating business environment. Stress-testing a complex supply chain at the network level helps identify sources of vulnerability while offering possible courses of action for improving resilience. To study the resilience of complex supply chain networks, researchers frequently adopt a graph theoretic perspective where different network structures are represented by a configuration of nodes (facilities) and links (transport). By exposing nodes and links to disruptions, the resilience of different supply chain network structures can be assessed. However, conceptualizing supply chain networks based only on a configuration of nodes and links disregards key operational characteristics that may affect the functionality of a complex supply chain and, thus, its resilience. To address this gap, this research compares the resilience of supply chain topologies that differ in three operational aspects: product structure, sourcing strategy, and production strategy. We expose different network topologies to a variety of disruptions and draw conclusions about key operational characteristics that affect the resilience of a complex supply chain. The automated approach we applied in this research toward the generation of different supply chain network topologies and their related simulation models can aid supply chain decision makers in stress testing the resilience of real-world supply chain networks.

Keywords: Supply chain management, Supply chain resilience, Supply chain risk management, Simulation, Exploratory modeling

5.1 Introduction

The expansion of today's business environments has been driving advances in supply chain management strategies in recent decades. Advances such as Just-In-Time strategies, outsourcing, globalization, and centralized distribution bring competitive advantages to supply chains, but they also increase the number of possible vulnerabilities (Christopher & Peck, 2004). Given the various sources of vulnerability, coupled with uncertainties in the business environments, today's supply chains face risks of short-term to long-term disruptions (Fahimnia, Tang, Davarzani, & Sarkis, 2015a; Jabbarzadeh, Fahimnia, Sheu, & Moghadam, 2016; Klibi, Martel, & Guitouni, 2010). The large number of supply chain disruption cases in the past decades has a clear implication for managers: in order to compete in today's turbulent business environment, companies need to strive for resilient supply chains (Sheffi, 2005). A resilient supply chain is capable of returning to its original or desired state after a disruption by reacting quickly through flexible and agile processes (Christopher, 2016). The starting point in assessing the resilience of a supply chain toward enhancing its resilience is to stress test the supply chain to identify vulnerable elements and to define appropriate mitigation strategies to manage these vulnerabilities by improving resilience. A common approach for stress testing a supply chain to measure its resilience is to expose individual elements of the supply chain to disruption and then measure the impact of the disruption on supply chain performance. However, in complex supply chains consisting of thousands of globally distributed and interdependent actors with different sourcing strategies, many disruptions have effects far beyond the disrupted element, and they propagate farther into the supply chain, affecting the supply chain's overall performance (Dolgui, Ivanov, & Sokolov, 2018; Ivanov, Sokolov, & Dolgui, 2014). This implies that besides the vulnerable supply chain elements themselves, the structure of the supply chain and the way different actors are connected and interact with each other also influence the effects of disturbances in a supply chain and determine its resilience. Here, supply chain managers need to have an understanding of the vulnerability relating to the structure of their supply chain instead of only focusing on the vulnerability of individual elements and trying to change their supply chain structure to a more resilient one (Kim, Chen, & Linderman, 2015a). To assess the resilience of supply chain network structures, many scholars adopt graph theory (Basole & Bellamy, 2014; Kim et al., 2015a; Zhao, Kumar, Harrison, & Yen, 2011). In graph theory-based studies, elements of a supply chain are represented as nodes and links (vertices and edges), and different configurations of nodes and links result in different topologies of supply chain networks. The three most common types of supply chain topologies in the resilience literature are the scale-free network, the small-world network, and the random network (Basole & Bellamy, 2014; Kim et al., 2015a). Li et al. (2020) argue that not all real-world supply chains can be described by only three types of topologies. The authors suggest that supply chain topologies should be described by a number of network characteristics. This implies that instead of focusing on a few topologies, one can generate a broader set of supply chain topologies by combining different network characteristics. To this end, Li et al. (2020) adopt a set of commonly used network characteristics from graph theory to generate different topologies. These characteristics include degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, clustering coefficient, eccentricity, information centrality, and communicability. Although this topological perspective of supply chain structures brings many insights regarding its resilience, it overlooks some important characteristics of a supply chain network that influence resilience in the real world. For example, how is the resilience of a given network structure affected by the prevalence of make-to-stock (MTS) versus make-to-order (MTO)? Or, how does the number of tiers in the supply chain and the connectivity between tiers through shared suppliers affect supply chain resilience?

To address this gap, this paper looks at a supply chain topology from a new perspective, where different topologies are described by a group of operational characteristics of a supply chain. In this research we consider six operational characteristics of a supply chain, which we believe are worthwhile addressing in making today's complex supply chains more resilient. We categorize the characteristics into three groups: product structure, sourcing strategy, and production strategy.

From the product structure perspective, we consider a network variable representing the percentage of components outsourced for each supplier in each tier of a supply chain. Outsourcing is defined as the strategy of receiving semi-finished or finished products or services from outside of the company, so-called third-party specialists, instead of producing these products or delivering these services internally (Dolgui & Proth, 2013). A company might decide to outsource functions such as distribution, manufacturing, accounting, and information systems (Christopher, 2016). Outsourcing is popular among complex supply chains because it allows supply chains to focus on their core business competencies.

From the sourcing strategy perspective, we consider four network variables representing the number of tiers, the number of suppliers of a supplier in each tier, the number of shared suppliers in each tier (a supplier who produces for more than one customer in a supply chain) and the percentage of faraway versus close-by suppliers in each tier (we use this variable as the simplification of the actual geographical dispersion of suppliers over a supply chain network). Outsourcing and globalization strategies create multi-tier and globally expanded supply chains (Mena, Humphries, & Choi, 2013). The motivation for setting up a global supply chain is access to domestically unavailable or cheaper resources, technical expertise, and access to new markets (Behdani, 2013). Using a shared supplier strategy, in which multiple actors of a supply chain source from the same set of suppliers, is popular nowadays because it contributes to benefits such as achieving economies of scale as well as increasing reliability and quality of supply (Qi et al., 2015).

From the production strategy perspective, we consider a network variable representing the percentage of suppliers with the Make-to-Order (MTO) production strategy in each tier, where the other suppliers use the Make-to-Stock (MTS) strategy. In order to cope with fluctuations in market demand, today's supply chains apply postponement strategies that delay supply chain activities until the demand information becomes available, avoiding unnecessary production (Yang & Burns, 2003). An MTO supplier manufactures the end product when the customer places the order.

The combination of different values of the operational network variables results in the generation of a variety of supply chain topologies. This paper explores how sensitive the resilience of different network topologies is to changes in the values of the operational network variables. We consider three performance measures for assessing resilience: change in market lead time, the time to detect disruption and total recovery time. Market lead time is the time between placing an order and receiving the shipment. A change in market lead time is calculated as the difference between the market lead time of an order during a disruption and the market lead time of that same order in a normal situation. The time to detect disruption is the time between the start of the adverse event and the ability to detect the first impact on supply chain performance. The total recovery time is the time between the detection of the disruption and the return to business as usual. Figure 1 represents the relation between the research variables of this research.

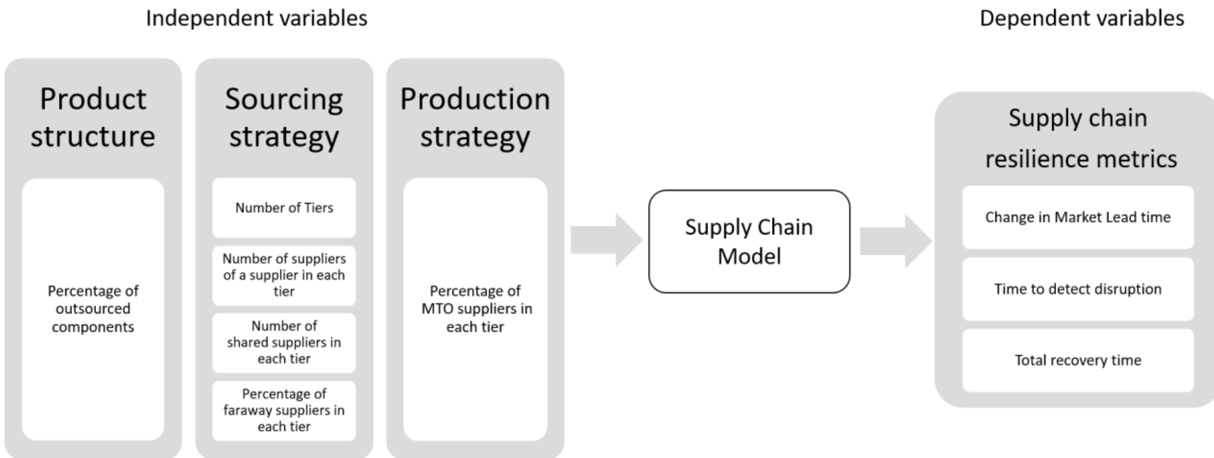


Figure 1. Conceptual framework of the research variables.

The remainder of this paper is organized as follows. In Section 5.2, we provide the background of the research. In section 5.3, we elaborate on the method we used in this research. Section 4 explains the experimental design for conducting the research. Section 5.5 presents the numerical results together with a discussion. Finally, conclusions are drawn in section 5.6.

5.2 Background of the research

Supply chain resilience has been a well-established area of study within supply chain risk management, with increasing attention and relevance in recent years. Resilience is a multidimensional and multidisciplinary concept. Ponomarov and Holcomb (2009) tried to develop a comprehensive and integrated definition of supply chain resilience by reviewing the concept of resilience from a variety of perspectives, including ecological, social, psychological, organizational, and economic disciplines. Based on their definition, resilience is "the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function". This definition of supply chain resilience comprises three dimensions: readiness, response, and recovery. There are two research directions in the literature on supply chain resilience. In the first direction, researchers look at supply chain resilience from a qualitative point of view and develop conceptual frameworks for identifying elements of a resilient supply chain together with their drivers (Blackhurst, Dunn, & Craighead, 2011; Bode & Macdonald, 2017; Christopher & Peck, 2004; Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007; Kamalahmadi & Parast, 2016; Pettit, Fiksel, & Croxton, 2010; Ponomarov & Holcomb, 2009; Wieland & Marcus Wallenburg, 2013). In the second direction, researchers develop or use various quantitative methods for measuring resilience of a supply chain and investigate the effect of various strategies for enhancing resilience (Fahimnia, Tang, Davarzani, & Sarkis, 2015b; Hasani & Khosrojerdi, 2016; Hosseini & Barker, 2016; Hosseini, Ivanov, & Dolgui, 2019; Ivanov, Dolgui, Sokolov, & Ivanova, 2017; Pires Ribeiro & Barbosa-Povoa, 2018; Rajagopal, Prasanna Venkatesan, & Goh, 2017).

As supply chains become more complex by involving many globally dispersed suppliers in multiple tiers with complex relations that highly influence the way disruptions propagate through supply chains, the network perspective becomes an emerging area in the literature of quantitative-based approaches toward supply chain resilience. Several researchers reveal that network structure has a significant impact on supply chain network resilience (Blackhurst, Rungtusanatham, Scheibe, & Ambulkar, 2018; Brintrup & Ledwoch, 2018; Dolgui et al., 2018; Ledwoch, Yasarcan, & Brintrup, 2018; Zhao et al., 2011)

Common to the approaches for studying the resilience of complex network structures is a comparison of different network structures by modeling the supply chain network as a graph with nodes and links. A graph-based approach has the advantage that it can use a variety of methods to provide insights into the supply chain network structures (Bier, Lange, & Glock, 2020; Kim, Chen, & Linderman, 2015b; Sokolov, Ivanov, Dolgui, & Pavlov, 2016). Network structures differ in graph-based characteristics such as degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, clustering coefficient, eccentricity, information centrality, and communicability. In line with graph-based approaches, our research compares different supply chain network structures created from different configurations using a number of operational features of a supply chain (rather than just a configuration of vertices and edges) to try to identify the most influential operational factors for resilience. We specifically include a number of operational characteristics such as the percentage of components outsourced for each supplier in each tier, the number of tiers, the suppliers of a supplier in each tier, the number of shared suppliers in each tier, the percentage of faraway suppliers and the percentage of suppliers with the MTO production strategy in each tier. Although several researchers have considered these operational characteristics in several supply chain management studies, to the best of the authors' knowledge, there is no research that reflects on the importance of these factors together with their interactions on the resilience of a supply chain.

5.3 Research method

In this research, we investigate how operational aspects of a supply chain's topology influence its resilience. In other words, we study the relation between a number of network-related attributes of a supply chain as independent variables and several resilience-related measures of the supply chain as dependent variables of the research.

A schematic overview of the steps of the proposed method for this research is provided in Figure 2. The first step is the generation of different supply chain topologies. Different topologies are generated by combining different values of six network-related variables: the percentage of assembled components in each tier, the number of tiers, the number of suppliers of a supplier in each tier, the number of shared suppliers in each tier, the percentage of faraway suppliers in each tier and the percentage of MTO suppliers in each tier. To generate a variety of networks, a Python-based network generator has been developed as part of this research. The generator can generate a variety of supply chain topologies by sampling across different values of the network-related variables. Instead of sampling, predefined values of network variables also can be given to the generator.

In the second step, we instantiate different supply chain simulation models based on the parameters of different topologies generated in the first step. In this research, supply chain model components are built in the simulation environment Simio (Houck & Whitehead, 2019) and connected to the network generator developed in the first step so that simulation models with different supply chain topologies are generated automatically. The details of the simulation model are given in chapter 3 of this dissertation.

In the third step, we explore the impact of disruption on different network topologies. To this end, we adopt exploratory modeling. Exploratory modeling is a model-based methodology that uses computational experiments to analyze uncertain and complex systems (Bankes, 1993; Kwakkel & Pruyt, 2013; Kwakkel, Walker, & Marchau, 2010; Moallemi et.al, 2020, Kwakkel, 2017; kwakkel & Haasnoot, 2019). Exploratory modeling involves exploring a wide set of scenarios that cover uncertainties pertaining to input variables and models for a variety of outcomes of interest and possible interventions with the aim of getting insights into systematic patterns of behavior of the system across the scenarios. In exploratory modeling, thousands of scenarios are generated and evaluated using the model(s) to generate a database of outcomes for each scenario. This database can be analyzed using data mining to draw conclusions about which assumptions do, and which ones do not make a difference for the outcomes. For example, one can identify which assumptions regarding the uncertain variables impact outcomes of interest significantly and which assumptions do not matter; or which combination of assumptions results in a particular outcome of interest. In this research we define seven disruption-related uncertainties for exploring a variety of disruption scenarios that a supply chain may encounter in the future: a disruption at a certain location (region of disruption, tier of disruption, disrupted component), the disrupted element, the disruption duration, the post-disruption capacity and the recovery rate of the disrupted element. To conduct exploratory modeling, we use a connector between the developed Simio library and the exploratory modeling and analysis (EMA) workbench (Kwakkel, 2017). EMA is an open source Python library that supports exploratory modeling by generating and executing a series of computational experiments and analyzing the results of these computational experiments. Results of the experiments are analyzed to draw conclusions on how changing of network variables influence the resilience of each network topology.

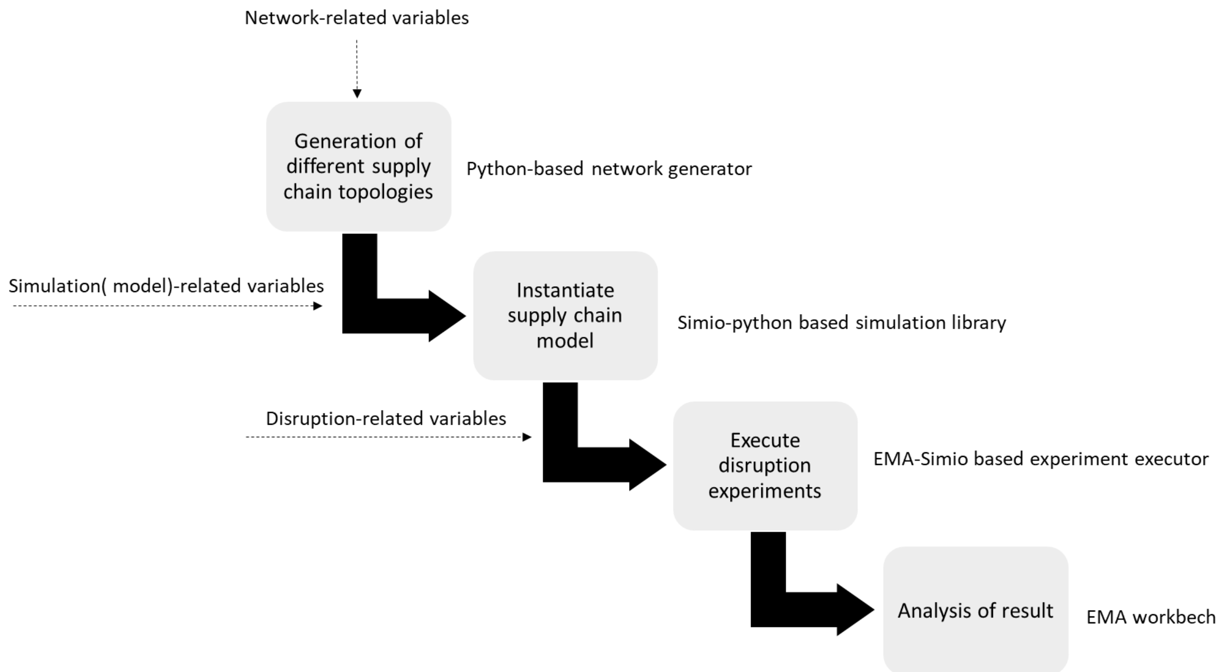


Figure 2. Steps of the research method.

5.4 Experimental design

In this section, we describe how we set up the experiments for the purpose of this research. We start with defining value ranges for each of the network variables. The list of network variables and their ranges are presented in Table 1. Then, using the network generator, we generate different network topologies by changing the values of network variables to enable the comparison of the resilience of the generated networks. We perform two sets of experiments. In the first set of experiments, we change the values of the network variables one at a time and keep the values of other variables constant. For example, we set the value of the variable "Number of tiers" to high (number 4) and set the values of the other six variables to their medium values to generate a High-Tier network. By doing so, we generate twelve different supply chain network topologies: High-Tier, Low-Tier, High-Supplier, Low-Supplier, High-Shared supplier, Low-Shared supplier, High-MTO, Low-MTO, High-Assemble, Low-Assemble, High-Faraway and Low-Faraway supply chain topologies. Here, we look at the direct effect of the network variables. Figure 3 shows a supply chain network generated by the network generator where the value of all network variables is set to "Medium".

In the second set of experiments, we look at the interaction effects of the network variables, where we change the values of two network variables at a time and keep the values of the other variables constant. As an example, we set the value of the variable "Number of tiers" to high (number 4), the value of the variable "Percentage of MTO suppliers in each tier" to low (25 percent), and the value of the rest of variables to medium to generate a High tier- Low MTO network. Out of all possible combinations, we select four network topologies to explore: High tier-Low MTO, High tier-High MTO, Low tier-Low MTO, and Low tier-High MTO. These networks are selected to answer the following question:

- How is the vulnerability of a high-tier supply chain affected by a change in the percentage of MTO suppliers? Is the result different for a low-tier supply chain?

Table 1: Values of six network-related variables for running experiments

Network-related variables	**Ranges**		
	Low	**Medium**	**High**
Number of tiers	2	3	4
Number of suppliers of a supplier in each tier	3	5	7
Number of shared suppliers in each tier	0	2	4
Percentage of MTO suppliers in each tier	25	50	75
Percentage of assembled components in each tier	25	50	75
Percentage of faraway suppliers in each tier	25	50	75

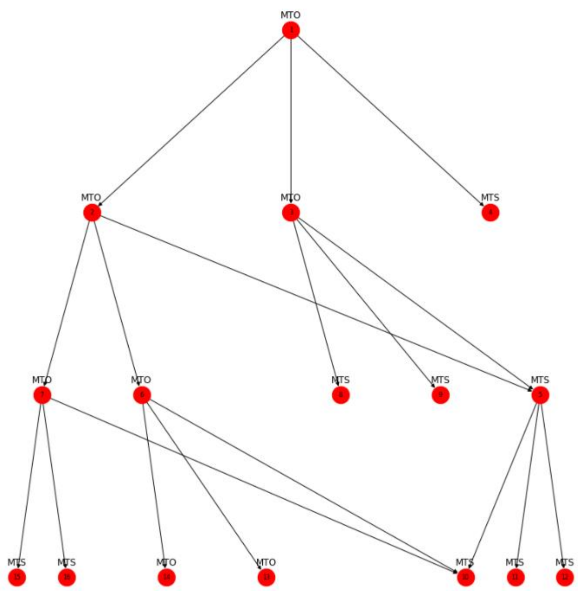


Figure 3. An example of a generated supply chain network with medium values for all network variables.

To assess the resilience of the network topologies, we expose the created supply chain models of the different topologies to a variety of disruption scenarios. To do so, we define seven disruption parameters and sample across different values. These parameters are disruption location (region of disruption, tier of disruption, disrupted component), disrupted element, disruption duration, post-disruption capacity, and recovery rate of the disrupted element. The categorical range associated with each disruption parameter is given in Table 2.

Table 2. Disruption-related parameters and their value ranges

Deep uncertainties	**Range**
Region	Close - Faraway- Both close and faraway
Tier	Each tier separately- All tiers
Component	Shared/Not shared among several suppliers
Disrupted element	Production plant-Transportation link-Inventory
Disruption duration	Long-Medium-Sort
Post-disruption capacity	Large-Medium-small
Recovery rate	Fast-Medium-Slow

We generate 1000 disruption scenarios by drawing values for the seven disruption parameter using Latin Hypercube sampling and expose each network topology to the disruptions scenarios. To ensure that the network topologies are each confronted with the exact same set of disruption scenarios we use seed management for generating the random values, both within Simio and in the EMA workbench. By doing so we ensure reproducibility of the experiments and also decrease the variance of the results to enable a better interpretation. The results of experiments are presented in the next section.

5.5 Results and discussion

In this section, we report the results of the simulation runs based on the experiments explained in section 5.4. First, we report the results of the direct effect of the network variables and then the results of the interaction effect of the network variables.

