Managing Supply Networks in Regulated Markets: three essays using simulation

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Abstract

We present a comprehensive overview of three research topics related to supply chain management. The first essay investigates the impact of a complexity reduction project conducted in the life science industry to improve financial performance. The essay presents the complex infrastructure of antibody manufacturing, distribution and the benefits of applying discrete event simulation to reduce complexity. The digital twin model allows us to evaluate multiple scenarios to support decision-making when redesigning a supply chain. Based on our analysis, we identify significant improvements. The second essay explores how supply chain risks can be identified in a dense supply network to mitigate the impact of disruptions. We developed a novel approach to help companies identify critical nodes in their supply network and apply risk mitigation strategies to reduce risk across the network. Our research shows that the combination of Social Network Analysis (SNA), network graph visualisation, and Monte Carlo Simulation (MCS) improves the ability of decision makers to identify and manage risks. Optimal inventory policies are crucial to supply chain management, especially when dealing with stochastic demand and lead time. The third essay explores the optimal inventory policies under these conditions. First, the fundamental concepts and models of inventory management and policies are discussed. The essay then delves into the complexities of managing inventory with stochastic demand and lead time, exploring four optimal inventory policies to minimise total inventory costs utilising a simulation optimisation approach. The essay concludes with a sensitivity analysis, and we present the four optimal inventory policies for different service levels.

Supervisors: Dr. Riccardo Mogre and Dr. Kieran Fernandes

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Nomenclature

BSL Base Stock Level

DC Distribution Center

E-BSL Expediting Base Stock Level

ERP Enterprise Resource Planning

FDA Food and Drug Administration

GMP Good Manufacturing Practice

IP Inventory Position

MCS Monte Carlo Simulation

MFG Manufacturing Facilities

OEM Original Equipment Manufacturer

PCR Polymerase Chain Reaction

ROP Reorder Point

RQ Research Question

SCM Supply Chain Management

S/N Signal and Noise

SKU Stock Keeping Unit

SNA Social Network Analysis

SND Supply Network Design

SNRS Supply Network Risk Spread

USA United States of America

WRI Word Risk Index

Declaration

The work in this thesis is based on research carried out at the Marketing and Management Department, Durham University Business School, England. No part of this thesis was submitted elsewhere for any other degree or qualification, and it is the sole work of the author unless referenced to the contrary in the text.

Some of the work presented in this thesis was published in conference proceedings - the relevant publications are listed below.

Publications

A. Schoechtel, and R. Mogre. Supply Chain Reduction in Regulated Markets. An essay presented at the Winter Simulation Conference. Phoenix, Arizona, December 2021.

A. Schoechtel, and R. Mogre. Supply Network Risk Identification and Mitigation Strategies. Managing Risk in Supply Networks. An essay presented at the Association for Supply Chain Management Conference. Brussels, Belgium, June 2023.

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Chapter 1

Introduction

The subject and research area of supply chain management has been intensively researched over the past few decades. Far-reaching results were achieved, and many research questions were answered. In addition to the research contribution, one core question has often been at the centre of attention: How can the supply chain of organisations be improved through optimisation to increase the profitability of companies and ensure their long-term success? Researchers have already recognised that effective supply chain management is a major strategic opportunity for companies to gain a competitive advantage (Heizer and Render, 2010). Due to the complexity and breadth of supply chain management as a research topic, different research foci have been established over the past decades, reduce the complexity, and allow researchers to explore and illuminate focal topics more intensively. In this context, supply chain management is crucial to ensure that supply chains function effectively, efficiently, and reliably in the face of uncertainty and complexity.

Three of these diverse thematic focal points are the areas of (1) reduction in supply chain complexity, (2) reduction of supply chain risk to increase the resilience of the supply network, and (3) optimal inventory policies. All three topics are essential for supply chain management research and have been shown to improve company competitiveness. (1) Supply Chain Complexity Reduction is important for companies because it can lead to streamlined operations and make it easier for companies to manage their resources. A simplified supply chain can be more adaptable to changes in demand, allowing companies to respond quickly to unexpected events. A streamlined supply chain can improve communication between suppliers, manufacturers, and customers, thereby reducing the number of errors and delays in the supply chain. A supply chain with reduced complexity can help businesses avoid unexpected costs due to disruptions, such as production delays, transportation bottlenecks, and reduce the risk of increased material cost and price. It can provide better customer service, allowing the company to respond more quickly to customer needs and better manage inventory levels. Overall, reducing the complexity of the supply chain can result in significant benefits for companies. (2) By decreasing the supply network risk, businesses can ensure that they have a stable supply of goods and services and minimise the impact of any potential disruptions. If the risk in the supply network is reduced, the risk of supply chain disruptions, such as those caused by natural disasters, political instability, or supplier bankruptcy, will decrease. Customers expect the timely delivery of high-quality products and services. A disruption in the supply network can cause delays, leading to customer dissatisfaction. Supply network disruptions can damage the reputation of a company. Consumers and stakeholders expect businesses to operate responsibly and sustainably. Finally, by reducing risk in the supply network, businesses can improve compliance with regulations and avoid legal penalties. (3) Optimal inventory policies are important because they can help businesses minimise inventory costs while ensuring they have enough inventory to meet customer demand. Maintaining excess inventory can be costly due to storage, handling, and maintenance expenses. At the same time, stockouts can lead to lost sales and dissatisfied customers. Optimal inventory policies can help businesses balance these costs, leading to significant cost savings. Moreover, customers expect timely delivery of products and services. Inventory is a significant investment for businesses. Businesses can allocate their resources more efficiently by using optimal inventory policies, such as minimising inventory levels and reducing the amount of capital tied to inventory.