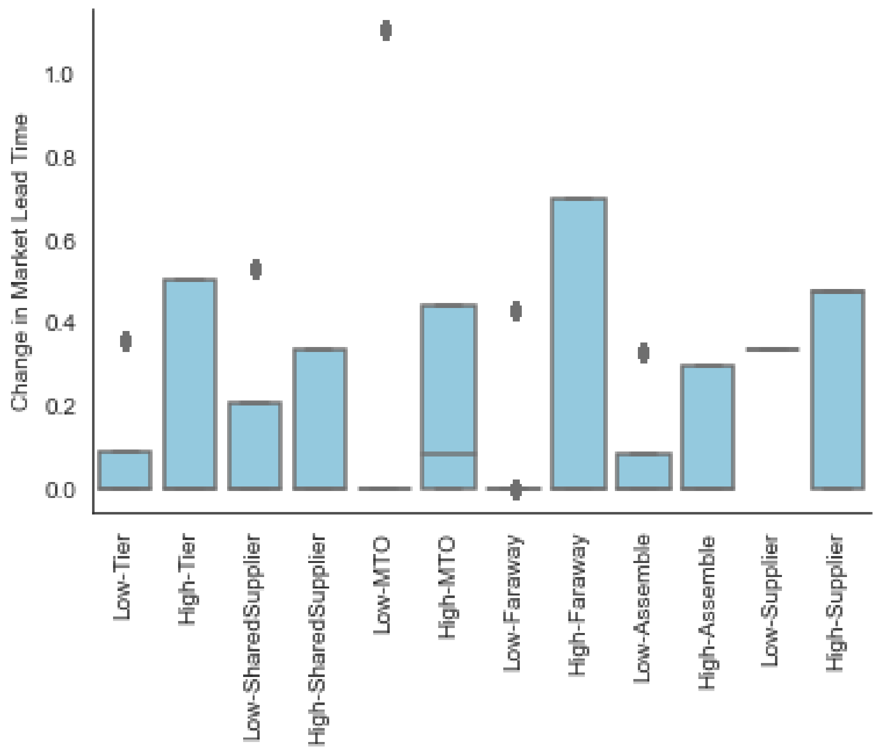
5.5.1 Direct effects

The output of the direct effect of the network variables is illustrated in Figure 4. The box plots in each sub-figure represent the variance of performance metrics for different networks across disruption scenarios. Before diving into the analysis of the results, it should be noted that in several disruption scenarios generated by the EMA workbench, the supply chain network under study is not affected. For example, in a network with only two tiers, a scenario of disruption in the fourth tier does not make any difference, or for a network with zero faraway suppliers, a disruption in a faraway supplier is meaningless. These non-disruptive scenarios generate values of zero for the performance metrics of our simulation model which results in a peak of zero values in our statistics that skew the data distributions. Therefore, we decided to drop the non-disruptive scenarios from our final data set for analysis.

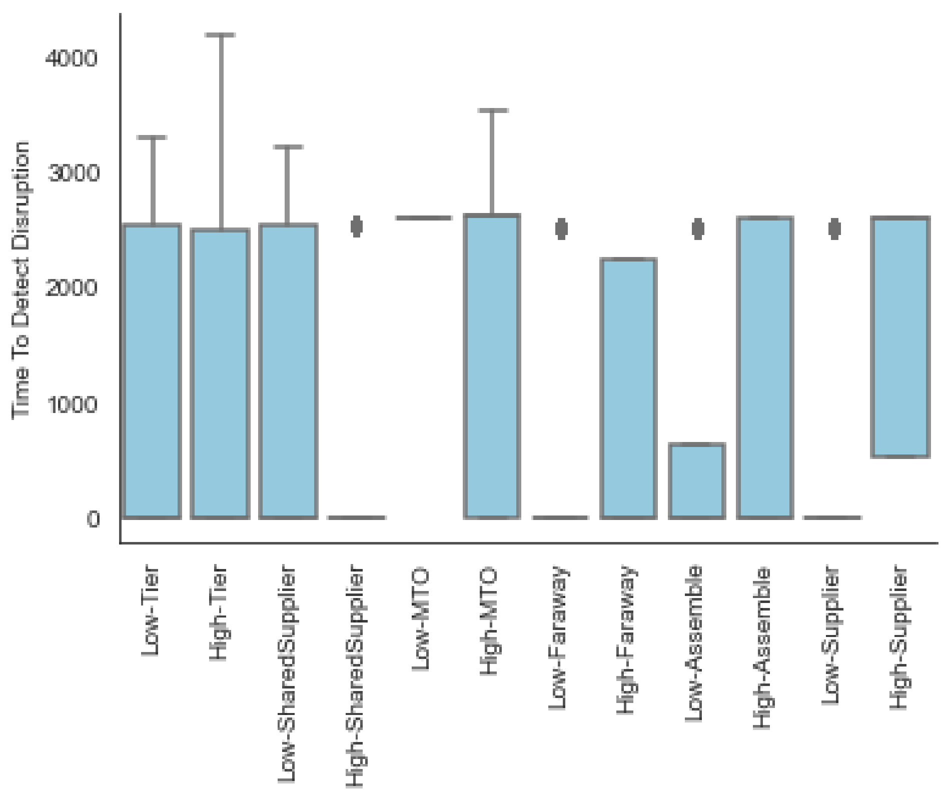
Regarding the performance metric "Change in market lead time", Figure 4(a) shows that networks with a high percentage of faraway suppliers, a high number of tiers, a high number of suppliers in each tier, and a high percentage of MTO suppliers experience the highest change in market lead time, and thus they are less resilient in terms of on-time delivery of the products to the final customers. These results support our expectation about the fact that when the depth, width and geographical dispersion of a supply chain increase, the vulnerability of the supply chain also increases. The high vulnerability of the network with a high percentage of MTO suppliers can be explained by the fact that in a network with a high percentage of MTO suppliers, production only starts when the actual order arrives. So there is no inventory of products in these supply chains to be considered as back-up or safety stock during the disruption. This is in line with the result for the change in market lead time of the network with a low percentage of MTO suppliers, which shows the lowest vulnerability among the networks.

Regarding the performance metric "Time to detect disruption", Figure 4(b) reveals that most of the networks are vulnerable. Exceptions are the networks with a high number of shared suppliers, a low percentage of faraway suppliers, a low percentage of assembled components, and a low number of suppliers. The reason behind the short disruption detection time in a supply chain with a high number of shared suppliers is that since disruption of a shared supplier affects several suppliers in a higher tier, the disruption propagates faster in these kinds of networks. Also, the detection of a disruption in nearby suppliers is much faster in the other networks. Among all, the networks with a high number of tiers and a high percentage of MTO suppliers experience the highest values for time to detect disruption. The network with a low percentage of MTO products experiences less variance in the results, but the values of the time to detect disruption are still quite high for this type of network. The reason is that a high amount of inventories of MTS suppliers in this network delays the detection of disruption since the MTS

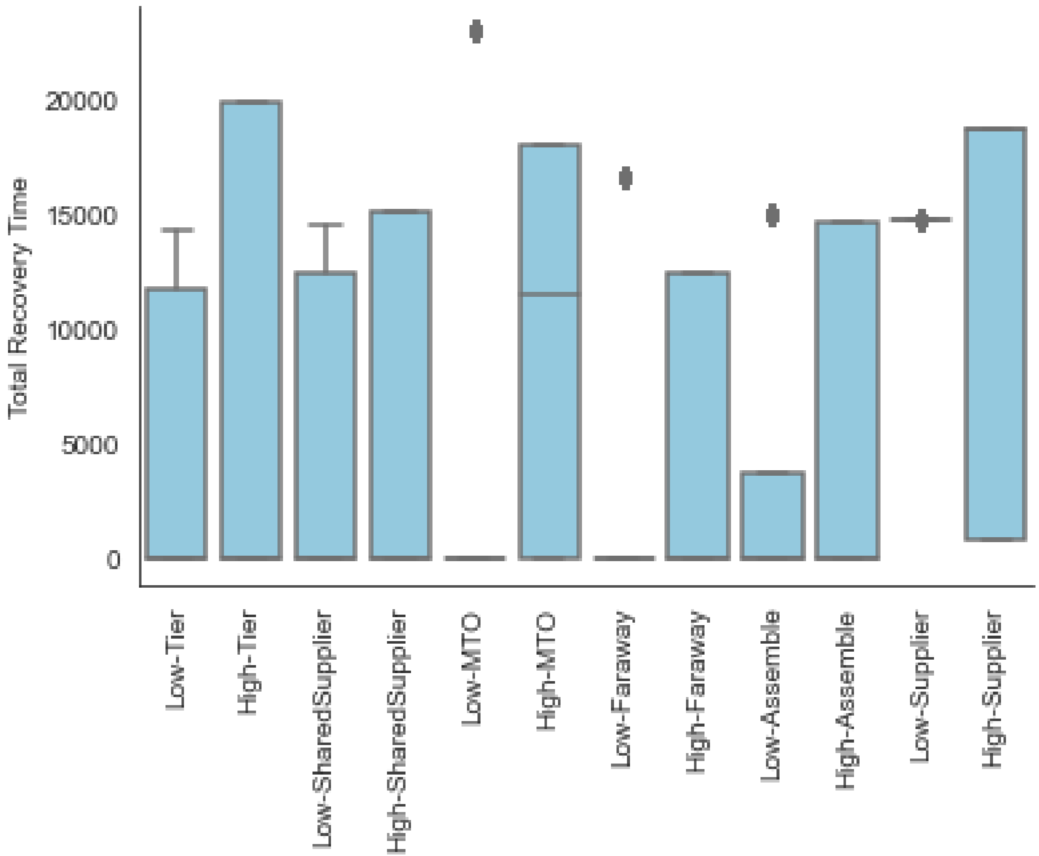
Regarding the performance metric "Total recovery time", Figure 4(c) shows that the networks with a high number of tiers, a high number of suppliers, a high percentage of MTO suppliers, and a high percentage of assembled components have the highest recovery time, and are thus more vulnerable to disruption. This result is in line with our expectation that the more complex a supply chain is, the longer it takes for it to get back to business as usual. The best performance in terms of recovery time belongs to the networks with a low percentage of faraway suppliers, a low percentage of MTO suppliers and low percentage of assembled components.


Change in Market Lead Time
1.0
0.8
0.6
0.4
0.2
0.0
Low-Tier
High-Tier
Low-SharedSupplier
High-SharedSupplier
Low-MTO
High-MTO
Low-Faraway
High-Faraway
Low-Assemble
High-Assemble
Low-Supplier
High-Supplier

(a)


Time To Detect Disruption
4000
3000
2000
1000
0
Low-Tier
High-Tier
Low-SharedSupplier
High-SharedSupplier
Low-MTO
High-MTO
Low-Faraway
High-Faraway
Low-Assemble
High-Assemble
Low-Supplier
High-Supplier

(b)



(c)

Figure 4: Distribution of disruption results over different network topologies.

We perform a more detailed analysis by statistical test in order to get better insights about meaningful differences between the networks that differ in the value of the same network variable. Here, we answer the questions of "How does the resilience of a supply chain network vary as a function of the number of tiers, number of suppliers of a supplier, number of shared suppliers, percentage of MTO suppliers, percentage of faraway suppliers, and percentage of assembled components in the network?" To answer these questions, we compare disruption results of High-Tier with Low-Tier, High-Supplier with Low-Supplier, High-Shared supplier with Low-Shared supplier, High-MTO with Low-MTO, High-Assemble with Low-Assemble and High-Faraway with Low-Faraway networks. To this end, we perform the Mann-Whitney U test, which is a statistical test that checks for any statistically significant differences between two data sets (Mann & Whitney, 1947). The Mann-Whitney U test compares the mean ranks of two datasets. The Mann-Whitney U test is non-parametric, so it does not rely on data distribution assumptions, which is the case in our research. However, before performing the Mann-Whitney U test, we check for the normality of the results by performing Kolmogorov–Smirnov (KS) test. The P value of KS test answers this question: What is the chance that a randomly selected value from the population with the larger mean rank is greater than a randomly selected value from the other population? We perform statistical test using IBM SPSS. The results are presented in Table 3. The results of KS test shows the rejection of normality of data distributions for all the networks. This means that we are eligible to perform Mann-Whitney U test. Regarding the change in market lead time, the result of Mann-Whitney U test shows that all two datasets have significant differences with each other (p-value of zero). The results show that higher values of the number of tiers, number of shared suppliers, percentage of MTO suppliers, percentage of faraway suppliers, percentage of assembled components, and number of suppliers in each tier result in higher vulnerability of a supply chain network in terms of delay in delivery of final product. The highest difference in change in market lead time belongs to High-Tier and Low-Tier networks. Regarding time to detect disruption also, high values of network variables result in longer detection of disruption. Except for high number of shared suppliers which results in faster propagation of disruption and therefore the detection of disruption. The highest difference belongs to the High-Supplier and Low-Supplier networks. Regarding total recovery time, results show that higher values of network variables results in longer recovery time. The highest difference belongs to High-MTO and Low MTO networks.

Table 3: results of statistical tests

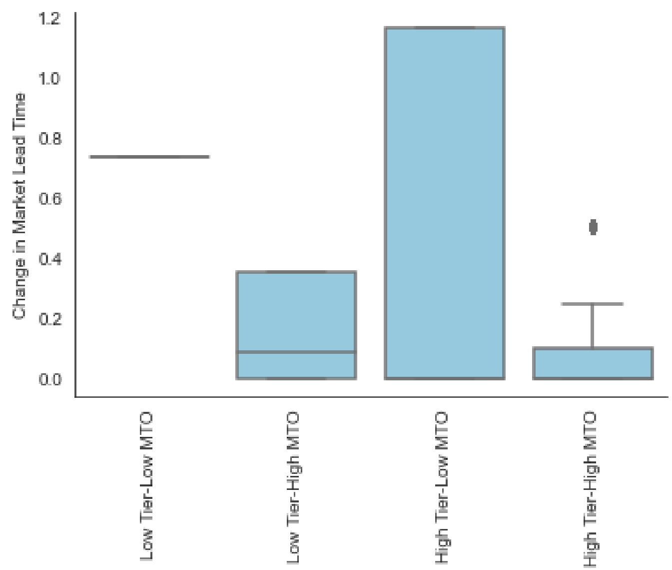
Network	Change in Market Lead Time			Time to detect disruption			Total recovery time		
	Kolmogorov–Smirnov Check for normality	Mann-Whitney U		Kolmogorov–Smirnov Check for normality	Mann-Whitney U		Kolmogorov–Smirnov Check for normality	Mann-Whitney U	
	p-value	Mean Rank	p-value	p-value	Mean Rank	p-value	p-value	Mean Rank	p-value
Low-Tier	0	679	0	0	751	0.035	0	706	0
High-Tier	0	911		0	793		0	866	
Low-Shared supplier	0	514	0	0	963	0	0	717	0.038
High-Shared supplier	0	918		0	851		0	755	
Low-MTO	0	607	0	0	351	0.017	0	707	0
High-MTO	0	1067		0	373		0	879	
Low-Faraway	0	655	0	0	720	0.043	0	736	0.03
High-Faraway	0	851		0	742		0	749	
Low-Assemble	0	625	0	0	634	0	0	684	0.01
High-Assemble	0	825		0	813		0	749	
Low-Supplier	0	184	0	0	517	0	0	184	0
High-Supplier	0	283		0	1083		0	283	

5.5.2 Interaction effect

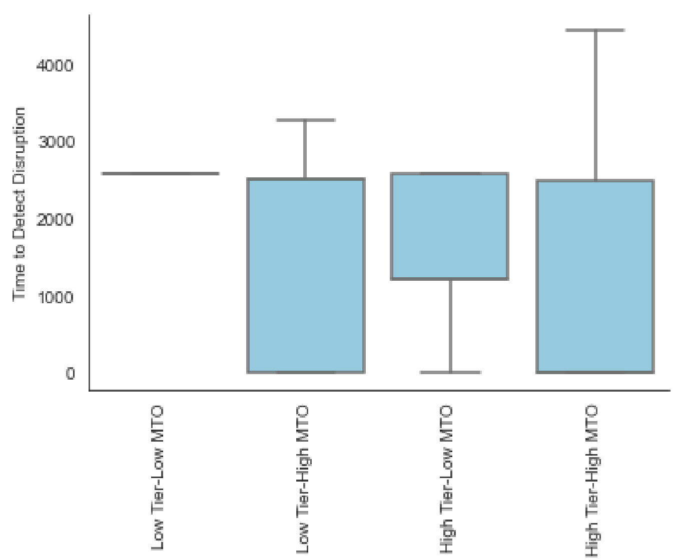
To show the interaction effect of the network variables, we select four combinations to represent in this paper. These combinations are selected to answer the following question:

How vulnerability of a supply chain with a high number of tiers is affected by the change in percentage of MTO suppliers? Is the result different for a supply chain with a low number of tiers?

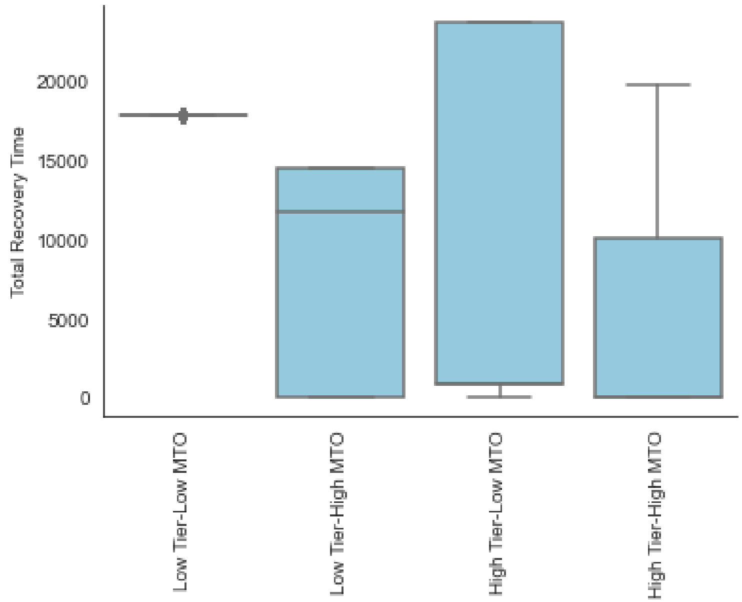
To answer the above question, we analyze the distribution of the disruption results of four networks, including Low Tier-Low MTO, Low Tier-High MTO, High Tier-Low MTO, High Tier-High MTO (Figure 5). As shown in Figure 5(a), in both networks with a low number of tiers and a high number of tiers, the change in market lead time increases when the percentage of MTO suppliers decreases. This behavior can be explained by the fact that networks with a low number of MTO suppliers include more MTS suppliers. As a result, based on the assumption of the simulation model, more disruptions ,in terms of inventory disruptions, occur in these networks, which results in experiencing a higher change in market lead time. However the network with higher tiers experience a higher variance and higher values for the market lead time. Figure 5(b) shows that in both the networks with a low number of tiers and those with a high number of tiers, the time to detect disruption increases when the percentage of MTO suppliers decreases. This behavior can also be explained by the high number of MTS suppliers since their stocks delay the detection of the disruption. However, networks with a high number of tiers experience higher values of time to detect disruption than those with a low number of tiers. Figure 5(c) shows that when the percentage of MTO suppliers decreases, the total recovery time increases. We can explain this behavior by the model assumption that does not contain a partial delivery of an order for MTS suppliers. Therefore, when a disruption happens, it takes a longer time for an MTS supplier to deliver the whole amount of disrupted products in comparison with an MTO supplier since they deliver per order, which is usually much smaller amounts. However, the highest values for recovery time belong to the networks with a high number of tiers.



(a)



(b)



(c)

Figure 5. Result of experiments with interaction effects of network variables.

5.6 Conclusions

The structure of a supply chain plays an important role in the propagation of disruption and thus, its resilience. This research provides supply chain decision makers with an approach for vulnerability assessment of their supply chain structure toward improving its resilience. Graph theory-based approaches for investigating the resilience of different supply chain topologies ignore consideration of important characteristics of a supply chain network because of the simplification of a supply chain network to the configuration of nodes and links. This paper provides an approach for tackling this problem. We look at a supply chain network topology from product structure, sourcing strategy, and production strategy perspectives, which is different from the typical graph theory-based perspective. The simulation-based approach we applied for modeling different topologies of a supply chain network allows exploration among detailed aspects of a supply chain, including operational aspects, that may contribute to the network's resilience. The modular and component-based approach we use for developing the supply chain simulation model in this research can be used further to generate a variety of real-world supply chain models consisting of any number of actors across several supply chain tiers all around the world. The models of the variety of supply chain topologies are generated in this research by different combinations of seven network variables: number of tiers, number of shared suppliers in each tier, percentage of MTO suppliers vs. MTS suppliers in each tier, percentage of faraway versus nearby suppliers in each tier, percentage of assembled components in each tier and number of sub-suppliers of a supplier in each tier. By stress-testing different supply chain topologies, we draw conclusions about the contribution of each network variable to the vulnerability of a supply chain topology. However, it is important to note that the findings from this study are dependent on the characteristics of our hypothetical supply chain which doesn’t fully capture the complexities of real-world supply chains. Therefore, while the results offer valuable insights, they should be interpreted with caution, and further studies are needed to validate the findings of this study in real-world supply chains.

The results show that deeper, wider, and more geographically dispersed network topologies are more vulnerable to disruption than shallow, narrow, and dense network topologies. This result can be interpreted by the fact that the increased number of tiers and geographical dispersion of a supply chain increases its complexity. This complexity results in more interdependencies among supply chain entities, which can increase vulnerabilities when an adverse event happens. Also, managing resources can be more challenging in a dispersed supply chain network. When adverse events happen, organizing and deploying resources in a dispersed network may result in longer and more intense disruption. Moreover, resource allocation in deeper and more dispersed networks might be more challenging due to the distribution of resources. This has a negative influence on addressing disruption quickly. On the other hand, due to the concentration of resources in dense networks, addressing disruption can be quicker despite the rapid propagation of disruption in such networks.

We also conclude that a high percentage of suppliers with MTS strategy in a network results in a late detection of disruption, while a high number of shared suppliers in a network result in a fast detection of disruption. Our results are also in line with the fact that as the complexity of a network decreases in terms of depth, width, and dispersion, the time to return to business as usual also decreases. In this research, we show that change in the number of tiers of a supply chain network has the highest impact on the vulnerability of market lead time. However, the percentage of MTO suppliers versus MTS suppliers in a network plays the most important role in total recovery time after disruption. The time to detect disruption is also mostly affected by the number of suppliers in each tier. We consider a consequence-based risk analysis approach toward modeling a disruption in the supply chain network. In contrast with conventional risk modeling approaches that rely on knowing the probability of occurrence and intensity of risk, the consequence-based risk approach focuses on analyzing the consequences of potential risks associated with a supply chain regardless of the root cause of the risk. To this end, we define a disruption with several parameters and sample across different values of those parameters for the generation of disruption scenarios. This approach enables supply chain risk management without having precise information about risk, which is the case for rare and extreme events.

There are several limitations to this study. Real-world supply chains are more complicated than the supply chain model we used in this research. We use a small-scale assemble-to-order supply chain to show the applicability of our approach. However, our scalable approach can be applied for stress testing much larger, real-world supply chains. No aspects of the applied method depend on the network size. Calculation times are expected to scale linearly with the network size since we do not optimize and just 'replay' the activities of the supply chain in the simulation model. In this research, we limit the operational aspects of a supply chain to seven variables. As future work, one can consider exploring other operational aspects of a supply chain network. In this research, the strategy to cope with disruption is acceptance and waiting till the disturbance is over. However, real-world supply chains apply different strategies to cope with disruptions. As future work, one can explore the effects of different mitigation strategies in different network topologies. The use of a simulation model coupled to a network generator makes it very easy to study supply chains with different topologies, different types of disturbances, different organizational components, and different mitigation strategies.

References

Bankes, S. (1993). Exploratory modeling for policy analysis. *Operations Research*, 41(3), 435-449.

Basole, R. C., & Bellamy, M. A. (2014). Visual analysis of supply network risks: Insights from the electronics industry. *Decision Support Systems*, 67, 109-120.

Behdani, B. (2013). Handling disruptions in supply chains: An integrated framework and an agent-based model, *Netherland: Delft University of Technology*. (Ph.D. thesis)

Bier, T., Lange, A., & 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.

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An empirically derived framework of global supply resiliency. Journal of Business Logistics, 32(4), 374-391.

Blackhurst, J., Rungtusanatham, M. J., Scheibe, K., & Ambulkar, S. (2018). Supply chain vulnerability assessment: A network based visualization and clustering analysis approach. *Journal of Purchasing and Supply Management*, 24(1), 21-30.

Bode, C., & Macdonald, J. R. (2017). Stages of supply chain disruption response: Direct, constraining, and mediating factors for impact mitigation. *Decision Sciences*, 48(5), 836-874.

Brintrup, A., & Ledwoch, A. (2018). Supply network science: Emergence of a new perspective on a classical field. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 28(3), 033120.

Christopher, M. (2016). *Logistics & supply chain management. Pearson Uk*

Christopher, M. and Peck, H. (2004), "Building the resilient supply chain", *International Journal of Logistics Management*, Vol. 15, No. 2, pp. 1-13.

Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007). The severity of supply chain disruptions: design characteristics and mitigation capabilities. *Decision Sciences*, 38(1), 131-156.

Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: an analysis and recent literature. *International Journal of Production Research*, 56(1-2), 414-430.

Dolgui, A., & Proth, J. M. (2013). Outsourcing: definitions and analysis. *International Journal of Production Research*, 51(23-24), 6769-6777.

Fahimnia, B., Tang, C. S., Davarzani, H., & Sarkis, J. (2015). Quantitative models for managing supply chain risks: A review. *European Journal of Operational Research*, 247(1), 1-15.

Hasani, A., & Khosrojerdi, A. (2016). Robust global supply chain network design under disruption and uncertainty considering resilience strategies: A parallel memetic algorithm for a real-life case study. *Transportation Research Part E: Logistics and Transportation Review*, 87, 20-52.

Hosseini, S., & Barker, K. (2016). A Bayesian network model for resilience-based supplier selection. *International Journal of Production Economics*, 180, 68-87.

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

Houck, D., & Whitehead, C. (2019, December). Introduction To Simio. In 2019 *Winter Simulation Conference (WSC)* (pp. 3802-3811). IEEE.

Sheffi, Y. (2005). Preparing for the Big One. Manufacturing Engineer, (November), 12–16.

Ivanov, D., Dolgui, A., Sokolov, B., & Ivanova, M. (2017). Literature review on disruption recovery in the supply chain. *International Journal of Production Research*, 55(20), 6158-6174.

Ivanov, D., Sokolov, B., & Dolgui, A. (2014). The Ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience' in disruption management. *International Journal of Production Research*, 52(7), 2154-2172.

Jabbarzadeh, A., Fahimnia, B., Sheu, J. B., & Moghadam, H. S. (2016). Designing a supply chain resilient to major disruptions and supply/demand interruptions. *Transportation Research Part B: Methodological*, 94, 121-149.

Kamalahmadi, M., & Parast, M. M. (2016). A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. *International Journal of Production Economics*, 171, 116-133.

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

Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: a critical review. *European Journal of Operational Research*, 203(2), 283-293.

Kwakkel, J. H., Walker, W. E., & Marchau, V. A. W. J. (2010, April). From predictive modeling to exploratory modeling: How to use non-predictive models for decisionmaking under deep uncertainty. In Proceedings of the 25th Mini-EURO Conference on Uncertainty and Robustness in Planning and Decision Making (URPDM2010), 15-17 April.

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, 96, 239-250.

Kwakkel, J. H., & Pruyt, E. (2013). Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. *Technological Forecasting and Social Change*, 80(3), 419-431.

Kwakkel, J. H., & Haasnoot, M. (2019). Supporting DMDU: A taxonomy of approaches and tools. *Decision making under deep uncertainty: From theory to practice*, 355-374.

Ledwoch, A., Yasarcan, H., & Brintrup, A. (2018). The moderating impact of supply network topology on the effectiveness of risk management. *International Journal of Production Economics*, 197, 13-26.

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

Economics, 223, 107529.

Mena, C., Humphries, A., & Choi, T. Y. (2013). Toward a theory of multi-tier supply chain management. *Journal of Supply Chain Management*, 49(2), 58-77.

Moallemi, E. A., Kwakkel, J. H., de Haan, F. J., & Bryan, B. A. (2020). Exploratory modeling for analyzing coupled human-natural systems under uncertainty. *Global Environmental Change*, 65(November 2019), 102186. https://doi.org/10.1016/j.gloenvcha.2020.102186

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring supply chain resilience: development of a conceptual framework. *Journal of Business Logistics*, 31(1), 1-21.

Ribeiro, J. P., & Barbosa-Povoa, A. (2018). Supply Chain Resilience: Definitions and quantitative modelling approaches–A literature review. *Computers & Industrial Engineering*, 115, 109-122.

Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, 20(1),124–143

Qi, A., Ahn, H. S., & Sinha, A. (2015). Investing in a shared supplier in a competitive market: Stochastic capacity case. *Production and Operations Management*, 24(10), 1537-1551.

Rajagopal, V., Venkatesan, S. P., & Goh, M. (2017). Decision-making models for supply chain risk mitigation: A review. *Computers & Industrial Engineering*, 113, 646-682.

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

Mann, H. B., & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *The Annals of Mathematical Statistics*, 50-60.

Wieland, A., & Wallenburg, C. M. (2013). The influence of relational competencies on supply chain resilience: a relational view. *International Journal of Physical Distribution & Logistics Management*, 43, pp. 300–320

Yang, B., & Burns, N. (2003). Implications of postponement for the supply chain. *International Journal of Production Research*, 41(9), 2075-2090.

Zhao, K., Kumar, A., Harrison, T. P., & Yen, J. (2011). Analyzing the resilience of complex supply network topologies against random and targeted disruptions. *IEEE Systems Journal*, 5(1), 28-39.

6 Supply chain ensemble modeling: supporting model-based decision making for supply chain resilience

This chapter has been based on a paper that is under review at a scientific journal.

This chapter addresses the third sub-question introduced in section 1.2. We investigate how uncertainties related to supply chain structure can be addressed in resilience practices. To this end, we adopt an ensemble modeling approach, which implies that instead of relying on one single supply chain structure, one can generate multiple structures for a supply chain using stochastic parameters and draw conclusions from a range of possible outcomes.

Abstract

Ex-ante stress testing of a supply chain to identify its vulnerabilities is crucial for improving resilience. Valid stress testing of a supply chain depends on the availability of reliable data about the supply chain structure and potential disruptive events. However, the complexity and globalization of today's supply chains make it difficult for decision makers to access supply chain data, especially from actors more than one tier upstream or downstream. As dynamic systems, supply chains also encounter changes in their structure and configuration over time. Moreover, various recent adverse events have revealed the limit to predictability of potential disruptions. Therefore, a major question is how to do stress testing of a supply chain despite structural and parametric uncertainties, as well as a lack of reliable data. Analogous to how model ensembles are used in for example climate modeling and weather forecasting, this paper proposes a framework to assist the generation of ensembles of supply chain networks, stress test the networks under an ensemble of disruption scenarios, and draw conclusions about the vulnerability of different supply chain networks that can help in improving their resilience. Using the proposed framework, decision makers can get insights into the resilience of their supply chain networks, even though they do not have access to precise information.

Keywords: Supply chain disruption and resilience; stress-testing; ensemble modeling; decision making under deep uncertainty; exploratory modeling.

6.1. Introduction

The complexity of today's supply chains, combined with globalization and fluctuations in business environments, cause a significant increase in the risk of supply chain disruptions. Several high-influence supply chain disruption cases over the past two decades have turned supply chain resilience into an increasingly important topic in the literature of supply chain risk management (Ivanov & Dolgui, 2021). To improve the resilience of a supply chain, stress testing to predict the impact of potential disruptions is crucial. The first step for stress testing a supply chain is to model its behavior under disruption. Mathematical analysis, simulation, and graphical modeling are the most dominant approaches in this regard (Rajagopal, Prasanna Venkatesan, & Goh, 2017). Common to these approaches is the use of a model that describes the supply chain network for testing both the impact of a set of disruption scenarios and the effectiveness of different mitigation strategies. Several papers study supply chain stress testing and resilience through model-based approaches (Hägele et al., 2023). Some researchers focus on improving supply chain resilience by increasing the preparedness of the supply chain for disruptive risks (Babazadeh & Razmi, 2012; Berger et al., 2022; Klibi & Martel, 2012; Sawik, 2011; 2013; Alikhani et al., 2023; Aldrighetti et al., 2021). For example, Alikhani et al. (2023) propose a framework for an efficient selection of resilience strategies in supply chain network design. The authors argue that because of various sources of disruption, selecting resilience strategies among several candidate options is challenging. To address this challenge the authors adopt resource dependence theory and two-stage stochastic programming to assess the positive or negative synergistic effects of a resilience strategy under resource constraints to identify a combination of strategies for resilient network design of a supply chain. For checking the reliability of their result, the authors propose a simulation-based stress testing approach together with a sensitivity analysis to see if the selected resilience strategies have satisfactory outcomes under disruption. Some researchers focus on analyzing the ripple effect of disruptions (Dolgui, Ivanov, & Rozhkov, 2020; Dolgui & Ivanov, 2021; Ivanov, Dolgui, & Sokolov, 2019; Ghadge et al., 2021; Hosseini & Ivanov, 2022). For example, Hosseini and Ivanov (2022) developed a framework based on Bayesian network analysis to calculate the ripple effect of a disruption in the resilience assessment of a supply chain. Digital supply chain twins, a virtual representation of a real supply chain for monitoring, adopting, and optimizing supply chain operations, is another direction of research which has received attention recently (Ivanov & Dolgui, 2020; Ivanov 2023; Frazzon, Freitag, & Ivanov, 2021). Ivanov (2023) proposes a decision-making framework for applying digital twins for stress-testing and resilience improvement of a supply chain.

In the studies of supply chain disruption management and supply chain resilience, researchers usually face the challenge of estimating the uncertainties about future disruptive events and the way a disruptive event propagates through the supply chain network. Also, the complexity of today's supply chains makes it hard for decision makers to access precise information on thousands of supply chain actors spread around the world, which is needed to build a valid model for stress testing of the supply chain to improve its resilience (Ambulkar, Blackhurst, & Grawe, 2015).

Furthermore, supply chains are dynamic and continuously change in size, shape, and configuration over time, e.g., by the selection of new partners, accessing new markets, sourcing from new locations, and developing new products (Dolgui & Ivanov, 2020; Gross, MacCarthy, & Wildgoose, 2018; MacCarthy et al., 2016). In these situations, stress testing of a supply chain should include structural uncertainty. The problem of uncertainty related to the structure of the supply chain in model-based approaches for supporting supply chain resilience has been addressed by some researchers. Klibi and Martel (2012) propose a risk-based modeling approach to generate plausible future scenarios for evaluating and designing supply chain networks. The authors define three event types to describe plausible future risks for supply chain networks: random, hazardous, and deeply uncertain events. A three-phase hazard modeling approach is then proposed by the researchers: (1) the modeling of supply chain network hazards, characterized by multihazards, vulnerability sources, and exposure levels; (2) the estimation of the arrival of an external event, its intensity, and its duration; and (3) the assessment of impact in terms of damage and time to recovery. A Monte Carlo approach is subsequently used to generate plausible future scenarios. In a more recent study that focuses on incorporating the structural dynamics of a supply chain for researching resilience, Ivanov and Dolgui (2019) propose an approach for supply chain disruption management that is less dependent on the certainty of knowledge about the environmental fluctuations that a supply chain may encounter. In the paper, the authors develop a framework for the design and management of low-certainty-need supply chains.

To model uncertainties related to future conditions of a system under study, including structural uncertainties, scholars from other disciplines, particularly in climate change and weather forecasting, increasingly use ensemble modeling or ensemble forecasting approaches. An ensemble approach implies that instead of relying on one single valid model to conceptualize the system under study, one can generate multiple models within the boundaries of several uncertain model parameters and draw conclusions from a range of possible outcomes (Gneiting & Raftery, 2005). This way, simulations of future conditions are generated with multiple models instead of just one model (Parker, 2013). The increasing application of ensemble modeling in the literature on climate change and weather forecasting is noticeable (Gneiting & Raftery, 2005; Storer, Gill, & Williams, 2020; Tsai, Elsberry, Chin, & Marchok, 2020; Wolff, O'Donncha, & Chen, 2020). Gneiting and Raftery (2005) argue that a single deterministic model for forecasting can be misleading since a 'best weather prediction' relies on 'best input data', which is not always available considering the many sources of uncertainties in the available data. The authors suggest using ensemble modeling for making weather forecasts by including multiple runs of numerical weather prediction models that differ in two uncertain model parameters: the initial conditions and the numerical representation of the atmosphere. Palmer (2002) also suggests using ensemble forecasts for weather and climate risk assessment. The author argues that it is crucial to include scenarios with extremes in ensemble modeling because events that happen rarely can still result in a significant financial loss.

This research explores the application of ensemble modeling for supply chain stress testing to improve supply chain resilience. Particularly, we focus on the data-driven simulation-based aspect of ensemble modeling that deals with parametrization and creation of simulation models from data sources, the combination of multiple simulation models to capture the behavior of complex systems, and the application of data analytics techniques to draw conclusions about complex relations within the system under study. The application of data-driven simulation-based approaches for supporting supply chain resilience is explored by several researchers, including

Ivanov (2023) who demonstrates how digital supply chain twins combined with real data and analytics can contribute to supply chain resilience improvement. Reviewing the literature shows that the application of ensemble modeling, which mainly focuses on combination of diverse models of a supply chain for addressing the uncertainties related to the structure of a complex supply chain, is still relatively new. An early example is Zhu et al. (2014), who study the application of ensemble modeling in addressing order priority in make-to-order systems.

Our research proposes a framework for ensemble modeling of a supply chain to improve its resilience, in cases where decision makers have to deal with imperfect information on the supply chain structure and on potential disruptions. We adopt exploratory modeling as the main research method. Exploratory modeling is a model-based approach that uses computational experiments to analyze systems with significant uncertainties. It involves exploring a comprehensive set of scenarios that cover uncertainties for input variables and models, for a variety of outcomes of interest and possible solutions, with the aim of getting insights into systematic patterns of behaviour of the system across the scenarios (Bankes, 1993; Kwakkel& Pruyt, 2013; Kwakkel, Walker, & Marchau, 2010; Moallemi et al., 2020). Exploratory modeling is an approach for supporting decision making under deep uncertainty (Kwakkel, 2017; Kwakkel & Haasnoot, 2019), where deep uncertainty describes a class of uncertainty that is not well modeled by the tools of probability and statistics (Bankes, 2002), e.g., because of non-linear behaviour in the system or unknown distributions of the likelihood and effects of (rare) events. Exploratory modeling has proven to be a promising approach with successful applications in different contexts, including economics (Lempert et al., 2006), water management, transportation management (Halim, Kwakkel, & Tavasszy, 2016b), energy management (Merrick & Weyant, 2019; Trutnevyte, Stauffacher, & Scholz, 2012), and climate adaptation (Lempert et al., 2013). The application of exploratory modeling for supply chains remains relatively unexplored. Among a few works, Paul and Venkateswaran (2020) study the problem of medicine supply chains during an epidemic, where they consider deep uncertainty related to epidemic behaviour. The authors applied exploratory modeling and analysis (EMA) to explore ensembles of many plausible behaviours of an epidemic characterized by deeply uncertain parameters in their supply chain models. The authors investigated critical combinations of input parameter ranges that would cause extreme numbers of casualties. Based on this, they were able to propose robust supply chain policies to avoid these extreme outcome scenarios.

This paper demonstrates the applicability of the exploratory modeling framework that uses ensemble modeling of supply chains to help increase their resilience. We characterize the supply chain network and the potential disruptions with a set of parameters and consider these parameters to be deeply uncertain variables. The problem of supply chain disruption management when precise information is missing, will be formulated as a problem of decision making under deep uncertainty, and as a result, it can benefit from approaches proposed in this field of research. The remainder of this paper is organized as follows: Section 6.2 explains the framework for supply chain ensemble modeling. Section 6.3 describes a software implementation of the proposed framework. Section 6.4 illustrates how our framework can be implemented using a sample case. Section 6.5 contains the discussion, and section 6.6 presents the conclusions of this research.

6.2 Supply chain ensemble modeling framework

Figure 1 presents the proposed framework for supply chain ensemble modeling to improve supply chain resilience. The heart of our framework is the XLRMs framework that is used in exploratory modeling for structuring the problem under study (Lempert, Popper, & Bankes, 2003). The elements of the XLRM framework are:

X: External factors; the uncertainties outside the control of decision makers.

L: Policy levers; the actions that the decision makers would like to explore. Since we do not consider mitigation strategies in this research, policy levers are not used in this study.

R: Relationships; one or more models representing the dependencies among external factors, policy levers, and performance metrics.

M: Performance metrics; the outcomes that decision makers are interested in.

Exploratory modeling systematically varies the assumptions about the external factors or external factors and policy levers (if applicable). Each unique set of assumptions is called a scenario. Thousands of scenarios with a varied set of external factors (and policy levers) are generated, and they are evaluated using the model(s) in order to generate a dataset of outcomes for these scenarios. This dataset can be analyzed to draw conclusions about which external factors do, and which ones do not make a difference for the outcomes. For example, one can identify which assumptions regarding the external factors impact outcomes of interest significantly, and which assumptions do not matter for the model; or which combination of assumptions results in a particular outcome of interest. This way, one can identify 'regions' in the outcome space that one should try to avoid, and 'regions' in the output space that are favorable. Relating this back to the external factors and policy levers, one can try to identify what (combinations of) factors and levers can prevent the system from ending up in an unfavorable outcome region.

The framework of supply chain ensemble modeling used in this research is shown in Figure 1. The framework consists of three components. In the rest of this section, we explain the components of the proposed framework in more detail.

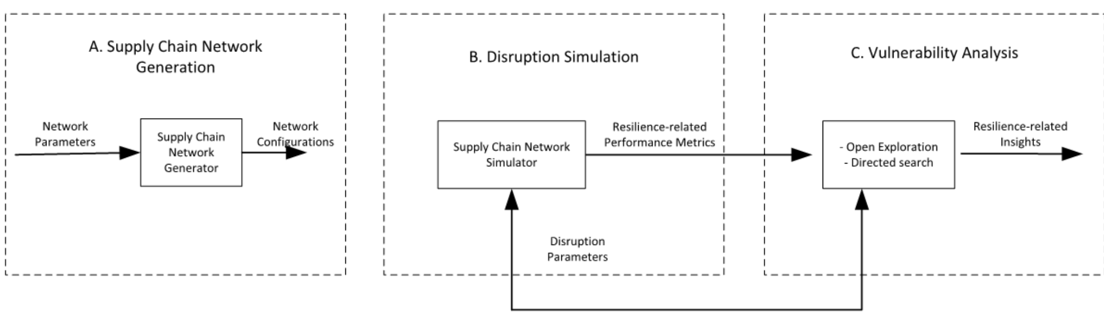


Figure 1. Framework for supply chain ensemble modeling to improve resilience.

6.2.1 Supply chain network generation

Our approach for supply chain ensemble modeling starts with generating an ensemble of supply chain networks for exploring supply chain resilience. We parameterize a supply chain network with a set of six supply chain network variables:

- **Number of tiers:** a variable representing the number of tiers in the supply chain.
- **Number of suppliers:** a variable representing the number of suppliers of a supplier in each tier.
- **Number of shared suppliers:** a variable representing the number of suppliers in each tier that produce for more than one customer in the supply chain.
- **Percentage of assembled components:** a variable representing in each tier which percentage of a product consists of assembled components made by a sub-supplier (using both push-based and pull-based sourcing), as opposed to the percentage of the product consisting of raw materials (using push-based sourcing).
- **Percentage of faraway suppliers:** a variable representing the percentage of faraway versus nearby suppliers in each tier.
- **Percentage of MTO suppliers:** a variable representing the percentage of suppliers in each tier with a make-to-order versus a make-to-stock production strategy.

These variables are used as input parameters of the supply chain network generator: a model that generates an ensemble of supply chain network configurations by sampling different combinations of the network-related parameters.

6.2.2 Disruption simulation

To explore the effect of potential disruptions on the different supply chain network configurations generated in step A, we parameterize a disruptive event with a set of disruption-related variables, including *disrupted tier, disrupted component, disrupted element, disrupted region, disruption duration, post-disruption capacity, and recovery rate of the disrupted element.* Each of these variables is treated as a deeply uncertain parameter where we do not know (or use) the distribution function of that parameter. In a sense, all parameters are sampled uniformly as a result (e.g., using Latin Hypercube Sampling), resulting in a good coverage of the overall disruption space and including a variety of combinations of the disruption-related variables. Of course, when for some variables, the distributions are known in reality, sampling can also be done as a combination of uniform sampling for the deeply uncertain variables and stochastic sampling for the variables for which a distribution is known. Yet, the uniform sampling will provide a good overview of the entire range of possibilities of disruptions that may occur.

Together with the supply chain network configurations (the output from step A), the disruption-related parameters are input to the 'supply chain network simulator' that models the impact of the disruption scenarios on the various supply chain network configurations. We consider three performance metrics for measuring the impact of disruptions: change in market lead time, time to detect the disruption, and recovery time from the disruption.

6.2.3 Vulnerability analysis

To investigate the vulnerability of a supply chain network for both network-related and disruption-related parameters, two search strategies can be applied: open exploration and directed search (Kwakkel & Haasnoot, 2019). Open exploration includes systematically exploring the set of plausible models to generate a set of computational experiments that covers the uncertainty/decision space. The approach involves systematically sampling points from the uncertainty space (in our case the n-dimensional space spanned by all uncertain network-related parameters and disruption-related parameters) together with their associated performance metrics by using techniques such as Monte Carlo sampling, Latin Hypercube sampling, or factorial methods. The generated set of computational experiments is analyzed using sensitivity analysis algorithms or scenario discovery algorithms, where the former answers the question of what the impacts of uncertain factors are on the output, and the latter answers the question of what the uncertain factors (or combination of uncertain factors) are that cause or predict the output of interest (Halim, Kwakkel, & Tavasszy, 2016a; Kwakkel & Pruyt, 2015; Moallemi et al., 2020). In this research, open exploration can be applied to answer questions such as: what are the most influential network-related and disruption-related factors that result in vulnerabilities of a supply chain, or what combination of factors results in a good or poor performance of a supply chain under disruption?

In contrast to open exploration, directed search explores the uncertainty space in a more goal-oriented manner to find particular points of interest. The directed search approach relies on optimization algorithms to answer questions such as: what is the best/worst case that can happen, or where are the boundaries in the uncertainty space that lead to a switch of outcomes? In this research, directed search can be applied to answer questions such as: which supply chain network configurations have the best/poorest performances under a worst-case disruption scenario?

6.3. Software implementation

To implement the proposed exploratory modeling framework, we developed several pieces of software and a simulation model:

(i) A Python-based network generator for generating supply chain network configurations from combinations of network-related parameters. The generator was specifically developed for this research. The parameters that can be varied to generate a specific type of network are given in section 6.2.1 above. Figure 2 shows an example of a supply chain network configuration created by the network generator. The generator also provides the data needed for creating simulation models of the network configurations.