Optimal inventory policies can help businesses to gain a competitive advantage by improving customer service, reducing costs, and enabling more efficient resource allocation.

Our work aims to examine and analyse these three research frameworks that have a wide-ranging impact on research and industry and present results for the Research Question (RQ)s posed below. Therefore, our work agrees strongly with research and the literature on one of the most important goals of supply chain management in times of economic crisis: to reduce total costs and improve customer service (Paulonis and Norton, 2008).

1.1 Research Questions

The following three focus themes reinforce each other and try to achieve the same goal: improving customer service, reducing total costs, and enabling more efficient resource allocation. We have derived the following RQs based on these three main topics.

RQ 1: What strategies can be implemented to reduce supply chain complexity in regulated markets while ensuring compliance with regulatory requirements and improving financial performance? This RQ aims to identify practical and effective strategies that companies operating in regulated markets can use to simplify their supply chains while maintaining compliance with regulatory standards. These strategies include optimising supply chain processes, reducing the number of suppliers, streamlining logistics, and adopting new technologies. The ultimate objective of the research is to help companies to achieve greater efficiency and agility in their supply chains while complying with regulatory requirements.

RQ 2: What impacts the supply network resilience of organisations in the regulated market environment, and what strategies can organisations adopt to mitigate these risks? This question explores supply network risks and how organisations can manage these risks effectively in regulated markets. Additionally, we explore using a risk management strategy to reduce risks and increase resilience.

RQ 3: What is the optimal inventory policy for a supply chain system facing stochastic demand and stochastic lead time, and how does it depend on factors such as inventory holding costs, stockout costs, lead time variability, and demand variability with the goal of minimising total costs while maintaining satisfactory service levels? This RQ seeks to understand how a company can best manage its inventory policy given the uncertain nature of both demand and lead time. The question also addresses the trade-offs that need to be considered, such as balancing the costs of holding inventory against the costs of stockouts and how variability in demand and lead time affects the optimal inventory policy. Answering this RQ provides valuable insight into how companies can optimise their inventory policies to improve their overall efficiency and performance in the supply chain.

In order to answer the first and second RQ, we had the opportunity to work with a biotech company in the life sciences sector. Through the provision of data and continuous feedback, the company's support allowed us to develop, evaluate and improve the components of each RQ and perform the key analysis. The results of our work show a high degree of consistency and validity. The answer to the third question is based on further development of the previous research conducted by Kostic (2019). The third RQ is based on a theoretical design of the model to understand the fundamental influences of optimal inventory policy and its effects on the inventory level when a system faces stochastic demand and lead time.

1.2 Structure

Our work is organised into three parts with five chapters; see Figure 1.1. Part 1 consists of the introduction and presentation of the RQs as well as the structure of the thesis.

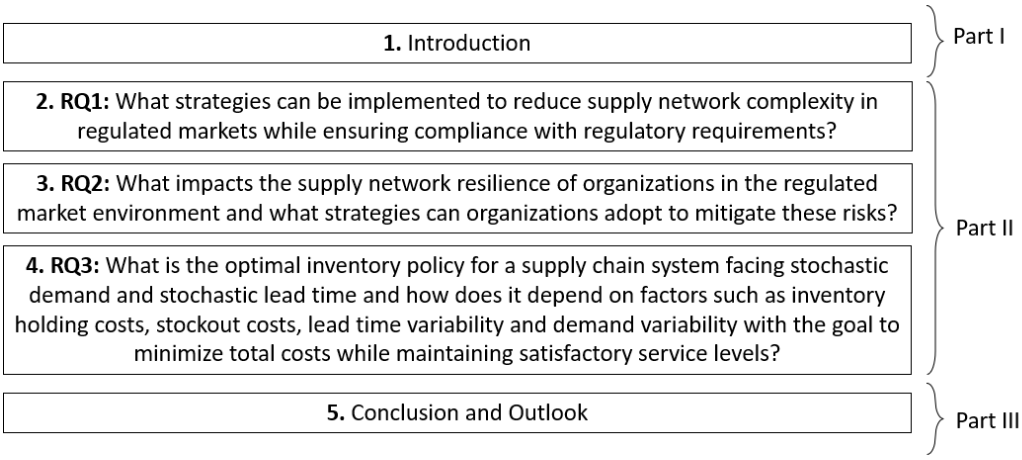

Figure 1.1: Structure of this work

Part 2 constitutes the main part of our research work. The second part of the thesis is divided into three chapters. The answer to the three RQs is the focus of each chapter. The chapters are structured as essays and form a self-contained framework with an introduction, a literature review, a presentation of the research gap, the investigation and the answer to the RQ, as well as an analysis, the results, a summary, and a research outlook. Finally, we conclude our work with a summary and an outlook in Chapter 5.

Chapter 2

Supply Chain Reduction in Regulated Markets

This chapter investigates the impact of a complexity reduction project conducted in the life science industry for regulated products to improve financial performance. The chapter presents the complex infrastructure of antibody manufacturing, its distribution network, and the benefits of applying discrete event simulation to reduce complexity in a regulated environment. The digital twin model allows us to evaluate multiple scenarios to support decision-making when redesigning a supply chain for regulated products. The base and complexity-reduced cases allow us to assess the potential benefits of complexity reduction on total supply chain costs and other key performance indicators. Based on our analysis, we identify significant improvements.

2.1 Introduction

Gaining competitive advantage and creating value for the customer by reconfiguring the value chain is an eminent task for each company (Porter, 1985). In a simplified value chain, the benefit for the customer is created by interdependent parties, sequentially linked by primary transforming inputs while adding value into outputs from the upstream to downstream supply chains (Christopher, 1998). This simplified chain analogy representation is helpful to plan, coordinate and manage the flow of products, information and services upstream and downstream of the supply chain (Mentzer et al., 2001; Sloane and O'Reilly, 2013), but the real world is much more complex and dynamic. To gain differentiation and competitive advantage in today's interconnected world, businesses must change their view of supply chains from a simplified chain analogy to an ecosystem view (Millar, 2015).

Operating in such an uncertain and dynamic environment makes a supply chain complex, with many interactions between actors through a complex network of explicit and implicit processes. These supply chains are often multilevel in nature (Serdarasan, 2013). Managing such a complex supply chain in an organisation with a broad geographical spread and many different regulatory structures makes monitoring and controlling operational performance even more complex for managers (Bozarth et al., 2009). Rapid company growth can leave little time to design robust supply chain processes, roles, and responsibilities. The complexity of worldwide-spanning supply chains has become a critical issue (Birkie and Trucco, 2020; Manuj and Sahin, 2011), which can adversely affect a firm's financial performance (Bozarth et al., 2009; Choi and Krause, 2006a). Studies showed that well-managed supply chain complexity improves supply chain performance (Blecker et al., 2005; Bozarth et al., 2009; Koudal and Engel, 2007). The importance of managing supply chain complexity in the regulated life sciences sector for business performance has been explored by just a limited number of publications (Birkie and Trucco, 2020; Lu and Shang, 2017; Gorane and Kant, 2017; Bode and Wagner, 2015; Vachon and Klassen, 2002). Furthermore, previous studies highlighted the complexity of supply chains in non-regulated sectors (Touboulic and McCarthy, 2019; Wu et al., 2016). Researchers were concerned with location-based complexity (Chaudhuri et al., 2020; Lu and Shang, 2017) customer base size, supply base size, product portfolio (Blecker et al., 2005), and buyer-supplier interaction are among the key factors of supply chain complexity Zhao et al. (2019). Various strategies have been proposed in the literature to overcome supply chain complexity through efficient collaboration, cooperation, and communication between buyers and suppliers to improve relationships and integration across company boundaries (Subramanian et al., 2015).

Globally structured life science companies face an ever-changing business environment, complex barriers, and financial risks while managing a supply chain worldwide. In the context of the focus of the current study, we pay particular attention to regulated market demands and the reduction of supply chain complexity in the life science industry to improve a company's financial performance. Most of the supply chain complexity management literature focuses on global manufacturing companies in classical sectors with far-reaching contributions to research and practice on managing supply chain complexity and increasing a company's financial performance. Research on supply chain complexity management in the field of regulated products is scares. Vaccine manufacturing and distribution gained significant attention with the emergence of the SARS-CoV-2 virus. The manufacturing and distribution of regulated products in the life science sector depends not only on the physical value creation process from upstream to downstream supply chain partners. A core characteristic of regulated environments is complying with regulations, formal standards, and far-reaching directives. Several regulatory bodies examine the implementation of rigorous standards to gain approval to be listed as a regulated product. Regulatory bodies protect public health by regulating human and biological drugs, animal drugs, medical devices, tobacco products, food, cosmetics, and electronic products emitting radiation (Commissioner, 2022). There is a plethora of different regulations and standards which apply across regulated domains. A large number of regulatory bodies require the implementation of the regulations and rigorously check their compliance. The US Food and Drug Administration (FDA) is one of the best-known regulatory bodies globally. These regulations, formal standards, and far-reaching directives add tremendous complexity to a regulated product manufacturer.