(ii) A Simio (Houck & Whitehead, 2019) based supply chain network simulator that is capable of automatically instantiating a discrete-event simulation model of each of the network configurations created by the network generator. The details of the simulation model are given in chapter 3 of this dissertation. The model can simulate any supply chain network generated in step A (supply chain network generation was explained in section 6.2.1) with arbitrary complexity. To instantiate supply chain models, a supply chain network configuration generated by the network generator is translated to the information needed for the discrete-event simulation model developed in Simio. This information is stored in input data tables, and the supply chain simulation model is instantiated automatically from these tables during the model initialization phase.

(iii) A Python-based package for performing exploratory modeling. We made a connector between Simio and the Exploratory Modeling and Analysis (EMA) workbench, an open-source Python library that supports exploratory modeling by generating and executing an ensemble of computational experiments, as well as the visualization and analysis of the results of these computational experiments (Kwakkel, 2017).

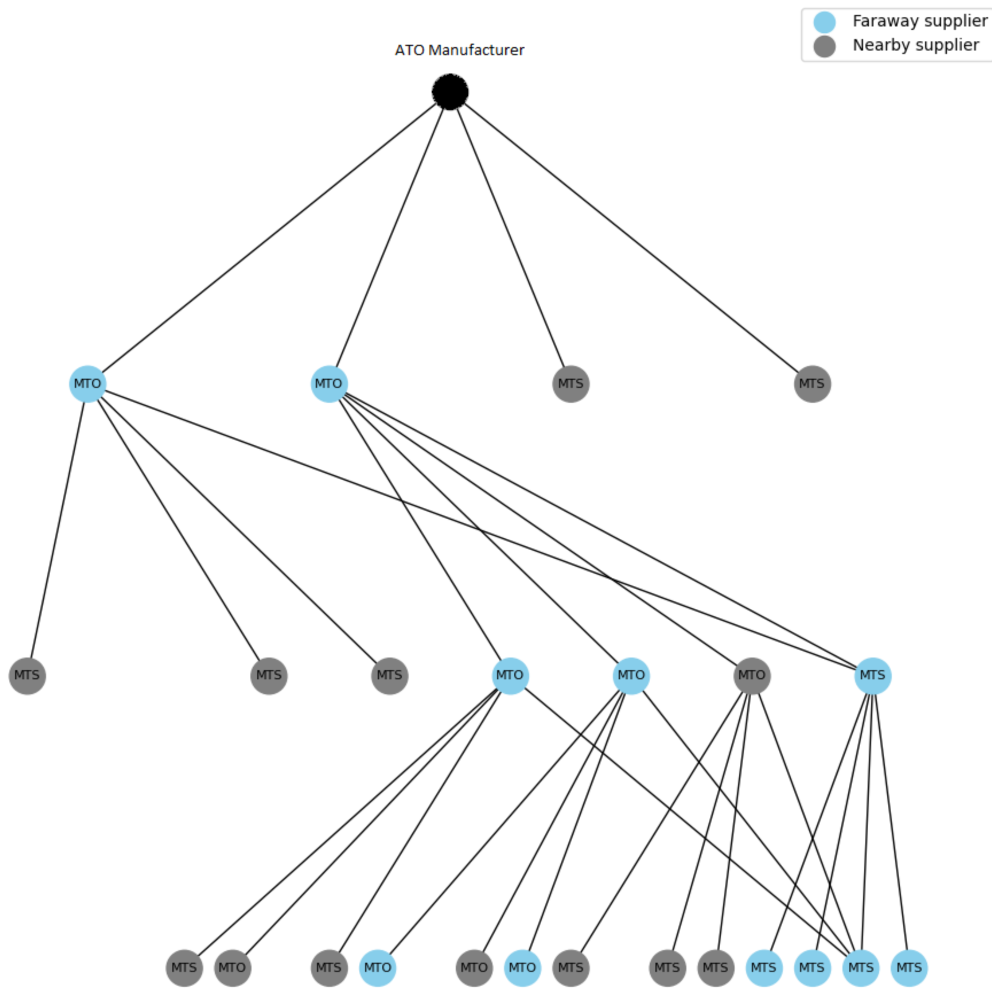


Figure 2. Example of a 3-tier supply chain network configuration created by the network generator.

6.4. Assessing supply chain vulnerability using the ensemble modeling framework

In this section, we demonstrate the implementation of our framework using a stylized and simplified supply chain network. Following the framework, we start with identifying network-related parameters and their value ranges for the generation of the ensemble of supply chain network configurations (see Table 1). The explanation of each network variable is given in section 6.2.1. We take 50 samples of the values of the network parameters, resulting in the generation of 50 different network configurations. In the next step, we define the disruption-related parameters and their value ranges (see Table 2). Note that we use nominal or ordinal values for the variables to keep the model simple; these values can be replaced by ranges in the supply chain model as well. For example, in our supply chain case, a short disruption duration refers to two to three weeks of disruption, a medium disruption duration refers to one to two months of disruption, and a long disruption duration refers to four to six months of disruption in a supply chain element. Similarly, a large post-disruption capacity refers to an availability of eighty percent of the normal capacity of the disrupted element after disruption, a medium post-disruption capacity refers to an availability of fifty percent of the normal capacity of the disrupted element after disruption, and a small post-disruption capacity refers to an availability of zero capacity of the disrupted element after disruption. Finally, a fast recovery rate of a disrupted element refers to the recovery of eighty percent of the lost capacity per day, a medium recovery rate of a disrupted element refers to the recovery of forty percent of the lost capacity per day, and a slow recovery rate of a disrupted element refers to the recovery of five percent of the lost capacity per day.

The generated supply chain network configurations, together with the disruption-related parameters, are inputs for the supply chain network simulator to explore the impact of the ensemble of disruption scenarios on resilience-related performance metrics of different supply chain networks. We take 200 samples over the values of the disruption parameters for each network configuration. Considering the 50 network configurations, this produces 10,000 experiments in total. We run the model for 220 weeks, in which the model reaches a steady state for all scenarios. We chose the warm-up period to be 16 weeks, to build up a representative inventory and work-in-progress for all supply chain actors. We assume a disruptive event is triggered in week 44, allowing us to gather statistics about the undisrupted period. To address stochasticity related to the production times and transportation times, five replications of each experiment are run using different seeds, and the average values of the performance metrics over five replications are considered for the analysis. We performed a sensitivity analysis and confidence interval analysis to explore how the number of replications influences the variability and reliability of the output results. We calculate the half-width of the 95% confidence intervals for the most important performance indicators and express them as a percentage of the mean value of the performance indicators. We ensure that five replications are sufficient in our case because they result in a percentage of the mean values being less than 5%, which is an acceptable level of precision in our simulation. In the following sub-sections, we demonstrate the results of the experiments.

Table 1. Network-related parameters and their possible values for the example case

Network-related variables	**Value ranges**
Number of tiers	1-4
Number of suppliers of a supplier in each tier	1-4
Number of shared suppliers in each tier	0-2
Percentage of assembled components in each tier	10%-90%
Percentage of faraway suppliers in each tier	10%-90%
Percentage of MTO suppliers in each tier	10%-90%

Table 2. Disruption-related parameters and their possible values for the example case

Disruption-related variables	Value ranges
Disrupted tier	Each tier separately - All tiers
Disrupted component	Shared/Not shared among several suppliers
Disrupted element	Production plant -Transportation link - Inventory
Disrupted region	Nearby - Faraway - Both nearby and faraway
Disruption duration	Long - Medium - Short
Post-disruption capacity	Large - Medium - Small
Recovery rate of the disrupted element	Fast - Medium - Slow

6.4.1 Result of open exploration

6.4.1.1 Feature scoring for identifying influential factors

A high-level analysis first looks at the impact of the model parameters on the outcomes of interest. Therefore, a feature scoring approach is used, which is a machine learning alternative to global sensitivity analysis for identifying the most influential uncertain factors on model outcomes (Geurts, Ernst, & Wehenkel, 2006). Several techniques exist to support feature scoring (Nahar et al., 2021). For this study, we selected the so-called 'extra-trees algorithm' mainly because of its accuracy in solving non-linear regression problems (Jaxa-Rozen & Kwakkel, 2018). Figure 4 and Figure 5 shows the results of the extra trees feature scoring for the network-related parameters and disruption-related parameters respectively. The figures indicate which of the parameters have the greatest relationship to the performance metrics. A higher number (color towards the yellow) implies a higher impact of the parameter (x-axis) on the performance metric (y-axis). The result of the feature scoring analysis in Figure 4 shows that among the network-related parameters, the number of tiers, the number of suppliers in each tier, and the percentage of MTO suppliers in each tier are three main factors that influence change in market lead time in case of a disruption. These factors also influence the time to recover from disruption and return to business as usual in a supply chain. The results also indicate that the time to detect a disruption in a supply chain is mainly influenced by the number of tiers in a supply chain. The result of the feature scoring analysis in Figure 5 also shows that among the disruption-related parameters, the tier in which the disruption takes place and the disrupted component (whether it is shared or not shared among several suppliers in a supply chain) are the two factors that influence all three supply chain performance indicators the most in case of a disruption.

Figure 4. Result of the feature scoring analysis over the network-related parameters.

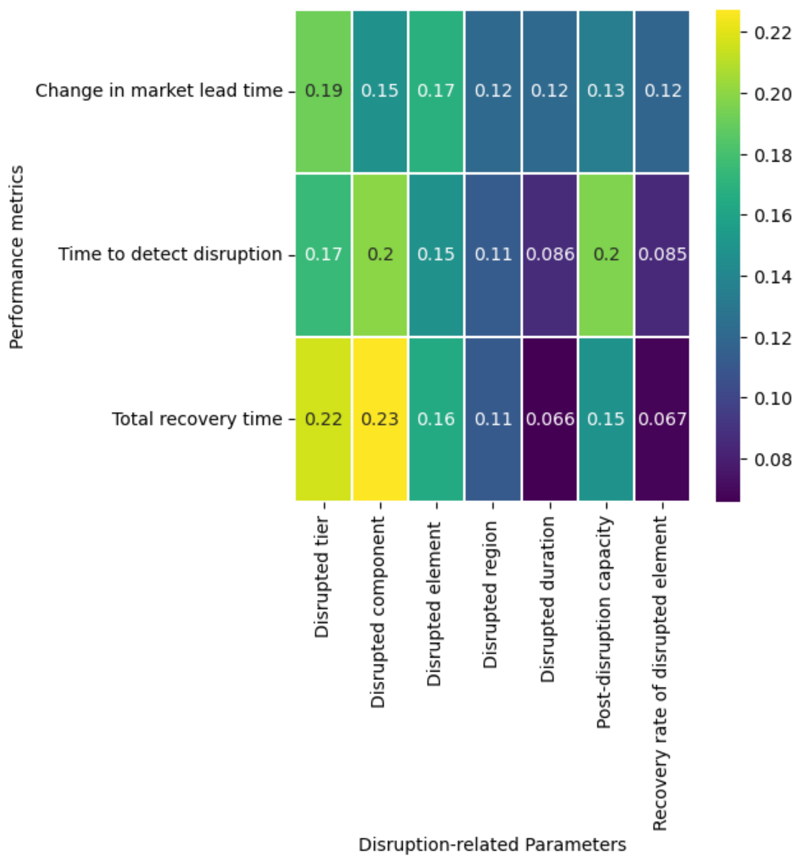


Figure 5. Result of the feature scoring analysis over the disruption-related parameters.

6.4.1.2 SHAP Analysis for analyzing interaction effects

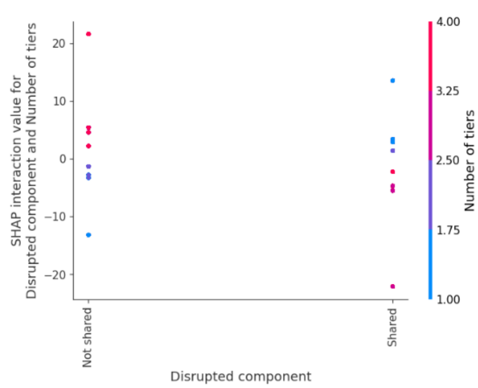
We also study the interaction effects between network-related and disruption-related parameters. We chose to apply SHAP (SHapley Additive exPlanations) analysis (Lundberg et al., 2020), which is a method for explaining the output of machine learning models. The approach relies on "Shapley values" from game theory to measure the interaction effects of the features of a model. In game theory, Shapley values show the contribution of a player to the final goal of the game. In machine learning, SHAP values measure the impact of model features on model output for a prediction. In a SHAP analysis, the features are ranked based on their importance, defined as their contribution to the model prediction. A feature with a high SHAP value is more important than a feature with a low SHAP value. SHAP analysis also allows for investigating how interactions between the features contribute to the model prediction. This can be done by calculating SHAP interaction values that quantify feature combinations' impact on model prediction. This is done by exploring how a model feature's impact changes when combined with several other features of the model. We apply the SHAP library, a Python-based package, to look at interaction effects between network-related and disruption-related parameters. The calculations are based on a gradient-boosted decision tree model trained on the dataset of the experiment results. More information can be found on the SHAP documentation website [1]. We calculate the SHAP interaction values for all

[1] See https://shap.readthedocs.io/en/latest/tabular_examples.html#tree-based-models and for more information, see the 'Basic SHAP Interaction Value Example in XGBoost' example.

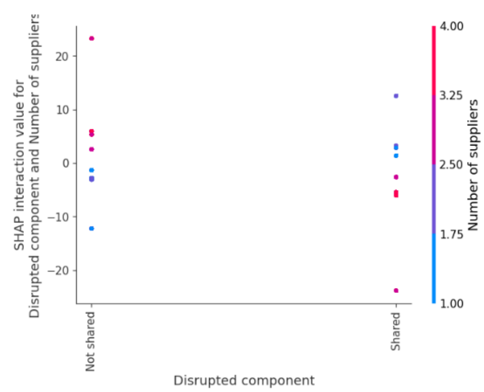
combinations of network-related and disruption-related parameters for each performance metric. In Figures 6 to Figure 8, we show only the significant and interpretable pairwise interaction effects of the parameters for each of the three performance metrics. The vertical spread of the SHAP interaction values in the figures describes the interaction effect between the two parameters. Figure 6(a), Figure 6(b), and Figure 6(c) show the interaction effect of the parameters for the performance metric 'Change in market lead time'. The figures show that the disruption-related parameter 'Disrupted component' has significant interaction effects with three network-related parameters, 'Number of tiers', 'Number of suppliers', and 'Percentage of MTO suppliers'. The results from the SHAP analysis indicate that the effect of a disruption of a non-shared component (which is produced only for a single customer within a network) on supply chain market lead time increases when the number of tiers and the number of suppliers increase in a supply chain (left side of Figure 6(a) and Figure 6(b)). However, the effect of a disruption of a shared component (which is produced for several suppliers within a network) on supply chain market lead time increases when the number of tiers and the number of suppliers decrease in a supply chain (right side of Figure 6(a) and Figure 6(b)). These results could be explained by the fact that in a supply chain, the components that are shared among several suppliers are mostly simple and less-complex components, e.g., standard parts, while the components that are produced for a single supplier are more customized and have a more complex design. The high number of tiers and suppliers in a supply chain implies that the customized components need to be produced with the collaboration of more suppliers, and if a disruption happens in such a network the effect on market lead time would be more. However, in small supply chains with a low number of tiers and suppliers, a disruption of a standard part that is shared among several suppliers could result in a significant effect on change in market lead time. Such an effect is less in complex supply chains as the delay caused by the disruption of standard parts could be absorbed by the long lead time of suppliers of more complex parts. Figure 6(c) on the left side shows that as the percentage of MTO suppliers decreases in a supply chain, the effect of disruption of non-shared components on supply chain market lead time increases. This result can be explained by the fact that a decrease in the number of MTO suppliers means an increase in the number of MTS suppliers and as a result, an increase in the inventory stock in the supply chain. A high inventory stock in a supply chain can increase vulnerability when unexpected adverse events happen. Figure 6(c) on the right side also shows that the effect of disruption of shared components on the supply chain market lead time increases as the percentage of MTO suppliers increases in a supply chain. This finding could be explained by the fact that in a supply chain with a high percentage of MTO suppliers, most of the components, including shared components, are produced based on customer orders. When a disruption happens in such a network, the customers of shared components should wait in a queue to receive their orders, and this affects market lead time. The higher the percentage of MTO suppliers in a network, the longer the queue for receiving the orders after the disruption, and thus, the effect on market lead time will be larger.

Figure 7(a) and Figure 7(b) show the interaction effects of the model parameters for the performance metric 'Time to detect disruption'. The figures show that the network-related parameter 'Percentage of MTO suppliers' has significant interaction effects with two disruption-related parameters, 'Disrupted tier' and 'Post-disruption capacity'. Figure 7(a) shows that as the percentage of MTO suppliers increases in a supply chain, which implies a decrease in the number of MTS suppliers, the effect of major loss of capacity (medium or small post-disruption capacity) on the time to detect disruption increases. This could be explained by the fact that the higher the percentage of MTO suppliers, the lower the inventory stock levels in a supply chain. High inventory stocks could delay the identification of a disruption. However, when there are no inventory stocks, a disruption might be recognized immediately. Figure 7(b) shows that as the percentage of MTO suppliers increases in a supply chain, the time to detect disruption in different tiers of a supply chain also increases. This could be explained by the fact that a higher number of MTO suppliers in a supply chain results in a longer market lead time of the final product, and therefore the disruption might not be recognized immediately in such supply chains. The figure shows a different pattern for disruptions in tier 1, which could be explained by the direct relation of the suppliers in tier 1 with the ATO focal company that results in the immediate detection of any disruption in tier 1.

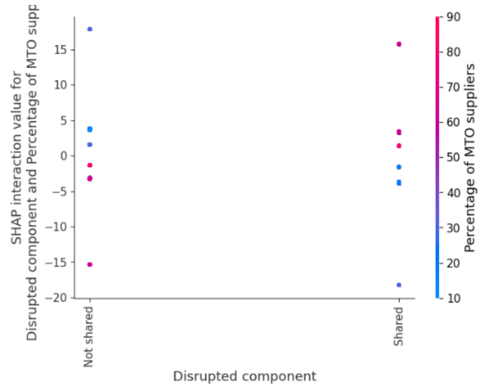
Figure 8(a), Figure 8(b), and Figure 8(c) show the interaction effects of the parameters for the performance metric 'Total recovery time'. The figures show that the disruption-related parameter 'Disrupted component' has significant interaction effects with two network-related parameters, 'Number of Suppliers' and 'Percentage of MTO suppliers'. Also, the disruption-related parameter 'Post-disruption capacity' has a significant interaction effect with the network-related parameter 'Percentage of MTO suppliers'. Figure 8(a) on the left side shows that the effect of a disruption of a non-shared component on the supply chain's total recovery time increases as the number of suppliers increases in a supply chain. However, the effect of a disruption of a shared component on supply chain recovery time increases when the number of suppliers decreases in a supply chain (right side of Figure 8(a)). These results could be explained by the fact that a high number of suppliers in a supply chain implies that the customized components need to be produced with the collaboration of more suppliers and if a disruption happens in such a network the effect on recovery time would be larger. However, in small supply chains with a low number of tiers and suppliers, a disruption of a standard part that is shared among several suppliers would result in a significant effect on recovery time. Such an effect is lower in complex supply chains as the delay caused by the disruption of standard parts could be absorbed by the long lead time of suppliers of more complex parts, and therefore the effect on recovery time would be less. Figure 8(c) shows that as the percentage of MTO suppliers increases in a supply chain, which implies a decrease in the number of MTS suppliers, the effect of a major loss of capacity (medium or small post-disruption capacity) on recovery time increases. This could be explained by the fact that a higher percentage of MTO suppliers means a lower number of inventory stock in a supply chain. The availability of inventory stock would accelerate the recovery from a disruption. However, when there is no inventory, the recovery time would increase.



(a)

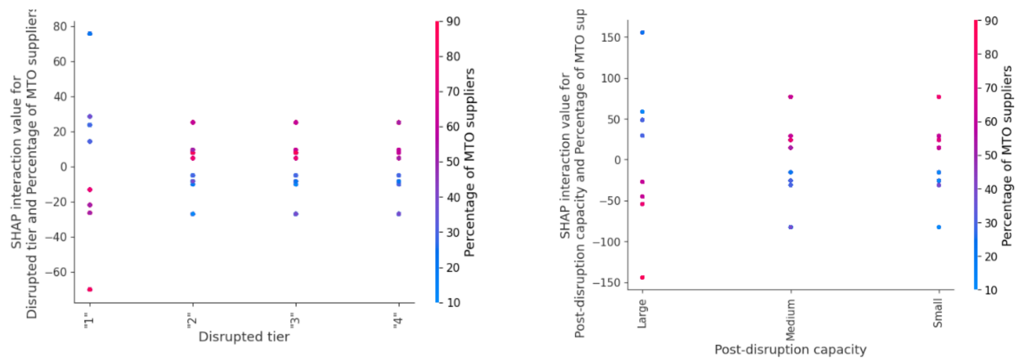


(b)



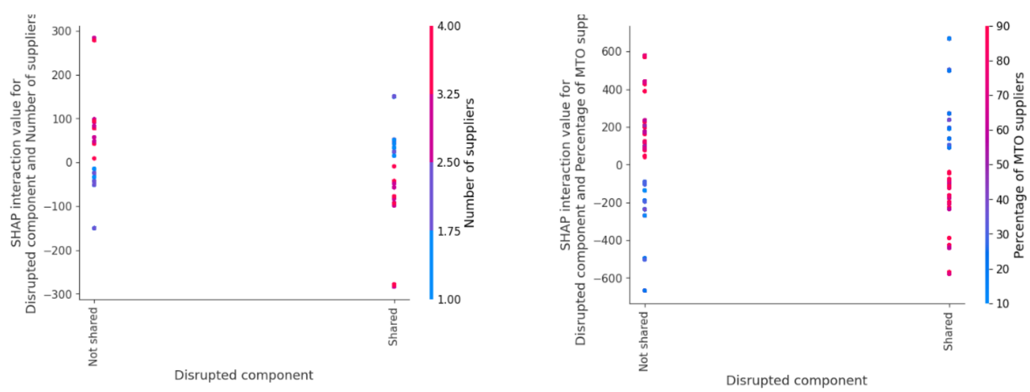
(c)

Figure 6. Plots of the SHAP interaction values for change in market lead time.

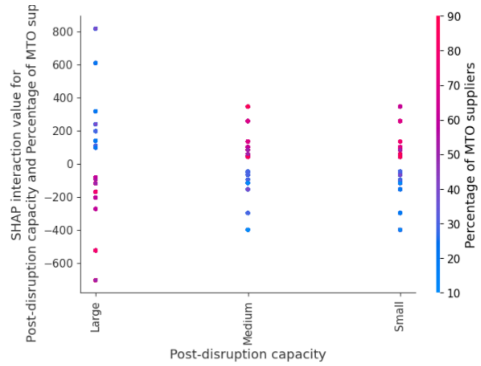


(a) (b)

Figure 7. Plots of the SHAP interaction values for time to detect disruption.



(a) (b)



(c)

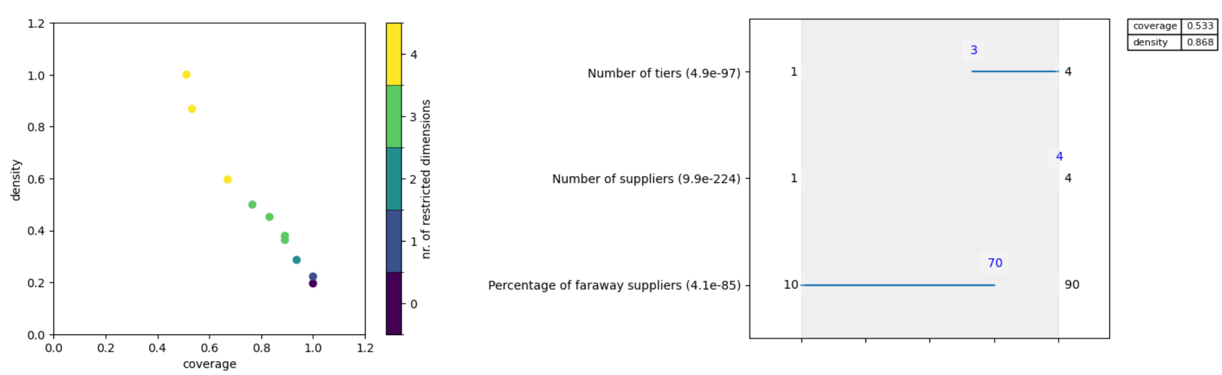
Figure 8. Plots of the SHAP interaction values for total recovery time.

6.4.1.3 Scenario discovery using PRIM for identifying important combinations of uncertainties

To get a more in-depth insight into how combinations of uncertainties affect the outcomes of interest, we apply scenario discovery (Bryant & Lempert, 2010). In scenario discovery, the computational experiments are subsequently analyzed with statistical machine learning algorithms to identify combinations of key factors that identify those situations where the objectives are met or are not met. For instance, in our supply chain case we are interested in identifying combinations of factors that cause an unacceptable supply chain performance in terms of high values for the change in market lead time. We are also interested in identifying combinations of factors that cause an acceptable supply chain performance in terms of a short time to detect disruption and a short recovery time. The scenario discovery method we use is the Patient Rule Induction Method (PRIM) (Friedman & Fisher, 1999). PRIM can be applied to identify combinations of values of input parameters of a model that result in specific outcomes of the model. To find these combinations, PRIM searches the entire dataset for patterns or trends and interprets them. It looks for a set of subspaces of the input space where the values of the output variables are noticeably different from their average values. PRIM describes such subspaces with 'boxes' in the input space. Several alternative boxes are generated by the PRIM algorithm in which the relation between input variables and outcomes of interest are labeled with a coverage (proportion of the total number of cases of interest), density (the fraction of the cases of interest with respect to the total number of cases in a box), and the number of restricted dimensions (limited set of dimensions of the model input space). When PRIM finishes the generation of the boxes, the decision maker can select a box for interpretation of the result based on a tradeoff between coverage, density, and restricted dimensions (Kwakkel, Auping, & Pruyt, 2013). For example, suppose a decision maker selects a box from the PRIM analysis with 80% coverage and 70% density to understand the relationship between input variables and the outcome of interest of a system. It means that the selected box describes the system based on 80 percent of the entire dataset and 70 percent of the outcome of interest. The high coverage value of a box ensures that the selected box is a reliable representative of the entire dataset. The high density value of a box ensures that the results interpreted by the box are statistically significant. In the rest of this section, we discuss the result of PRIM analysis for this research.

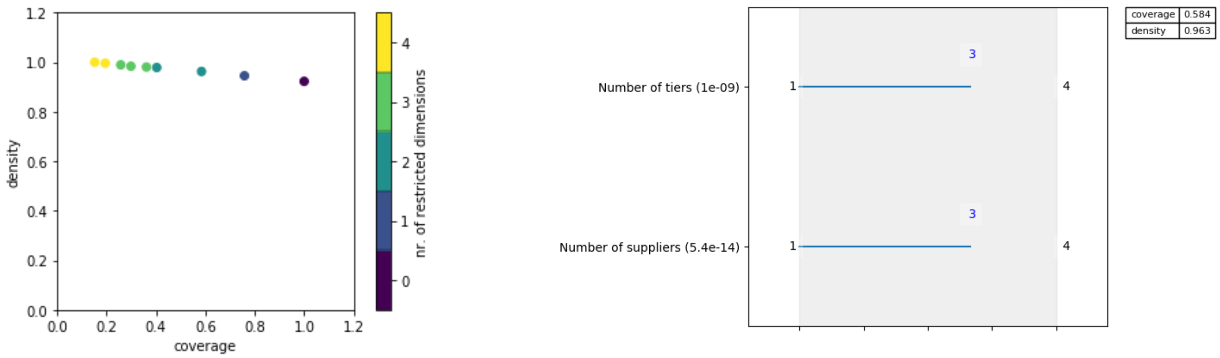
The first step in applying PRIM is to specify the result of interest. For example, suppose that for 'Change in market lead time' we are interested in values higher than 2500 time units, for 'Time to detect disruption' we are interested in values less than 3000 time units, and for 'Total recovery time' we are interested in values less than 1000 time units. Figure 9, Figure 10, and Figure 11 show the results of the PRIM analysis for change in market lead time, time to detect disruption, and total recovery time, respectively. Figures 9(a), 10(a), and 11(a) show the tradeoffs between coverage, density, and the number of restricted dimensions for each of the three performance measures. The colored dots represent PRIM boxes with different coverage, density, and restricted dimensions. We are typically interested in a scenario with high coverage and density. Figure 9(b), Figure 10(b), and Figure 11(b) represent the result of a selected PRIM box for each of the performance metrics. The top right corner of the figures shows the coverage and density of the selected boxes. The input variables in selected boxes are represented on the left side of the figures, where the statistical significance (p-value) of the value range of an input variable is represented between brackets. Figure 9(b) shows that with a coverage of 53% and a density of 86% (box 10 in Figure 9(a)), supply chains with three or four tiers, where a supplier in each tier has four suppliers in which up to 70 percent of those suppliers are faraway, are vulnerable to a change in the market lead time of more than 3000 time unit. In other words, 53 percent of the poor supply chain performance in terms of change in market lead time results from supply chain networks with three or four tiers where a supplier in each tier has four suppliers, in which up to 70 percent of those suppliers are faraway.

Figure 10(b) shows that with a coverage of 58% and a density of 96% (box 3 in Figure 10(a)), supply chains with fewer than three tiers where a supplier in each tier has fewer than three suppliers, perform the best in terms of time to detect disruption. Figure 11(b) shows that with a coverage of 46% and a density of 94% (box 4 in Figure 11(a)), supply chains with two tiers or one tier can have acceptable performance in terms of total recovery time of less than 1000 time units, over a range where suppliers in each tier assemble components in between 20 and 90 percent of the cases.



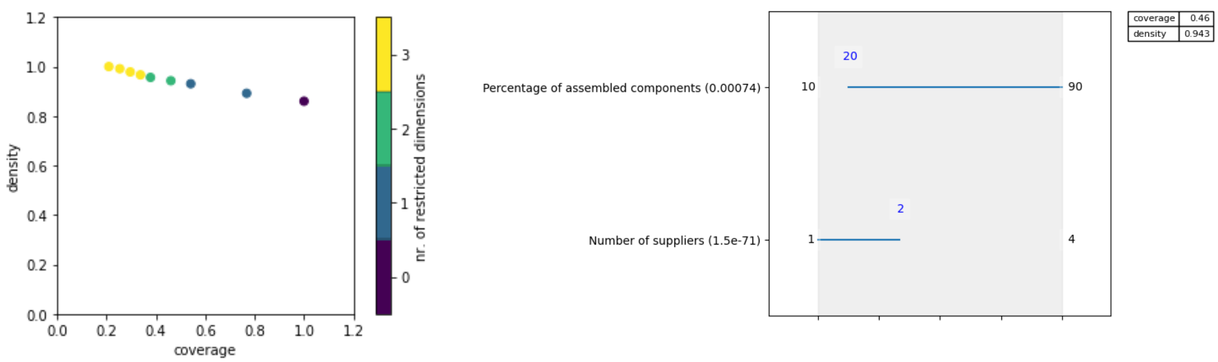
(a) (b)

Figure 9. Result of the PRIM analysis for change in market lead time with tradeoff between coverage and density (left) and the selected box information (right).



(a) (b)

Figure 10. Result of the PRIM analysis for time to detect disruption with tradeoff between coverage and density (left) and the selected box information (right).



(a) (b)

Figure 11. Result of the PRIM analysis for total recovery time with tradeoff between coverage and density (left) and the selected box information (right).

6.4.2 Results of directed search

Besides using open exploration, the vulnerability analysis can be complemented by a directed search. Directed search relies on optimization techniques to answer questions such as: what is the best that could happen or what is the worst that could happen? In this research, we use a directed search to answer the question of which supply chain network configuration has the worst performance under a worst-case disruption scenario. Answering such a question provides insight into the most vulnerable network configurations in need of improved resilience. Here, we use an optimization algorithm to search over the network-related parameters for a reference scenario for disruption in which all disruption-related parameters take their extreme values (worst-case scenario). We formulate the multi-objective optimization problem as follows:

Decision variables:

- *Number of tiers*
- *Number of suppliers of a supplier in each tier*
- *Percentage of MTO suppliers in each tier*
- *Percentage of assembled components in each tier*
- *Percentage of faraway suppliers in each tier*
- *Number of shared suppliers in each tier*

Objectives (note that we are interested in the worst case)

- *Maximize change in market lead time*
- *Maximize time to detect disruption*
- *Maximize total recovery time*

Solving the above optimization problem gives us information about those combinations of network variables (leading to different supply chain structures in this research) that have a poor performance in case of disruption. Knowing the network variables that lead to poor performance helps supply chain decision makers to avoid or redesign their supply chain as part of their risk management practices. To solve this multi-objective optimization problem, we used ε-NSGA2, a state-of-the-art genetic algorithm for solving multi-objective optimization problems (Reed, Kollat, & Devireddy, 2007). In order to make sure that the algorithm has converged to the optimal solutions, the number of functional evaluations (nfe) should be around 10,000. Due to limited available computer power, we only used 100 nfe to show the applicability of the approach. The Pareto front solution sets are shown in Table 3. The results include the values of six network-related parameters as model decision variables and three supply chain performance metrics as model objectives. Each result shows a combination of values for the network-related parameters that represent a supply chain structure (network type) with poor performance in case of a massive disruption. We label each of the 11 optimization results in the table to make it easier to refer to them in the discussion section. For example, we label the solution in the first row of Table 3 "network Type 1", which indicates a supply chain structure with 4 tiers, 3 suppliers of a supplier, 40% MTO suppliers in each tier, 60% assembled components in each tier, 80% faraway suppliers in each tier, and 1 shared supplier in each tier.

Figure 12 also shows the values of the objective functions of the problem from the optimization using a parallel coordinates plot. These plots are useful for visualizing data with three dimensions or more. Each vertical line represents a dimension in the data set. In our case, we have three vertical lines, each representing a supply chain performance metric. In a parallel coordinates plot, a data point with several dimensions is illustrated by a line connecting the vertical lines. In our case, a data point consists of three objective values from the optimization solution (the three last columns in Table 3). We have 11 data points in total. These data points are illustrated by colored lines in Figure 12. The worst solution is the straight line at the top of Figure 12, where all three performance metrics have their highest values. However, Figure 12 shows that each solution indicates a tradeoff between the three objective functions. This means the solutions are non-dominated and there is not a solution with superior performance for all three objectives. Therefore, decision makers need to make a tradeoff between the solutions based on their preference for one of the performance indicators. For example, in our sample, the results of the optimization in Table 3 show that supply chain designs similar to network types 9, 4, and 3 should be avoided by decision makers who consider a change in market lead time as the main resilience-related performance metric of their supply chain. Similarly, supply chain designs similar to network types 11, 7, and 2 should be avoided by decision makers who consider time to detect disruption as the main resilience-related performance metric of their supply chain.

Table 3. Optimization results for worst-case scenario

	Decision variables						**Objectives**		
	Number of tiers	Number of suppliers of a supplier in each tier	Percentage of MTO suppliers in each tier	Percentage of assembled components in each tier	Percentage of faraway suppliers in each tier	Number of shared suppliers in each tier	Change in market lead time	Time to detect disruption	Total recovery time
Network type 1	4	3	40	60	80	1	6444	4600	27327
Network type 2	2	2	60	30	90	0	5894	4633	26894
Network type 3	4	4	60	60	30	1	6924	4506	30285
Network type 4	4	3	90	80	80	1	6995	4504	30842
Network type 5	3	2	40	60	90	1	6392	4603	19310
Network type 6	4	2	80	70	50	2	6836	4602	26678
Network type 7	2	3	30	50	50	1	5887	4635	26891
Network type 8	3	4	50	20	30	1	6692	4529	30281
Network type 9	3	3	40	80	30	0	7094	4298	25949
Network type 10	4	3	20	60	60	2	5877	4601	29077
Network type 11	2	4	30	50	70	0	5807	4644	26347

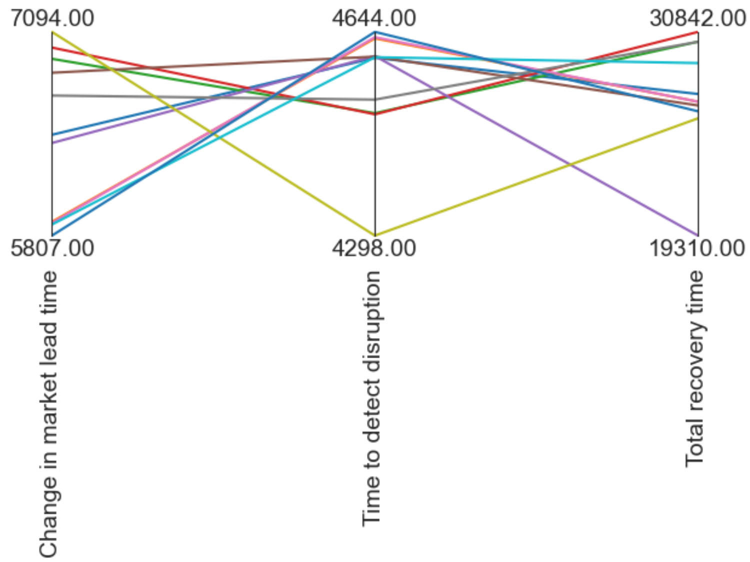


Figure 12. Parallel coordinates plot showing tradeoffs between optimization solutions.

6.5. Discussion and managerial insights

This paper proposes supply chain ensemble modeling as a data-driven model-based decision-making approach for supporting stress testing of a supply chain to improve its resilience, considering the lack of access to precise data about the structure of a complex supply chain as well as the unpredictability of disruptive events. Many recent supply chain disruptions, such as the COVID-19 pandemic or the war in the Ukraine, highlight that to ensure continuity of their business in case of adverse events, supply chain managers need to be prepared by identifying vulnerability sources of their supply chain and implementing proper disruption management actions. The literature includes a variety of model-based approaches, including simulation and optimization models, for tackling the problem of supply chain stress testing to potentially improve resilience. Earlier research typically points out that the quality of model-based approaches for supporting supply chain resilience relies on the availability of data and information. However, the unpredictable nature of disruptive events and their low frequency makes historical-based estimation of a disruption and recovering from it challenging. In light of this challenge, there is a growing research field in data-driven model-based decision-making approaches for supporting supply chain resilience improvement. These approaches rely on supply chain data analytic methods for assessing the vulnerability of a supply chain and improving its resilience. One of the main challenges for conducting reliable data-driven stress testing of a supply chain is the unavailability of complete and high-quality data about disruptions and about the entire supply chain network structure. Disruptions are mostly deeply uncertain events that can hardly be predicted based on historical data. In addition, globalization and the complexity of today's supply chains, which result in an expansion of network boundaries and an increasing number of nodes and links in a network, make it hard for decision makers to capture precise and aggregated information about the many actors of a supply chain and their interactions, especially actors beyond the second or third tier of the network. This research contributes to the literature of data-driven model-based decision-making approaches for supply chain stress testing by studying supply chain ensemble modeling. Ensemble modeling involves exploring the range of possible outcomes by running a large set of simulations that differ in assumptions and parameter values. Ensemble modeling has proven to be a promising approach to deal with the difficulty of making predictions in highly uncertain complex systems such as weather forecasts. In this research, we demonstrate how supply chain ensemble modeling can contribute to the theory and practice of supply chain stress testing and resilience.

In supply chain ensemble modeling, a large ensemble of plausible supply chain models and disruption scenarios are generated and explored using computational experiments for reasoning about the vulnerabilities of a supply chain, which is a first step in making supply chains more resilient. This paper contributes to the literature on model-based supply chain stress testing by considering the uncertainty regarding the structure of a supply chain in supply chain stress testing, which is rooted in a lack of access to precise and aggregated information about the complete set of supply chain actors. Where most of the studies in the literature consider developing a single model for assessing the impact of disruptions on supply chain performance, this paper considers an ensemble of plausible models in order to incorporate uncertainties in the dynamics of the supply chain network as well as unavailability of information about the structure of complex supply chains. For generating the ensemble of supply chain structures, we characterize a supply chain with several network-related parameters, i.e., number of tiers, number of suppliers, number of shared suppliers, percentage of assembled components, percentage of faraway suppliers, and percentage of MTO suppliers. Different combinations of these network parameters generate different supply chain structures. These structures are generated automatically by a Python-based network generator, and subsequently used in a data-driven approach to instantiate the corresponding simulation models. This way, we contribute to the literature of supply chain modeling and simulation by allowing a modeler to create, run, and adjust a variety of supply chain simulation models without programming. Our approach allows simulation-based analysis of a supply chain even when there is a lack of information about the supply chain structure to build a reliable simulation model. Our approach also contributes to the literature on supply chain disruption management by enabling disruption modeling where an estimation of disruption attributes, such as the likelihood of occurrence, magnitude, and propagation, is largely unknown. Therefore, we propose a consequence-based risk analysis approach for modeling disruptions. In contrast with conventional risk modeling approaches that deal with identifying the root cause of a risk and determining its characteristics, such as probability of occurrence and intensity, the consequence-based risk approach focuses on analyzing the consequences of potential risks associated with a supply chain regardless of the root cause of the risk. For example, no matter whether a strike or congestion in a port disturbs a waterborne transportation activity within the supply chain, the focus is on answering the question of what will happen if that transport activity is disrupted. To explore the variety of disruption scenarios, we characterize a risk consequence with several parameters, including disrupted tier, disrupted component, disrupted element, disrupted region, disruption duration, post-disruption capacity, and recovery rate of the disrupted element. Different combinations of these disruption parameters generate different disruption scenarios. We also look at scenarios of compound risks rather than only focusing on single points of failure, which are mostly addressed in model-based stress testing approaches in the literature. Considering only the impact of individual disruptions is misleading because a combination of unexpected events, or an event that impacts multiple actors in the supply chain at the same time, may have diverse and complicated effects that should be considered in resilience practices. To generate ensemble supply chain structures and disruption scenarios, we perform exploratory modeling: a model-based technique that can systematically explore a large ensemble of plausible scenarios. The application of exploratory modeling, which facilitates the generation of thousands of what-if scenarios about supply chain structures and disruptions and their analysis, is another contribution of this research to the literature on scenario-based supply chain stress testing approaches. The literature on scenario-based approaches for supply chain stress testing usually covers only a limited set of scenarios for representing future risks. These selected scenarios are typical disruptions that could happen (or already did happen) in critical elements of a supply chain. However, it is insufficient to rely on human reasoning for selecting possible disruption scenarios, given the complexity of today's supply chains and the unpredictable nature of disruptive events. Another contribution of our research relates to considering the a posteriori approach for treating uncertainty. Probability-based approaches for stress testing of a supply chain mostly adopt an a priori approach for treating uncertainty, which implies that for making good decisions for improving a supply chain's resilience, all information about uncertainties should be present before performing the stress testing. However, our approach adopts an a posteriori analysis, which explores the space of plausible assumptions about uncertainties to increase the reliability of stress testing across a large range of possible futures of a supply chain. In our approach, we don't give priority to any of the scenarios to minimize the risk of making a wrong judgment, which is common in ex-ante stress testing of a complex supply chain in an unpredictable business environment.

Supply chain ensemble modeling provides supply chain decision makers with an approach to tackle the challenges of stress testing their supply chain in practice. While the complexity of today's supply chains makes it hard for supply chain decision makers to completely understand the structure of their supply chain and model it, the ensemble modeling approach still allows decision makers to investigate vulnerabilities of their supply chain by exploring a variety of supply chain structures, which are generated based on different input parameters and assumptions about a supply chain network. Ensemble modeling allows supply chain decision makers to investigate the robustness of different strategies for managing vulnerabilities of the supply chain by testing them under a variety of supply chain structures and under many disruption scenarios (the aspect of ensemble modeling of possible interventions is out of the scope of this paper). The ensemble modeling approach proposed in this research allows supply chain decision makers to deal with the unpredictability of disruptive risks. While a big challenge for a decision maker in supply chain stress testing is to define a range of potential disruption scenarios that can affect supply chain functionality, ensemble modeling allows a systematic exploration of the disruption scenarios, which helps decision makers to investigate a wide range of scenarios that might have remained uninvestigated with human reasoning.

The used exploratory modeling approach allows the identification of extreme events that have a huge impact on supply chain performance and therefore must be considered by decision makers in risk management practices. By simulating low-probability, high-impact events, exploratory modeling helps a decision maker to identify vulnerabilities, assess potential risks, and develop robust strategies for mitigating adverse consequences. The consequence-based risk analysis proposed in this research allows a decision maker to investigate potential consequences of disruptions in the supply chain network, rather than searching for the possible causes of a disruption and their frequency of occurrence and magnitude, which are often impossible to predict for an adverse event. The modular simulation modeling approach we developed in this research allows supply chain decision makers to model any real-world supply chain without facing programming complexities. Analyzing the result of exploratory modeling with data mining approaches can provide supply chain decision-makers with insights about the vulnerability of their supply chain.

The results from the feature scoring analysis help supply chain decision makers draw conclusions about the most influential network factors and disruption factors that contribute to the vulnerability of their supply chain. Decision makers can focus on those parameters in developing proper resilience improvement actions and leave out the factors that do not contribute much to the vulnerability of their supply chain. While feature score analysis only looks at the influence of individual network-related or disruption-related factors on supply chain vulnerability, the SHAP analysis can provide decision makers with insights into interaction effects between a network-related and a disruption-related parameter. Such results can help decision makers to identify which disruption-related factors can be mitigated by specific network configurations. For example, one implication of SHAP results of the supply chain sample in this research is that in order to improve resilience in terms of change in market lead time in supply chains with a high number of tiers and suppliers, the vulnerability of non-shared components should be decreased, while in supply chains with a high percentage of MTO suppliers, more attention should be given to suppliers of shared components. The results from the PRIM analysis help supply chain decision makers to identify the main network-related parameters that jointly contribute to desired or undesired supply chain performance across an ensemble of disruption scenarios. For example, in our supply chain sample, the PRIM analysis shows that 53 percent of the poor supply chain performance in terms of change in market lead time results from supply chain networks with three or four tiers where a supplier in each tier has a high number of suppliers, where up to 70 percent of those suppliers are faraway. These kinds of results could help decision makers design or adapt a specific supply chain network that supports their preference for resilient performance. The results from the optimization can provide decision makers with insights about network structures with best/worst performance under a specific scenario of disruption. It helps decision makers to identify the optimized configuration of the supply chain network that satisfies their objectives in terms of resilience. Supply chain decision makers can adapt the structure of their supply chains in such a way that they steer away from the more vulnerable network configurations and incorporate characteristics of the less vulnerable configurations.

The supply chain ensemble modeling approach proposed in this research can contribute to several emerging concepts in supply chain management, including viable supply chains, reconfigurable supply chains, and digital supply chain twins (Ivanov, 2022; Ivanov & Dolgui, 2020; Dolgui, Ivanov, & Sokolv, 2020, Ivanov & Dolgui, 2021). Ensemble modeling can contribute to improving the viability of a supply chain, which is defined as the ability of a supply chain to survive in the changing business environment by replanning and redesigning its structure. Ensemble modeling allows for assessing the robustness and flexibility of a supply chain by exploring as many future scenarios as possible, where the scenarios are generated systematically through exploratory modeling, including unexpected scenarios that may be overlooked in conventional best-estimation scenario definition approaches. Ensemble modeling can contribute to the viability of intertwined supply chains by taking into account uncertainties related to the structure of such deeply interconnected and interdependent supply chains. Ensemble modeling can also help in the design of reconfigurable supply chains by allowing decision makers to explore an ensemble of configurations of a supply chain and the way they respond under different scenarios. Finally, ensemble modeling can support the concept of digital supply chain twins. A digital supply chain twin, a computerized digital supply chain model for representing the supply chain state in real time, is proposed by researchers to support the visibility of a supply chain to improve its resilience. Ensemble modeling could help to include missing information due to network complexity in digital supply chain twins.

Using all available actual information about the supply chain is crucial for the successful implementation of supply chain ensemble modeling in practice. A supply chain decision maker needs to collect relevant data from several sources such as ERP records, inventory management records, supplier records, transportation records, internal reports, and surveys and interviews. For the information that cannot be obtained, the network generator will generate plausible assumptions.

As we applied an exploratory modeling approach for the generation of supply chain network structures and disruption scenarios, we had several challenges regarding scenario generation, complexity reduction, and the robustness of scenarios. For scenario generation, we characterized both the supply chain structure and the disruption with several parameters. By combining those parameters, a variety of supply chain networks and disruption scenarios are generated. By exploring the parameters' uncertainty space, we ensure the generation of a comprehensive set of scenarios, including typically overlooked scenarios and rare events. The network generator developed in this research generates a variety of network scenarios based on the combination of different values of the network parameters. Some combinations of the values of network parameters generate infeasible network structures. These infeasible network structures are excluded automatically from the analysis by the network generator. To avoid a combinatorial explosion, we had to make a tradeoff between interpretability and the number of uncertain parameters in the scenario generation. We limited the number of network-related and disruption-related parameters to avoid a high dimensional uncertainty space, which would make the interpretation of the results more difficult. We checked the robustness of the generated set of scenarios by applying a sensitivity analysis to several key model assumptions. Another check we carried out was that the generated scenarios consider both optimistic and pessimistic scenarios regarding the future. We refined the process of scenario generation in an iterative way based on the feedback we got from the robustness check.

6.6. Conclusions

This paper tackles the problem of model-based stress testing of a supply chain where there is limited access to reliable information about the supply chain structure and about future disruptive events. We proposed an approach using supply chain ensemble modeling supported by exploratory modeling, the latter being a method for supporting decision making under deep uncertainty with an emphasis on finding decisions that have satisfactory outcomes under as many scenarios as possible. In our approach, rather than estimating the probability distribution of uncertain parameters of the model, which is common in conventional supply chain stress-testing approaches, we explore a wide set of scenarios that cover uncertainties in several network-related and disruption-related parameters to generate a database of outcomes of supply chain performance. This database can subsequently be analyzed to get insights into systematic patterns of behavior of supply chain networks across the scenarios.

We faced several limitations in conducting this research. The first one is related to the computational limitations that cause very long run times for the optimization algorithm to converge, due to the fact that each functional evaluation is based on several replications of running the supply chain simulation model. Therefore, we used only 100 functional evaluations for the optimization algorithm to show the feasibility of the implementation of directed search. More computer power and possibly a more efficient implementation of the data-driven simulation model are needed to ensure that the optimization algorithm converges to the best solutions. A second limitation of this study is the generation of disruption scenarios with equal probability in the exploratory modeling. In practice, a decision maker might prefer to give priority to disruption scenarios with a higher probability. There is an emerging research direction in the literature on exploratory modeling that focuses on the a posteriori assignment of likelihood to exploratory results. This can be a direction of future work for this research. A third limitation of this research is that our supply chain model is not as complex as a real word supply chain. We explore the importance of six network-related and seven disruption-related parameters in the resilience of supply chain networks, and we study a single assemble-to-order end product. One direction of research can be the identification of other drivers of supply chain resilience. We also did not yet include mitigation strategies to cope with disruptions. A final direction of further research is to explore the effect of different mitigation strategies on the resilience of different supply chain structures. By using the mitigation strategies as deeply uncertain variables, the effectiveness and robustness of the mitigation strategies can be analyzed by the same techniques that were introduced in this paper.

References

Aldrighetti, R., Battini, D., Ivanov, D., & 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.

Alikhani, R., Ranjbar, A., Jamali, A., Torabi, S. A., & Zobel, C. W. (2023). Towards increasing synergistic effects of resilience strategies in supply chain network design. *Omega*, *116*, 102819.

Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. *Journal of operations management*, *33*, 111-122.

Babazadeh, R., & Razmi, J. (2012). A robust stochastic programming approach for agile and responsive logistics under operational and disruption risks. *International Journal of Logistics Systems and Management*, *13*(4), 458-482.

Bankes, S. (1993). Exploratory modeling for policy analysis. *Operations research*, *41*(3), 435-449.

Bankes, S. C. (2002). Tools and techniques for developing policies for complex and uncertain systems. *Proceedings of the National Academy of Sciences*, *99*(suppl_3), 7263-7266.

Berger, N., Schulze-Schwering, S., Long, E., & Spinler, S. (2023). Risk management of supply chain disruptions: An epidemic modeling approach. *European Journal of Operational Research*, *304*(3), 1036-1051.

Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. *Technological Forecasting and Social Change*, *77*(1), 34-49.

Dolgui, A., & Ivanov, D. (2020). Exploring supply chain structural dynamics: New disruptive technologies and disruption risks. *International journal of production economics*, *229*, 107886.

Dolgui, A., & Ivanov, D. (2021). Ripple effect and supply chain disruption management: new trends and research directions. *International Journal of Production Research*, *59*(1), 102-109.

Dolgui, A., Ivanov, D., & Rozhkov, M. (2020). Does the ripple effect influence the bullwhip effect? An integrated analysis of structural and operational dynamics in the supply chain. *International Journal of Production Research*, *58*(5), 1285-1301.

Dolgui, A., Ivanov, D., & Sokolov, B. (2020). Reconfigurable supply chain: The X-network. *International Journal of Production Research*, *58*(13), 4138-4163.

Frazzon, E. M., Freitag, M., & Ivanov, D. (2021). Intelligent methods and systems for decision-making support: Toward digital supply chain twins. *International journal of information management*, *57*, 102281.

Friedman, J. H., & Fisher, N. I. (1999). Bump hunting in high-dimensional data. *Statistics and computing*, *9*(2), 123-143.

Geurts, P., Ernst, D., & Wehenkel, L. (2006). Extremely randomized trees. *Machine learning*, *63*, 3-42.

Ghadge, A., Er, M., Ivanov, D., & Chaudhuri, A. (2022). Visualisation of ripple effect in supply chains under long-term, simultaneous disruptions: a system dynamics approach. *International Journal of Production Research*, *60*(20), 6173-6186.

Gneiting, T., & Raftery, A. E. (2005). Weather forecasting with ensemble methods. *Science*, *310*(5746), 248-249.

Goodall, P., Sharpe, R., & West, A. (2019). A data-driven simulation to support remanufacturing operations. *Computers in Industry*, *105*, 48-60.

Gross, T., MacCarthy, B. L., & Wildgoose, N. (2018). Introduction to dynamics of manufacturing supply networks. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *28*(9).

Hägele, S., Grosse, E. H., & Ivanov, D. (2023). Supply chain resilience: a tertiary study. *International Journal of Integrated Supply Management*, *16*(1), 52-81.

Halim, R. A., Kwakkel, J. H., & Tavasszy, L. A. (2016a). A scenario discovery study of the impact of uncertainties in the global container transport system on European ports. *Futures*, *81*, 148-160.

Halim, R. A., Kwakkel, J. H., & Tavasszy, L. A. (2016b). A strategic model of port-hinterland freight distribution networks. *Transportation Research Part E: Logistics and Transportation Review*, *95*, 368-384.

Hosseini, S., & Ivanov, D. (2022). A new resilience measure for supply networks with the ripple effect considerations: A Bayesian network approach. *Annals of Operations Research*, *319*(1), 581-607.

Houck, D., & Whitehead, C. (2019, December). Introduction To Simio. In *2019 Winter Simulation Conference (WSC)* (pp. 3802-3811). IEEE.

Ivanov, D. (2022). 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. (2023). Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability. *International Journal of Production Economics*, *263*, 108938.

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International journal of production research*, *58*(10), 2904-2915.

Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, *32*(9), 775-788.

Ivanov, D., & Dolgui, A. (2019). Low-Certainty-Need (LCN) supply chains: a new perspective in managing disruption risks and resilience. *International Journal of Production Research*, *57*(15-16), 5119-5136.

Ivanov, D., & Dolgui, A. (2021). OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications. *International Journal of Production Economics*, *232*, 107921.

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International journal of production research*, *57*(3), 829-846.

Jaxa-Rozen, M., & Kwakkel, J. (2018). Tree-based ensemble methods for sensitivity analysis of environmental models: A performance comparison with Sobol and Morris techniques. *Environmental Modelling & Software*, *107*, 245-266.

Klibi, W., & Martel, A. (2012). Scenario-based supply chain network risk modeling. *European Journal of Operational Research*, *223*(3), 644-658.

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environmental Modelling & Software*, *96*, 239-250.

Kwakkel, J. H., Walker, W. E., & Marchau, V. A. W. J. (2010, April). From predictive modeling to exploratory modeling: How to use non-predictive models for decisionmaking under deep uncertainty. In *Proceedings of the 25th Mini-EURO Conference on Uncertainty and Robustness in Planning and Decision Making (URPDM2010), 15-17 April*.

Kwakkel, J. H., Haasnoot, M., & Walker, W. E. (2015). Developing dynamic adaptive policy pathways: a computer-assisted approach for developing adaptive strategies for a deeply uncertain world. *Climatic Change*, *132*, 373-386.

Kwakkel, J. H., & Haasnoot, M. (2019). Supporting DMDU: A taxonomy of approaches and tools. *Decision making under deep uncertainty: From theory to practice*, 355-374. Cham, Switzerland: Springer International Publishing.

Kwakkel, J. H., & Pruyt, E. (2013). Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty. *Technological Forecasting and Social Change*, *80*(3), 419-431.

Kwakkel, J. H., & Pruyt, E. (2015). Using system dynamics for grand challenges: the ESDMA approach. *Systems Research and Behavioral Science*, *32*(3), 358-375.

Kwakkel, J. H., Auping, W. L., & Pruyt, E. (2013). Dynamic scenario discovery under deep uncertainty: The future of copper. *Technological Forecasting and Social Change*, *80*(4), 789-800.

Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006). A general, analytic method for generating robust strategies and narrative scenarios. *Management science*, *52*(4), 514-528.

Lempert, R., Kalra, N., Peyraud, S., Mao, Z., Tan, S. B., Cira, D., & Lotsch, A. (2013). Ensuring robust flood risk management in Ho Chi Minh City. *World Bank Policy Research Working Paper*, (6465).

Lempert, R. J. (2003). Shaping the next one hundred years: New methods for quantitative, long-term policy analysis. *Santa Monica, CA:RAND.*

Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., ... & Lee, S. I. (2020). From local explanations to global understanding with explainable AI for trees. *Nature machine intelligence*, *2*(1), 56-67.

MacCarthy, B. L., Blome, C., Olhager, J., Srai, J. S., & Zhao, X. (2016). Supply chain evolution–theory, concepts and science. *International Journal of Operations & Production Management*, *36*(12), 1696-1718.

Merrick, J. H., & Weyant, J. P. (2019). On choosing the resolution of normative models. *European Journal of Operational Research*, *279*(2), 511-523.

Moallemi, E. A., Kwakkel, J. H., de Haan, F. J., & Bryan, B. A. (2020). Exploratory modeling for analyzing coupled human-natural systems under uncertainty. *Global Environmental Change*, *65*, 102186.

Nahar, N., Ara, F., Neloy, M. A. I., Biswas, A., Hossain, M. S., & Andersson, K. (2021). Feature selection based machine learning to improve prediction of Parkinson disease. In *Brain Informatics: 14th International Conference, BI 2021, Virtual Event, September 17–19, 2021, Proceedings 14* (pp. 496-508). Springer International Publishing.

Palmer, T. N. (2002). The economic value of ensemble forecasts as a tool for risk assessment: From days to decades. *Quarterly Journal of the Royal Meteorological Society: A journal of the atmospheric sciences, applied meteorology and physical oceanography*, *128*(581), 747-774.

Parker, W. S. (2013). Ensemble modeling, uncertainty and robust predictions. *Wiley interdisciplinary reviews: Climate change*, *4*(3), 213-223.

Paul, S., & Venkateswaran, J. (2020). Designing robust policies under deep uncertainty for mitigating epidemics. *Computers & Industrial Engineering*, *140*, 106221.

Rajagopal, V., Venkatesan, S. P., & Goh, M. (2017). Decision-making models for supply chain risk mitigation: A review. *Computers & Industrial Engineering*, *113*, 646-682.

Reed, P., Kollat, J. B., & Devireddy, V. K. (2007). Using interactive archives in evolutionary multiobjective optimization: A case study for long-term groundwater monitoring design. *Environmental Modelling & Software*, *22*(5), 683-692.

Sawik, T. (2011). Selection of supply portfolio under disruption risks. *Omega*, *39*(2), 194-208.

Sawik, T. (2013). Integrated selection of suppliers and scheduling of customer orders in the presence of supply chain disruption risks. *International Journal of Production Research*, *51*(23-24), 7006-7022.

Storer, L. N., Gill, P. G., & Williams, P. D. (2020). Multi-diagnostic multi-model ensemble forecasts of aviation turbulence. *Meteorological Applications*, *27*(1), e1885.

Trutnevyte, E., Stauffacher, M., & Scholz, R. W. (2012). Linking stakeholder visions with resource allocation scenarios and multi-criteria assessment. *European Journal of Operational Research*, *219*(3), 762-772.

Tsai, H. C., Elsberry, R. L., Chin, W. C., & Marchok, T. P. (2020). Opportunity for early warnings of Typhoon Lekima from two global ensemble model forecasts of formation with 7-day intensities along medium-range tracks. *Atmosphere*, *11*(11), 1162.

Wolff, S., O'Donncha, F., & Chen, B. (2020). Statistical and machine learning ensemble modelling to forecast sea surface temperature. *Journal of Marine Systems*, *208*, 103347.

Zhang, C., Huang, Y., Javed, A., & Arhonditsis, G. B. (2019). An ensemble modeling framework to study the effects of climate change on the trophic state of shallow reservoirs. *Science of the total environment*, *697*, 134078.

Zhu, L. Y., Ma, Y. Z., & Zhang, L. Y. (2014, August). Ensemble model for order priority in make-to-order systems under supply chain environment. In *2014 International Conference on Management Science & Engineering 21th Annual Conference Proceedings* (pp. 321-328). IEEE.

7 Conclusions and recommendations

In this chapter, we synthesize the findings for each research question introduced in Chapter 1 and then answer the main research question of this thesis. Next, we elaborate on the scientific reflection of our approach and the implications of this research for practice.

7.1 Conclusions

After reviewing the limitations of the current model-based approaches for supporting supply chain resilience, we posed the main research question of this thesis in Chapter 1 as follows:

What is an adequate approach for model-based risk analysis of a supply chain to support its resilience?

To answer the above question, we formulated three sub-questions. These questions are revisited below.

Question 1: How can consequence-based risk analysis overcome the challenges of conventional risk analysis approaches for improving supply chain resilience?

This research question was answered in Chapter 4 of this dissertation. Drawing on the limitations of model-based approaches for supporting supply chain resilience, which mainly arise from the unpredictable nature of disruptive risks, we proposed the concept of consequence-based risk analysis of a supply chain in which, rather than considering the root cause of a disruption and its characteristics such as frequency of occurrence and magnitude, one focuses on consequences of plausible disruptions at elements within the supply chain. A big challenge for performing an efficient consequence-based risk analysis of a supply chain is analyzing a comprehensive set of future disruption scenarios that the supply chain may encounter. Also, resilience practices for overcoming supply chain disruptions must be effective under as many disruption scenarios in the future as possible. To answer this research question, we adopted robust decision making (RDM), a common approach for addressing decision making under deep uncertainty, and we formulated the problem under study with the XLRM framework. We defined a set of characteristics for disruption and considered them as deeply uncertain parameters of the problem. These parameters include disruption location (region of disruption, tier of disruption, disrupted component), disrupted element, disruption duration, post-disruption capacity, and recovery rate of the disrupted element. We also identified some characteristics of resilience practices as policy levers of the problem. We defined a number of resilience-related measures for measuring the performance of the supply chain under disruption. We modeled the relations within the supply chain as well as the behavior of the supply chain under disruption. Then, we generated a database of a wide set of plausible disruption scenarios and their impact on performance measures using exploratory modeling. Then, by analyzing the result, we got information about the vulnerability of a supply chain as well as robust resilience practices that work fine under a broad set of disruption scenarios. We concluded that RDM helps improve the resilience of complex supply chains that suffer from high uncertainty regarding future disruptions. Our approach enables the identification of sources of vulnerabilities that are hard to detect by human reasoning, such as vulnerabilities beyond the first or second tier of the supply chain network. The proposed approach helps to assess the robustness of different resilience responses to these vulnerabilities.

Question 2: What operational aspects affect the resilience of a supply chain structure?

This research question was addressed in Chapter 5 of this dissertation. Drawing on the need for considering supply chain structure in assessing and improving supply chain resilience, we identified limitations in the current approaches. These approaches mostly consider a graphical perspective to the structure of a supply chain and ignore operational aspects in measuring resilience. To address this, we proposed a new approach that is capable of comparing the resilience of several supply chain structures that differ in three operational aspects: product structure, sourcing strategy, and production strategy. Using exploratory modeling, we exposed different network structures to various disruption scenarios to derive key operational characteristics that affect a supply chain's resilience. Our analysis supports our expectation that deeper, wider, and more geographically dispersed network topologies are more vulnerable to disruption than shallow, narrow, and dense ones. We also concluded that a high percentage of suppliers with an MTS strategy in a network results in late disruption detection. In contrast, a high number of shared suppliers results in fast disruption detection. Our results also align with the fact that the time to return to business as usual decreases as a supply chain network's complexity decreases in depth, width, and dispersion. In this research, we showed that a change in the number of tiers of a supply chain network has the highest impact on the vulnerability of market lead time. Additionally, the percentage of MTO suppliers versus MTS suppliers in a network plays the most critical role in total recovery time after disruption. The time to detect disruption is also affected by the number of suppliers in each tier.

Question 3: 3. How to do model-based stress testing of a supply chain despite a lack of precise information about the supply chain structure?

This research question was addressed in chapter 6 of this dissertation. Because of the lack of reliable information about the structure of a complex supply chain, and considering the structural dynamics of a complex supply chain over time, we proposed ensemble modeling of a supply chain to answer the third research question. In this approach, rather than considering a single structure for a supply chain, an ensemble of supply chain structures is generated and analyzed to determine the vulnerability sources in need of resilience practices. For the analysis, we adopted the exploratory modeling approach in which a large set of supply chain models and disruption scenarios are generated by parametrizing a supply chain and disruptive risks and sampling over them using computational experiments. We showed that by using the proposed approach, decision-makers could get insights into the resilience of the supply chain networks that fit their supply chains the most without having access to complete information on the supply chain structure and its parameters. The approach helps to address structural uncertainties associated with complex supply chains.

7.2 Scientific reflections

The research questions that we address in this research all have roots in the complexity of supply chains and the unpredictability of adverse events that make access to data and information for improving supply chain resilience challenging. This research contributes to the literature on supply chain risk management by introducing the concept of consequence-based risk analysis, which focuses on assessing the consequences of plausible risks for the disruption of elements along the supply chain rather than focusing on the root cause of these risks. Consequence-based risk analysis helps identify the most critical vulnerabilities in need of resilience investment. This approach allows for adequate supply chain risk management despite incomplete information on the risks in terms of their likelihood and frequency. To address the challenge of implementing consequence-based risk analysis in complex supply chains, this research treated the problem of supply chain resilience as a problem of decision making under deep uncertainty (DMDU). Specifically, we applied exploratory modeling, which deals with using models to explore the future rather than predict it. Although exploratory modeling has successful applications in other disciplines, specifically climate adaptation, supply chain risk management literature has not yet benefited from this approach. This research showed that supply chain resilience can be supported by exploratory modeling approach by enabling supply chain disruption management without knowing precise values of the disruption attributes such as the probability of occurrence, magnitude, and propagation, as well as the supply chain structure. Because uncertainties are inherent aspects of many supply chain processes, more research can be done to explore how other supply chain management problems, such as strategic, tactical, and operational planning, can be addressed by an exploratory modeling approach. For example, exploratory modeling can help supply chain decision makers explore the impact of a wide range of possible futures, such as economic fluctuations or market dynamics, on strategic decisions, such as network design or facility locations. This allows the identification of the strategies that are robust across many futures. Regarding tactical planning, exploratory modeling allows exploration among different inventory policies or supply chain configurations under various scenarios about demand fluctuations or supply disruptions. Exploratory modeling also allows exploration of daily operations of the supply chain under a variety of situations, such as machine failures or unexpected transportation delays.

Recent supply chain disruption cases due to unlikely events such as a pandemic and geopolitical tensions show that considering deep uncertainty in supply chain risk management practices is crucial nowadays for a business's success. The applicability of other DMDU approaches to supply chain management problems can be explored in future studies. Interested readers can use Kwakkel and Hassnoot (2019), in which the authors review various approaches and tools for supporting decision making under deep uncertainty.

We developed a supply chain simulation model to explore disruptive events' impact on supply chain performance and evaluated different resilience practices. To this end, we adopted a modular modeling approach in which pre-built model components were developed to generate different simulation models automatically by assembling different configurations of model components. This approach can reduce the modeling complexity, and it enables the simulation model's scalability from small to significant size supply chain networks. For the simulation experiments, we adopted the discrete-event simulation formalism to capture interactions of technical elements of the supply chain and to define the supply chain processes and queues. Since several resilience practices are concerned with the behavior of the actors within a supply chain, such as coordination, negotiation, and information sharing, one research direction is to incorporate the social interaction of the supply chain actors into the supply chain simulation model. This can be done with an agent-based modeling approach. variety of social interactions within a supply chain, such as supplier-buyer communication, collaboration on forecasting, or real-time data sharing, can be nicely modeled in the agent-based simulation formalism.

For modeling supply chain behavior, we tried to capture the complexities of a real-world supply chain as much as possible. Of course, considering every detail of supply chain behavior is neither possible nor value-adding. So, we made several simplification assumptions in the modeling process to focus on the main scope of our study. For example, since this research focuses more on the stress-testing of a supply chain to identify vulnerability sources, we model mitigation strategies against disruption at a high level where a mitigation strategy is modeled by fulfilling the disrupted element within a given time and cost, either with a backup capacity, a redundant capacity, or waiting for the repair of the disrupted capacity. A research direction is to explore the efficiency of different mitigation strategies by more detailed modeling of the mitigation actions. For example, the impact of having multiple suppliers with different reliability levels and the costs associated with switching between them can be explored in future research. Moreover, the availability of alternative transportation modes and the costs and delays associated with these alternatives can be explored in response to disruptions.

While we conducted extensive sensitivity analysis and scenario testing to ensure the robustness and validity of our model, a direction for future research could be comparing our model with analytical models to understand the alignment between the simulation outcomes and theoretical expectations, thereby enhancing the overall validity of our model.

To demonstrate and test the implementation of the approach, we used a stylized supply chain using the components of the developed simulation model. The stylized supply chain has enough complexity to represent and test several aspects of our approach. However, applying the approach to a real-world supply chain can reveal new insights about the applicability and results of our approach.

In the exploratory modeling approach that we used in this research, an equal probability was assigned to each scenario for generating disruption scenarios. Although this approach allows for stress-testing of a supply chain, regardless of risk information, it is always worthwhile to prioritize disruption scenarios with a higher chance of occurrence. There is an emerging research direction in the literature of exploratory modeling with a focus on the a posteriori assignment of likelihood to experimental results that can also be applied to this research (Shavazipour, Kwakkel, & Miettinen, 2019).

In this research, we consider several operational characteristics of a supply chain in resilience study, including the MTS-MTO strategy of suppliers, multi-tier supply chain networks, shared sub-suppliers, and region-based suppliers. These characteristics are relatively unexplored aspects of supply chain resilience research. We also look at compound risk instead of only focusing on a single point of failure, as addressed mainly by other researchers.

This research contributes to the literature on supply chain resilience by considering the structure of a supply chain and its uncertainties in the vulnerability assessment of a supply chain. Rather than focusing on graphical approaches for demonstrating the structure of a supply chain, this research applies a simulation approach to model the structure of a supply chain. This approach allows for consideration of detailed operational aspects of the supply chain in studying the resilience of its structure.

This research proposes ensemble modeling of a supply chain to address the challenge of accessing reliable information about the structure of a supply chain due to the complexity and dynamics of today's supply chains. In contrast with the common approach of developing a single model for a stress test of a supply chain, this paper considers an ensemble of plausible models for doing so to incorporate uncertainties pertaining to future dynamics of the supply chain network as well as the unavailability of information about the structure of complex supply chains.

7.3 Implications for practice

The importance of stress-testing the supply chain to identify vulnerability sources needing improvement is evident, especially nowadays, when supply chains experience short to long-term disruptions due to unpredictable events such as natural disasters, pandemics, political tensions, etc.

Supply chain decision makers ignore disruptive risks in their planning because they believe they happen rarely. However, several recent supply chain disruption cases that resulted in the loss of reputation and market share of famous companies shed light on the fact that for a successful business, disruptive risks should be considered besides operational risks in supply chain planning.

Supply chains can be made resilient enough to survive a severe disruption. However, there are several challenges for a supply chain to be made resilient. Below, we point out these challenges.

- Supply chain decision makers typically ignore disruptive risks in their planning because they believe it is a waste of money to consider rare events that might never happen.
- Supply chain decision makers believe efficient risk management depends on the availability of reliable risk information. However, such information is not available for disruptive risks because they are very unpredictable by their nature.
- The complexity of today's supply chains results in the unavailability of information from supply chain actors, especially those highly upstream.
- In complex supply chains with hundreds of actors spreader throughout the world, decision making about supply chain resilience practices becomes challenging because many stakeholders have several or even conflicting interests.
- Addressing supply chain resilience in complex supply chains is a complex problem because it involves many decision variables; therefore, coming up with a single optimal solution is impossible.
- Addressing resilience in a real-world supply chain can be challenging because of the complexity of developing a reliable simulation model of the supply chain to mimic it's complex characteristics.

This research provides supply chain decision makers with an approach to overcome the above challenges as explained below:

- A robust decision making approach toward identifying resilience practices results in identifying efficient strategies for the future. This approach addresses the concern of decision makers about the waste of developing resilience strategies that are efficient only under a limited set of disruption scenarios.
- The consequence-based risk analysis approach focuses on exploring the consequences that a potential disruption might have on supply chain performance rather than considering the root

cause of the interruption. Also, the exploratory modeling approach, which focuses on exploring the future rather than predicting it, enables an efficient stress-testing of a supply chain toward improving its resilience despite a lack of information about the disruptions. These approaches address the concerns of decision makers about the unavailability of information for a reliable supply chain risk analysis.

- Ensemble modeling of a supply chain for considering the uncertainty of the structure of the supply chain can address the challenge of accessing information about dispersed actors in complex and global supply chains.
- Treating supply chain resilience as a decision making under deep uncertainty problem, and applying exploratory modeling analysis, allows several stakeholders to incorporate their respective interests into newly developed resilience practices. Our analysis enables decision makers to make tradeoffs among the solutions that fit the interests of different stakeholders best.
- Finally, this research's modular simulation modeling approach helps to reduce the complexity of modeling real-world supply chains.

References

Kwakkel, J. H., & Haasnoot, M. (2019). Supporting DMDU: A taxonomy of approaches and tools. Decision making under deep uncertainty: From theory to practice, 355-374.

Shavazipour, B., Kwakkel, J. H., & Miettinen, K. (2021). Multi-scenario multi-objective robust optimization under deep uncertainty: A posteriori approach. *Environmental Modelling & Software*, *144*, 105134.

Summary

Advances in supply chains together with more turbulence in today's business environments, increase the vulnerability of supply chains to disruption. Various cases of supply chain disruptions in recent decades have revealed that besides focusing on efficiency, improving resilience is also crucial for a supply chain to be competitive in the marketplace. Resilience, an emerging topic in supply chain risk management, refers to the capability of a supply chain to recover quickly from a disruption by having proper risk mitigation and contingency plans. Various supply chain resilience frameworks have been put forward in which principles of a resilient supply chain as well as drivers for achieving resilience are identified qualitatively. Also, various quantitative methods have been developed to address different aspects of supply chain resilience. These methods propose models for assessing the vulnerability of a supply chain to disruptive risks as well as evaluating mitigation and recovery policies against disruption. The first step in improving supply chain resilience, or in general, improving supply chain risk management, is to identify and assess risks. The approaches toward assessing risk mostly depend on the availability of information about the disruptive risks. These approaches assume a known probability of occurrence of a disruptive risk and its magnitude, or the methods provide ways to estimate these risk parameters. Although probability-based approaches toward risk modeling work fine for common supply chain disturbances or operational risks, they cannot deal with less frequent or unknown disruptions. The main reason for this is that information related to rare events can hardly be obtained, and even if the information becomes available, it may not be a reliable representation of the future due to the unpredictability of these kinds of risks. Also, probability-based approaches usually give the same weight to both high frequency-low impact events and low frequency-high impact events, resulting in an underestimation of the losses due to the aggregation over time horizons.

Moreover, managers typically ignore disruptive risks because they believe that the probability of their occurrence is very low so the risks can be neglected. Therefore, model-based approaches for supporting supply chain resilience should be capable of assessing the vulnerability of a supply chain despite unknown or incomplete information about disruptive

risks. In this research, we suggest a consequence-based approach toward the supply chain risk analysis. Instead of focusing on identifying the root cause of risk and determining its characteristics, such as the probability of occurrence and intensity, one concentrates on analyzing the negative impact of the disruption on supply chain performance. For example, no matter whether a strike or congestion in a port disturbs a water transportation activity within the supply chain, the focus is on answering the question of what will happen if that transport activity is disrupted. Similarly, the focus is not on understanding whether a flood, bankruptcy, or cyber-attack stops a supplier's functionality within the supply chain; instead, we try to answer what will happen if that supplier stops working. However, a big challenge in using consequence-based risk analysis of a supply chain is the complexity of supply chains, consisting of thousands of interdependent and globally distributed actors. As a result, generating a comprehensive set of possible disruptive events is hard. Also, developing effective disruption management strategies under many possible scenarios is another challenge that should be addressed in resilience practices.

The way in which a disruptive event propagates through a supply chain network depends on the structure of the supply chain. Therefore, the vulnerability of a supply chain has a direct relation with the structure of the supply chain. Considering the structure of the supply chain network in resilience practices and analyzing supply chain disruptions at the network level is crucial. To compare the resilience of different supply chain network structures, researchers frequently adopt a graph theoretical perspective and focus on the topology of the supply chain. From this perspective, different network structures imply different configurations of nodes (facilities) and links (transport links). By exposing nodes and links to disruptions, supply chain resilience can be assessed. However, conceptualizing different supply chain networks based only on a different configuration of nodes and links disregards key operational characteristics that may also affect supply chain functioning and, thus, its resilience. Therefore, in comparing the resilience of different supply chain structures, it is worthwhile to consider the operational aspects of the supply chains as well.

A successful supply chain resilience practice depends on reliable stress-testing of the supply chain. A reliable stress test of a supply chain depends on the availability of information about the supply chain structure, where relations among different actors of the supply chain are clear. However, the complexity and globalization of today's supply chains make it difficult for decision makers to access data and information, especially from actors more than a few tiers upstream or downstream. Also, as a dynamic system, a supply chain is confronted with changes in its structure and configuration over time. Here, there is a need for an approach for stress testing a supply chain that can deal with a lack of information about the structure of the supply chain.

We started our research by conducting a literature review on model-based approaches for supporting supply chain resilience. This results in the development of the idea of consequence-based risk analysis of a supply chain, which is the underpinning approach toward risk assessment in this research. The approach focuses on the consequence of plausible disruptions at elements within the supply chain rather than focusing on the root cause of disruption. A more extensive discussion of consequence-based risk analysis is given in chapter 2 of this dissertation.

In the next step of our research, we developed a supply chain simulation model for performing experiments related to this research. The main objective of the simulation model is to assess the impact of disruption scenarios on supply chain performance as well as evaluate the effectiveness of various resilience practices. To this end, we adopt a modular modeling approach in which pre-built and parameterizable model elements are developed so that different simulation models can be generated automatically from different configurations of these model elements. The approach using parameterized simulation elements implies that the modeler can create, run, and adjust the simulation model without reprogramming. This approach reduces the complexity of the modeling process, and it supports the scalability of the simulation model from small to large supply chain networks. We implemented the modular simulation model in Simio, a general-purpose discrete-event simulation package. There are four main model elements in our model: market, manufacturer, supplier, and inventory. A wide variety of supply chain models can be generated by instantiating different configurations of these model elements. In order to generate input data for the simulation, we use a Python-based network generator and connect it to our Simio-based simulation library. The network generator is capable of generating a variety of supply chain networks based on several supply chain characteristics, including the number of tiers, percentage of assembled components in each tier, number of suppliers of a supplier in each tier, number of shared suppliers in each tier, percentage of faraway versus nearby suppliers in each tier and the percentage of MTO versus MTS suppliers in each tier. Different supply chain network topologies can be generated by choosing different values of these network-related variables. The supply chain networks can be randomly generated by sampling across different values of the network-related variables or by giving the generator predefined values of network variables. The generator then automatically instantiates the components of the simulation model as well as the input data tables for the simulation model based on the supply chain network topology. More elaboration on the simulation model and network generator is given in chapter 3 of this dissertation.

In chapter 4 of this dissertation, we investigated how robust decision making can assist in consequence-based risk analysis of a supply chain. Drawing on the limitations of model-based approaches for supporting supply chain resilience that mainly arise from the unpredictable nature of disruptive risks, we proposed the concept of consequence-based risk analysis of a supply chain. A big challenge for performing an efficient consequence-based risk analysis of a supply chain is analyzing a comprehensive set of disruption scenarios that the supply chain may encounter in the future. Also, resilience practices for overcoming supply chain disruptions must be effective under as many possible future disruption scenarios as possible. To address these challenges, we adopted robust decision making (RDM), a common approach for addressing decision making under deep uncertainty. We formulated the problem within the XLRM framework (where X stands for external factors, L stands for policy levers, R stands for relationships, and M stands for performance metrics) and defined various characteristics of disruptions as deeply uncertain parameters. These parameters include disruption location (region of disruption, tier of disruption, disrupted component), disrupted element, disruption duration, post-disruption capacity, and recovery rate of the disrupted element. Similarly, we identified characteristics of resilience practices as policy levers and defined resilience-related metrics to assess supply chain performance during disruptions. We simulated supply chain relations and behavior under disruption. Using exploratory modeling, a comprehensive database of plausible disruption scenarios was generated. Analyzing these scenarios revealed insights into supply chain vulnerability and identified resilient practices effective across multiple disruption scenarios. Our study demonstrated that RDM enhances the resilience of complex supply chains facing uncertain disruptions. By uncovering vulnerabilities beyond the immediate supply chain tiers, our approach facilitates the evaluation of robust responses to these challenges.

In chapter 5 of this dissertation, we explored which operational aspects of a supply chain affect its resilience. Network-level stress testing of a supply chain plays an important role in resilience practices. However, the common graphical perspective to the structure of a supply chain network may ignore key operational aspects of the supply chain that can affect resilience. We proposed an approach in which we compared the resilience of several supply chain structures that differ in three operational aspects, including product structure, sourcing strategy, and production strategy. Using exploratory modeling, we exposed different network structures to a variety of disruption scenarios to draw conclusions about key operational characteristics that affect the resilience of a supply chain. Our analysis confirmed our hypothesis that deeper, wider, and more geographically dispersed network topologies are more susceptible to disruptions compared to shallow, narrow, and dense network configurations. Furthermore, we found that a high percentage of suppliers employing the MTS (Make to Stock) strategy in a network led to delayed disruption detection, while a high number of shared suppliers in a network resulted in fast detection of a disruption. Our results were also in line with the fact that as the complexity of a supply chain network decreases in terms of depth, width, and dispersion, the time to return to business as usual also decreases. In this research, we showed that a change in the number of tiers of a supply chain network had the highest impact on the market lead time. On the other hand, the percentage of MTO (Make to Order) suppliers versus MTS suppliers in a network played the most important role in the total recovery time after a disruption. The time to detect disruption also was mostly affected by the number of suppliers in each tier.

In chapter 6 of this dissertation, we investigated how to do model-based stress testing of a supply chain despite a lack of required information about the supply chain structure. Given the challenge of obtaining reliable information about the structure of complex supply chains to enhance resilience and recognizing the importance of accounting for structural dynamics over time, we proposed ensemble modeling as a solution. Rather than focusing on a single supply chain structure, this approach involves generating and analyzing an ensemble of structures to identify vulnerability sources requiring resilience practices. To implement this, we employed an exploratory modeling approach, generating a large set of supply chain models and disruption scenarios through parametrization and computational experiments. Our findings demonstrate that this method enables decision-makers to gain insights into the resilience of supply chain networks that best suit their specific needs, even in the absence of precise information. Moreover, it effectively addresses structural uncertainties inherent in complex supply chains.

In the final chapter 7 of this dissertation, we elaborated on the scientific reflection of our work together with implications for supply chain decision makers. This research showed that supply chain resilience could be improved by the exploratory modeling approach, despite unknown information regarding disruption attributes such as the probability of occurrence, magnitude, and propagation and despite ambiguity about the structure of the supply chain.

Given the inherent uncertainties present in various supply chain processes, this research showed that there is ample opportunity for further exploration into how the exploratory modeling approach can effectively tackle other supply chain management issues. This includes strategic, tactical, and operational planning.

To investigate the effects of disruptive events on supply chain performance and to assess various resilience strategies, a simulation model of a supply chain was developed. To achieve this goal, we have adopted a modular modeling approach, where pre-designed model components allow for the automatic generation of diverse simulation models from different configurations. This method not only simplifies the modeling process but also facilitates scalability from small to large supply chain networks. In developing the simulation model, we tried to capture the complexities of real-world supply chains. However, accounting for every detail in our models was neither feasible nor beneficial. Therefore, we have made several simplifying assumptions to focus on the primary objectives of our study. We developed a simulation model of a stylized supply chain that captures sufficient complexity of a supply chain. However, applying our approach to real-world supply chains may yield additional insights about this study.

For the generation of disruption scenarios in this research, an equal probability is assigned to each scenario. However, it might be worthwhile to give more priority to disruption scenarios with a higher chance of occurrence. There is an emerging research direction in the literature of exploratory modeling that focuses on an a posteriori assignment of likelihood to exploratory results, which could be applied to this research as well.

This research provides supply chain decision makers with an approach to overcome several challenges in improving the resilience of their supply chains. First, the robust decision making approach helps in the development of resilience strategies that remain effective across a wide range of potential futures. This approach can tackle decision makers' concerns about investing resources into developing resilience strategies that are only effective under a limited number of disruption scenarios. Second, consequence-based risk analysis approach applied to this research emphasizes on exploring the potential impact of disruptions on supply chain performance rather than solely focusing on the root cause of the disruption. Additionally, the exploratory modeling approach concentrates on exploring the future rather than predicting it. Together, these approaches can efficiently stress test supply chains to enhance resilience, even when detailed disruption information is not available. Third, ensemble modeling of a supply chain can address the challenge of accessing information about dispersed actors of complex and global supply chains in resilience practices. Fourth, treating supply chain resilience as a decision making under deep uncertainty problem and applying exploratory modeling analysis enables consideration of various stakeholders' preferences in resilience practices and allows them to make tradeoffs among potential solutions.

Samenvatting

Nieuwe ontwikkelingen in handelsketens (supply chains), gecombineerd met meer turbulentie in de hedendaagse zakelijke omgeving, zorgen voor een grotere kwetsbaarheid van handelsketens voor verstoringen. Verschillende voorbeelden van verstoringen van handelsketen in de afgelopen decennia hebben aangetoond dat naast het focussen op efficiëntie, het verbeteren van de veerkracht (resilience) ook cruciaal is voor een handelsketen om concurrerend te zijn. Veerkracht, een opkomend onderwerp in het risicobeheer van handelsketens, verwijst naar het vermogen van een handelsketen om snel te herstellen van een verstoring door te beschikken over de juiste risicobeperkingsmaatregelen en noodplannen. Er zijn verschillende raamwerken voor de veerkracht van handelsketens ontwikkeld waarin zowel de principes als de praktische methoden voor een veerkrachtige handelsketen kwalitatief worden geïdentificeerd. Ook zijn er kwantitatieve methoden ontwikkeld om verschillende aspecten van de veerkracht van de handelsketen te bepalen. Binnen deze methoden worden modellen gebruikt voor het beoordelen van de kwetsbaarheid van een handelsketen voor ontwrichtende risico's en voor het evalueren van mitigatie- en herstelmaatregelen tegen ontwrichting. De eerste stap bij het verbeteren van de veerkracht van een handelsketen, of in het algemeen, het verbeteren van het risicobeheer van een handelsketen, is het identificeren en beoordelen van risico's. De benaderingen voor het beoordelen van risico's zijn sterk afhankelijk van de beschikbaarheid van informatie over de ontwrichtende risico's. Deze benaderingen gaan uit van een bekende waarschijnlijkheid van het optreden van een risico en het effect van de verstoring, of de methoden bieden manieren om deze risicoparameters te schatten. Hoewel deze op waarschijnlijkheid gebaseerde benaderingen van risicomodellering prima werken bij algemene verstoringenhandelsketen of bij operationele risico's, kunnen ze niet omgaan met minder frequente of onbekende verstoringen. De belangrijkste reden hiervoor is dat informatie met betrekking tot zeldzame gebeurtenissen vaak niet kan worden verkregen, en zelfs als de informatie beschikbaar komt, is deze mogelijk geen betrouwbare weergave van de toekomst vanwege de onvoorspelbaarheid van dit soort risico's. Bovendien geven op waarschijnlijkheid gebaseerde benaderingen gewoonlijk hetzelfde gewicht (expected value) aan zowel gebeurtenissen met een hoge frequentie en een lage impact als aan gebeurtenissen met een lage frequentie en een hoge impact, wat resulteert in een onderschatting van mogelijke verliezen als gevolg van de aggregatie over de tijdshorizon.

Daarnaast negeren managers ontwrichtende risico's doorgaans omdat ze denken dat de kans dat deze zich voordoen zeer laag is, zodat de risico's kunnen worden verwaarloosd. Dit zorgt ervoor dat modelgebaseerde benaderingen ter ondersteuning van de veerkracht van handelsketens in staat moeten zijn om de kwetsbaarheid van een handelsketen te beoordelen, ondanks onbekende of onvolledige informatie over de ontwrichtende risico’s. In dit onderzoek stellen wij daarom voor om te focussen op de consequenties van de risico's in de risicoanalyse van de handelsketen. In plaats van het identificeren van de hoofdoorzaak van risico's en het bepalen van de kenmerken van de risico's, zoals de waarschijnlijkheid dat het risico zich voordoet en de intensiteit van de gevolgen, concentreert men zich alleen op het analyseren van de negatieve impact van de verstoring op de prestaties van de handelsketen. Het is onbelangrijk of een staking of congestie in een haven een transportactiviteit binnen de handelsketen verstoort; het gaat om het beantwoorden van de vraag wat er zal gebeuren als die transportactiviteit wordt verstoord. Op dezelfde manier ligt de nadruk niet op het begrijpen of een overstroming, een faillissement of een cyberaanval de functionaliteit van een leverancier binnen de handelsketen belemmert; in plaats daarvan proberen we te beantwoorden wat er zal gebeuren als die leverancier niet meer functioneert. Een grote uitdaging bij het gebruik van een risicoanalyse die op consequenties gebaseerd is, handelsketen is de complexiteit van handelsketens, die bestaan uit duizenden onderling afhankelijke en wereldwijd verspreide actoren. Als gevolg hiervan is het moeilijk om een alomvattende verzameling van mogelijke ontwrichtende gebeurtenissen te identificeren. Ook het ontwikkelen van effectieve strategieën voor het beheer van verstoringen onder een veelheid van mogelijke scenario’s is een uitdaging die moet worden aangepakt voor het ontwikkelen van veerkrachtige handelsketen.

De manier waarop een ontwrichtende gebeurtenis zich door een handelsketen verspreidt, is afhankelijk van de structuur van de handelsketen. Daarom heeft de kwetsbaarheid van een handelsketen een directe relatie met de structuur van de handelsketen. Het in beschouwing nemen van de structuur van de handelsketen (handelsnetwerk of supply chain netwerk) en het analyseren van verstoringen op netwerkniveau zijn van cruciaal belang om de veerkracht van een handelsketen te vergroten. Om de veerkracht van verschillende netwerkstructuren van de handelsketen te vergelijken, gebruiken onderzoekers vaak een theoretisch perspectief gebaseerd op grafentheorie, en concentreren ze zich op de topologie van de handelsketen. Vanuit dit perspectief worden verschillende netwerkstructuren voorgesteld als verschillende configuraties van knooppunten (faciliteiten) en verbindingen (transport). Door knooppunten en verbindingen bloot te stellen aan verstoringen kan de veerkracht van de handelsketen worden beoordeeld. Bij het conceptualiseren van verschillende handelsketens die alleen gebaseerd zijn op een andere configuratie van de knooppunten en verbindingen, wordt echter voorbijgegaan aan belangrijke operationele kenmerken die ook van invloed kunnen zijn op het functioneren van de handelsketen, en dus op de veerkracht ervan. Bij het vergelijken van de veerkracht van verschillende structuren van handelsketens is het daarom belangrijk om ook de operationele aspecten van de handelsketen mee te nemen.

Het vergroten van de veerkracht van een handelsketen is afhankelijk van de beschikbaarheid van betrouwbare stresstests voor handelsketens. Een betrouwbare stresstest voor een handelsketen is afhankelijk van de beschikbaarheid van informatie over de structuur van de handelsketen, waarbij de relaties tussen verschillende actoren in de handelsketen duidelijk zijn. De complexiteit en de mondialisering van de hedendaagse handelsketens maken het voor besluitvormers echter moeilijk om toegang te krijgen tot relevante informatie, vooral van actoren die zich meer dan een paar lagen stroomopwaarts of stroomafwaarts bevinden. Bovendien wordt een handelsketen als dynamisch systeem geconfronteerd met veranderingen in de structuur en configuratie in de loop van de tijd. Er is dus behoefte aan een aanpak voor het stresstesten van een handelsketen, die kan omgaan met ontbrekende informatie over de structuur van de handelsketen.

We zijn ons onderzoek begonnen met een literatuuronderzoek naar modelgebaseerde benaderingen voor het ondersteunen van de veerkracht van handelsketens. Dit resulteerde in de ontwikkeling van het idee van een risicoanalyse die gebaseerd is op gevolgen in plaats van op de oorzaken van de verstoring. De aanpak richt zich op de gevolgen van plausibele verstoringen bij elementen binnen de handelsketen, in plaats van een focus op de achterliggende oorzaak van de verstoring. Een uitgebreidere discussie over de gevolg-gebaseerde risicoanalyse wordt gegeven in hoofdstuk 2 van dit proefschrift.

In de volgende stap van ons onderzoek hebben we een supply chain-simulatiemodel ontwikkeld voor het uitvoeren van de experimenten gerelateerd aan dit onderzoek. Het hoofddoel van het simulatiemodel is het beoordelen van de impact van verstoringsscenario's op de prestaties van de gemodelleerde handelsketen en het evalueren van de effectiviteit van verschillende oplossingen voor het vergroten van de veerkracht. Daartoe hanteren we een data-gebaseerde modelleringsaanpak waarbij vooraf gebouwde en parametriseerbare modelelementen worden ontwikkeld, zodat verschillende simulatiemodellen automatisch kunnen worden gegenereerd op basis van verschillende configuraties van deze modelelementen. De aanpak waarbij gebruik wordt gemaakt van geparametriseerde simulatie-elementen houdt in dat de modelbouwer het simulatiemodel kan creëren, uitvoeren en aanpassen zonder opnieuw delen te hoeven programmeren. Deze aanpak vermindert de complexiteit van het modelleringsproces en ondersteunt de schaalbaarheid van het simulatiemodel van kleine tot grote handelsnetwerken. We hebben het data-gebaseerde simulatiemodel geïmplementeerd in Simio, een universeel discrete-event simulatiepakket. Er zijn vier belangrijke modelelementen in ons model: markt, fabrikant, leverancier en voorraad. Er kan een grote verscheidenheid aan supply chain-modellen worden gegenereerd door verschillende combinaties van deze modelelementen te instantiëren. Om invoergegevens voor de simulatie te genereren, gebruiken we een op Python gebaseerde netwerkgenerator en verbinden deze met onze Simio simulatiebibliotheek. De netwerkgenerator is in staat een verscheidenheid aan handelsnetwerken te genereren op basis van verschillende kenmerken van de handelsketen, waaronder het aantal niveaus, het percentage geassembleerde componenten in elke laag, het aantal leveranciers van een leverancier in elke laag, het aantal gedeelde leveranciers in elke laag, het percentage leveranciers dat dichtbij of ver weg is in elk niveau, en het percentage MTO (Make to Order) versus MTS-leveranciers (Make to Stock) in elk niveau. Er kunnen verschillende netwerktopologieën voor de handelsketen worden gegenereerd door verschillende waarden van deze netwerkvariabelen te kiezen. Er kunnen willekeurige handelsnetwerken worden gegenereerd door de waarden van de netwerkvariabelen te bemonsteren, of specifieke handelsnetwerken door de generator vooraf gedefinieerde waarden van de netwerkvariabelen te geven. De generator instantieert vervolgens automatisch de componenten van het simulatiemodel, evenals de invoertabellen voor het simulatiemodel, gebaseerd op de topologie van het handelsnetwerk. Meer uitleg over het simulatiemodel en de netwerkgenerator wordt gegeven in hoofdstuk 3 van dit proefschrift.

In hoofdstuk 4 van dit proefschrift hebben we onderzocht hoe robuuste besluitvorming (Robust Decision Making of RDM) kan helpen bij een op consequenties gebaseerde risicoanalyse van een handelsketen. Voortbouwend op de beperkingen van modelgebaseerde benaderingen voor het vergroten van de veerkracht van handelsketens, die voornamelijk voortkomen uit de onvoorspelbare aard van ontwrichtende risico's, hebben we het concept van een op consequenties gebaseerde risicoanalyse van een handelsketen voorgesteld. Een grote uitdaging hierbij is het analyseren van een rijke set aan verstoringsscenario's waarmee de handelsketen in de toekomst te maken kan krijgen. Ook moeten de oplossingen voor het vergroten van de veerkracht voor het overwinnen van verstoringen in de handelsketen effectief zijn onder zoveel mogelijk verstoringsscenario's. Om deze uitdagingen het hoofd te bieden, gebruiken we RDM, een methode voor het besluitvorming onder diepe onzekerheid (deep uncertainty). We formuleerden het probleem binnen het XLRM-raamwerk en definieerden verschillende kenmerken van verstoringen als diep-onzekere parameters. Deze parameters omvatten de locatie van de verstoring (regio van de verstoring, mate van de verstoring, het verstoorde onderdeel), het verstoorde element, de duur van de verstoring, de capaciteit na de verstoring en de herstelsnelheid van het verstoorde element. Op dezelfde manier hebben we beleidsmaatregelen voor het vergroten van veerkracht geïdentificeerd , die kunnen helpen om de prestaties van de handelsketen tijdens verstoringen te vergroten. Hiertoe hebben we supply chain-relaties en gedrag onder verstoring gesimuleerd en bestudeerd. Met behulp van exploratory modellen is een uitgebreide database met plausibele verstoringsscenario's gegenereerd. Het analyseren van deze scenario's bracht inzichten aan het licht over de kwetsbaarheid van de handelsketen, en het stelde ons in staat om beleidsmaatregelen te identificeren die effectief zijn in meerdere verstoringsscenario's. Ons onderzoek heeft aangetoond dat RDM de veerkracht vergroot van complexe handelsketens die met diep-onzekere verstoringen worden geconfronteerd. Door kwetsbaarheden bloot te leggen die een of meerdere lagen weg liggen in de handelsketen, vergemakkelijkt onze aanpak de evaluatie van robuuste beleidsmaatregelen om de problemen in handelsketens aan te pakken.

In hoofdstuk 5 van dit proefschrift hebben we onderzocht welke operationele aspecten van een handelsketen de veerkracht ervan beïnvloeden. Stresstesten op netwerkniveau van een handelsketen spelen een belangrijke rol bij het vergroten van veerkracht. Een focus met een puur grafisch perspectief op de structuur van een handelsnetwerk kan echter voorbijgaan aan de belangrijke operationele aspecten van het handelsnetwerk die de veerkracht kunnen beïnvloeden. We stelden een aanpak voor waarin we de veerkracht van verschillende supply chain-structuren vergeleken die verschillen op drie operationele aspecten, waaronder productstructuur, sourcingstrategie en productiestrategie. Met behulp van exploratory modeling hebben we verschillende netwerkstructuren blootgesteld aan een breed scala van verstoringsscenario's om conclusies te trekken over de belangrijkste operationele kenmerken die de veerkracht van een handelsketen kunnen beïnvloeden. Onze analyse bevestigde onze hypothese dat diepere, bredere en meer geografisch gespreide netwerktopologieën gevoeliger zijn voor verstoringen dan ondiepe, smalle en geografisch geconcentreerde netwerkconfiguraties. Verder ontdekten we dat wanneer een hoog percentage leveranciers de MTS-strategie in een netwerk toepaste, er een vertraagde detectie van verstoringen ontstond, terwijl een groot aantal gedeelde leveranciers in een netwerk resulteerde in een snelle detectie van een verstoring. Onze resultaten toonden ook aan dat naarmate de complexiteit van een handelsnetwerk afneemt in termen van diepte, breedte en geografische spreiding, de tijd om terug te keren naar de normale gang van zaken ook afneemt. In dit onderzoek hebben we laten zien dat een verandering in het aantal lagen van een handelsnetwerk de grootste impact heeft op de doorlooptijd van orders. Aan de andere kant speelt het percentage MTO-leveranciers versus MTS-leveranciers in een netwerk de belangrijkste rol in de totale hersteltijd na een verstoring. De tijd om verstoringen te detecteren wordt ook grotendeels beïnvloed door het aantal leveranciers in elke laag.

In hoofdstuk 6 van dit proefschrift hebben we onderzocht hoe modelgebaseerde stresstests van een handelsketen kunnen worden uitgevoerd, ondanks een gebrek aan de noodzakelijke informatie over de structuur van de handelsketen. Gegeven de uitdagingen voor het verkrijgen van betrouwbare informatie over de structuur van complexe handelsketens om de veerkracht te vergroten en het erkennen van het belang van structurele dynamiek, hebben we ensemble modeling als oplossing voorgesteld. In plaats van zich te concentreren op een enkele supply chain-structuur, omvat deze aanpak het genereren en analyseren van een verzameling van structuren om bronnen van kwetsbaarheid te identificeren die veerkracht vereisen. Om dit te implementeren, hebben we een exploratoty modeling aanpak gebruikt, waarbij we een groot aantal supply chain-modellen en verstoringsscenario's hebben gegenereerd door middel van parametrisering en computerexperimenten. Onze bevindingen tonen aan dat deze methode besluitvormers in staat stelt inzicht te krijgen in de veerkracht van handelsnetwerken die het beste aansluiten bij hun specifieke behoeften, zelfs bij gebrek aan nauwkeurige informatie. Bovendien pakt het op effectieve wijze structurele onzekerheden aan die inherent zijn aan complexe handelsketens.

In het laatste hoofdstuk van dit proefschrift, hoofdstuk 7, gingen we dieper in op de wetenschappelijke reflectie van ons werk, samen met de implicaties voor besluitvormers in de handelsketen. Dit onderzoek toonde aan dat de veerkracht van handelsketens kan worden verbeterd door de exploratory modeling aanpak, ondanks onbekende informatie over risicoattributen zoals de waarschijnlijkheid, omvang en frequentie, en ondanks ambiguïteit over de structuur van de handelsketen.

Gegeven de inherente onzekerheden die aanwezig zijn in verschillende supply chain-processen, heeft dit onderzoek aangetoond dat er volop mogelijkheden zijn voor verder onderzoek naar de manier waarop de verkennende modelleringsaanpak andere problemen op het gebied van supply chain-management effectief kan aanpakken. Dit omvat strategische, tactische en operationele planning.

Om de effecten van ontwrichtende gebeurtenissen op de prestaties van de handelsketen te onderzoeken en verschillende veerkrachtstrategieën te beoordelen, werd een simulatiemodel van een handelsketen ontwikkeld. We hebben een modulaire en datagedreven modelleringsaanpak aangenomen, waarbij vooraf ontworpen modelcomponenten de automatische generatie van diverse simulatiemodellen uit verschillende configuraties mogelijk maken. Deze methode vereenvoudigt niet alleen het modelleringsproces, maar vergemakkelijkt ook de schaalbaarheid van kleine tot grote handelsnetwerken. Bij het ontwikkelen van het simulatiemodel hebben we geprobeerd de complexiteit van echte handelsketens vast te leggen. Het was echter niet haalbaar en ook niet nuttig om elk detail van de werkelijkheid in onze modellen te verwerken. Daarom hebben we verschillende aannames voor de modellen gedaan om ons te concentreren op de primaire doelstellingen van ons onderzoek. We hebben een simulatiemodel ontwikkeld van een gestileerde handelsketen die voldoende complexiteit van een handelsketen weergeeft. Het toepassen van onze aanpak op echte handelsketens kan echter aanvullende inzichten over dit onderzoek opleveren.

In dit onderzoek wordt voor het genereren van verstoringsscenario's aan elk scenario een gelijke waarschijnlijkheid toegekend. Het kan echter de moeite waard zijn om meer prioriteit te geven aan verstoringsscenario's met een grotere kans. Er is een opkomende onderzoeksrichting in de literatuur van exploratory modeling die zich richt op het a posteriori toekennen van waarschijnlijkheid aan exploratory resultaten, die ook op dit onderzoek zou kunnen worden toegepast.

Dit onderzoek biedt besluitvormers in de handelsketen een aanpak om verschillende uitdagingen bij het verbeteren van de veerkracht van hun handelsketens te overwinnen. Ten eerste helpt de robuuste besluitvormingsaanpak (RDM) bij de ontwikkeling van veerkrachtstrategieën die effectief blijven in een breed scala aan potentiële toekomstmogelijkheden. Deze aanpak kan de zorgen van besluitvormers wegnemen over het investeren van middelen in het ontwikkelen van veerkrachtstrategieën die alleen effectief zijn onder een beperkt aantal ontwrichtingsscenario's. Ten tweede legt de op consequenties gebaseerde risicoanalyse die in dit onderzoek wordt toegepast de nadruk op het onderzoeken van de potentiële impact van verstoringen op de prestaties van de handelsketen, in plaats van zich uitsluitend te concentreren op de hoofdoorzaak van de verstoring. Bovendien concentreert de exploratory modeling aanpak zich op het verkennen van de toekomst in plaats van deze te voorspellen. Samen kunnen deze benaderingen handelsketens op een efficiënte wijze aan stresstests onderwerpen om de veerkracht te vergroten, zelfs als er geen gedetailleerde informatie over verstoringen beschikbaar is. Ten derde kan de ensemble modellering van een handelsketen de uitdaging aanpakken van het ontbreken van informatie over verspreide actoren binnen complexe en mondiale handelsketens. Ten vierde maakt het behandelen van veerkracht van de handelsketen als een besluitvormingsprobleem onder deep uncertainty en het toepassen van expolratory modeling het mogelijk om de voorkeuren van verschillende actoren in overweging te nemen bij het ontwikkelen van maatregelen voor het vergroten van veerkracht, en hen in staat te stellen afwegingen te maken tussen mogelijke oplossingen.

About the author

Bahareh Zohoori was born on 18 June 1983 in Shiraz, Iran. She obtained his bachelor's degree in industrial engineering from Shiraz Azad University in Iran. She then worked for five years in industries in Iran. Inspired by challenges in the supply chain management area, she continued her studies in a master program of industrial engineering at the Malaysia University of Technology. Her passion for applying state-of-the-art knowledge in addressing real-world complex SCM challenges persuade her to start her Ph.D. at the Delft University of Technology, working on supply chain disruption management toward improving resilience.

Publications

Journal publications and International conference presentations/publications

- Zohoori, B., Verbraeck, A., Kwakkel, J. H. (2024). "The relation between supply chain topology and resilience: a simulation study" (Manuscript under review).
- Zohoori, B., Verbraeck, A., Kwakkel, J. H. (2024). "Designing resilient supply chains using consequence-based risk analysis and robust decision making" (Manuscript under review).
- Zohoori, B., Verbraeck, A., Kwakkel, J. H. (2024). "Supply chain ensemble modeling: a framework for supporting model-based decision aiding toward supply chain resilience" (Manuscript under review).
- Zohoori, B., Verbraeck, A., Bagherpour, M., & Khakdaman, M. (2019). Monitoring production time and cost performance by combining earned value analysis and adaptive fuzzy control. Computers & Industrial Engineering, 127, 805-821. https://doi.org/10.1016/j.cie.2018.11.019
- Khakdaman, M., Wong, K. Y., Zohoori, B., Tiwari, M. K., & Merkert, R. (2015). Tactical production planning in a hybrid Make-to-Stock–Make-to-Order environment under supply, process and demand uncertainties: a robust optimisation model. International Journal of Production Research, 53(5), 1358-1386.

  https://doi.org/10.1080/00207543.2014.935828
- Khakdaman, M., Zeinahvazi, M., Zohoori, B., Nasiri, F., & Wong, K. Y. (2013, February). Healthcare system simulation using Witness. In Journal of Physics: Conference Series (Vol. 410, No. 1, p. 012109). IOP Publishing.
- Consequence-based risk analysis using exploratory modeling, DMDU Annual Meeting, 5-7 November 2019, Delft, The Netherlands
- Supply chain resilience in High-Tech industries, TRAIL PhD Congress, 8 Nov 2019, TRAIL Research school, Utrecht, The Netherlands
- International Conference on Mathematical Modelling in Physical Sciences, 3–7 September 2012, Budapest, Hungary

TRAIL Thesis Series

The following list contains the most recent dissertations in the TRAIL Thesis Series. For a complete overview of more than 400 titles, see the TRAIL website: www.rsTRAIL.nl.

The TRAIL Thesis Series is a series of the Netherlands TRAIL Research School on transport, infrastructure and logistics.

Zohoori, B., *Model-based Risk Analysis of Supply Chains for Supporting Resilience,* T2024/7, October 2024, TRAIL Thesis Series, the Netherlands

Poelman, M.C., *Predictive Traffic Signal Control under Uncertainty: Analyzing and Reducing the Impact of Prediction Errors*, T2024/6, October 2024, TRAIL Thesis Series, the Netherlands

Berge, S.H., *Cycling in the age of automation :Enhancing cyclist interaction with automated vehicles through human-machine interfaces*, T2024/5, September 2024, TRAIL Thesis Series, the Netherlands

Wu, K., *Decision-Making and Coordination in Green Supply Chains with Asymmetric Information*, T2024/4, July 2024, TRAIL Thesis Series, the Netherlands

Wijnen, W., *Road Safety and Welfare*, T2024/3, May 2024, TRAIL Thesis Series, the Netherlands

Caiati, V., *Understanding and Modelling Individual Preferences for Mobility as a Service,* T2024/2, March 2024, TRAIL Thesis Series, the Netherlands

Vos, J., *Drivers' Behaviour on Freeway Curve Approach,* T2024/1, February 2024, TRAIL Thesis Series, the Netherlands

Geržinič, N.*, The Impact of Public Transport Disruptors on Travel Behaviour*, T2023/20, December 2023, TRAIL Thesis Series, the Netherlands

Dubey, S., *A Flexible Behavioral Framework to Model Mobilityon-Demand Service Choice Preference*, T2023/19, November 2023, TRAIL Thesis Series, the Netherlands

Sharma, S., *On-trip Behavior of Truck Drivers on Freeways: New mathematical models and control methods*, T2023/18, October 2023, TRAIL Thesis Series, the Netherlands

Ashkrof, P., *Supply-side Behavioural Dynamics and Operations of Ride-sourcing Platforms,* T2023/17, October 2023, TRAIL Thesis Series, the Netherlands

Sun, D., *Multi-level and Learning-based Model Predictive Control for Traffic Management*, T2023/16, October 2023, TRAIL Thesis Series, the Netherlands

Brederode, L.J.N., *Incorporating Congestion Phenomena into Large Scale Strategic Transport Model Systems*, T2023/15, October 2023, TRAIL Thesis Series, the Netherlands

Hernandez, J.I., *Data-driven Methods to study Individual Choice Behaviour: with applications to discrete choice experiments and Participatory Value Evaluation experiments*, T2023/14, October 2023, TRAIL Thesis Series, the Netherlands

Aoun, J., *Impact Assessment of Train-Centric Rail Signaling Technologies*, T2023/13, October 2023, TRAIL Thesis Series, the Netherlands

Pot, F.J., *The Extra Mile: Perceived accessibility in rural areas*, T2023/12, September 2023, TRAIL Thesis Series, the Netherlands

Nikghadam, S., *Cooperation between Vessel Service Providers for Port Call Performance Improvement*, T2023/11, July 2023, TRAIL Thesis Series, the Netherlands

Li, M., *Towards Closed-loop Maintenance Logistics for Offshore Wind Farms: Approaches for strategic and tactical decision-making*, T2023/10, July 2023, TRAIL Thesis Series, the Netherlands

Berg, T. van den, *Moral Values, Behaviour, and the Self: An empirical and conceptual analysis*, T2023/9, May 2023, TRAIL Thesis Series, the Netherlands

Shelat, S., *Route Choice Behaviour under Uncertainty in Public Transport Networks: Stated and revealed preference analyses*, T2023/8, June 2023, TRAIL Thesis Series, the Netherlands

Zhang, Y., Flexible, *Dynamic, and Collaborative Synchromodal Transport Planning Considering Preferences*, T2023/7, June 2023, TRAIL Thesis Series, the Netherlands

Kapetanović, M., *Improving Environmental Sustainability of Regional Railway Services*, T2023/6, June 2023, TRAIL Thesis Series, the Netherlands

Li, G., *Uncertainty Quantification and Predictability Analysis for Traffic Forecasting at Multiple Scales*, T2023/5, April 2023, TRAIL Thesis Series, the Netherlands

Harter, C., *Vulnerability through Vertical Collaboration in Transportation: A complex networks approach*, T2023/4, March 2023, TRAIL Thesis Series, the Netherlands

Razmi Rad, S., *Design and Evaluation of Dedicated Lanes for Connected and Automated Vehicles*, T2023/3, March 2023, TRAIL Thesis Series, the Netherlands

Eikenbroek, O., *Variations in Urban Traffic*, T2023/2, February 2023, TRAIL Thesis Series, the Netherlands

Wang, S., *Modeling Urban Automated Mobility on-Demand Systems: an Agent-Based Approach*, T2023/1, January 2023, TRAIL Thesis Series, the Netherlands

Szép, T., *Identifying Moral Antecedents of Decision-Making in Discrete Choice Models*, T2022/18, December 2022, TRAIL Thesis Series, the Netherlands

Zhou, Y., *Ship Behavior in Ports and Waterways: An empirical perspective*, T2022/17, December 2022, TRAIL Thesis Series, the Netherlands