The complexity of supply chains can also positively affect competitiveness (Aitken et al., 2016). Companies in the life science sector use patents, high regulatory barriers, and standards to protect their business from rivals. Regulatory barriers and product complexity (e.g. patents and proprietary knowledge) can be considered process and product-induced intangible complexity. Entering a regulated market from scratch without an already existing business in the regulated sector is very time intense, costly, and complicated. Strategically, relevant complexity drivers of companies in the non-regulated market are, for instance, high product and customer diversity or a highly customised product portfolio. These complexity drivers give firms a superior advantage over competitors (Aitken et al., 2016). However, this complexity also plays an essential role in the market we are looking at, as the partner company has an extensive product portfolio and aims for broad diversification. Therefore, it can be clearly stated that well-managed product complexity plays an essential role in the life science sector.

New technologies and the outbreak of the global COVID pandemic are leading to new challenges in the regulatory landscape in the life science industry. New country-specific regulatory bodies emerge across the globe. Companies operating in regulated markets regularly face new and additional requirements and directives with even higher compliance demands. Furthermore, health care is costly, and pressure on health insurers has increased significantly during the COVID-19 crisis. Personalised medical treatment is on the rise and is very expensive (Mathur and Sutton, 2017). New technologies such as Block-Chain and the Internet of Things have changed the global supply chain landscape. The trend of adopting digital technologies in the life sciences sector is increasing. It is almost considered indispensable (Steinwandter et al., 2019). It provides the building blocks for personalised medicine and risk assessment, more effective clinical trials, and an optimised research and development process (Babu, 2023). Decision-making needs to be transformed in this fast-paced environment utilising a digital representation of a physical system. Such a digital twin system can support predicting the future with scenario planning but also supports scalability and the use of available digital data (Laybourne, 2023). Companies in the regulated life science sector must adapt quickly to these changing environments and redesign their supply chains to manage complexity and improve the firm's financial performance to stay competitive. Within this broader trend, we presented a digital twin model to reduce the complexity of a supply chain devoted to the production of antibodies.

The manufacturing and distribution of antibodies have recently gained significant attention because they are widely used in SARS-CoV-2 test kits. Improving the supply chain and expanding antibody production is critical due to their wide-ranging medical applications. This is difficult and time-consuming to achieve due to the complexity of antibody manufacturing and purification processes (Li et al., 2010). Our model offers a relevant contribution to solving this problem.

Section 2 reviews the existing supply chain complexity literature, paying particular attention to the life science industry's supply chain complexity cost drivers. Section 3 describes the complex manufacturing process of antibodies, the problem description, and the study objective. We present the conceptual model of our partner company's antibody supply chain, the actual base case model (As-Is model), and the complexity-reduced supply chain model (To-Be model). Section 4 of the essay tests the two conceptual models using data gathered from our partner company in the life science industry. We end the essay by discussing our results on the complexity reduction study for the regulated industry, implications for managers, and directions for future research.

2.2 Related Work

Previous studies and investigations identified that bio-pharmaceutical manufacturing and distribution is fragmented, highly complex, and a high-cost factor for companies. Big biotech and pharmaceutical companies reduced the number of companies through consolidations and integrations of competitors to gain scale effects and lower costs. However, the supply chain continues to increase in complexity, mainly due to supply chain restrictions during the pandemic in the life science industry. The research and development of life science products is complex, as is the complexity of supply chains that operate on a global scale, and many countries are part of this global supply structure. Company executives and supply chain managers align their strategic and operational decisions with the ongoing regulatory and macroeconomic events that constantly change the shape of the competitive and operational environment (Rossetti et al., 2011). In a biopharma supply chain, the number of consumption and manufacturing points, the role and number of intermediaries, the long lead times for raw materials and the unpredictable nature of biopharma manufacturing have created a web of uncertainties and interdependencies (Goetschalckx et al., 2002). These factors lead to significant costs associated with biopharma production, warehousing, and distribution, in our case, antibodies. We have limited our analysis to a single company to study these circumstances in a complexity reduction project in the life science sector.

Manufacturers in this sector do not consider having adequate logistics infrastructure (Rossetti et al., 2011). The logistics infrastructure often lies with a third-party logistics provider because companies have not built up logistics competencies in the past. Our study supports this research, as our partner company has only recently recognised logistics and supply chain processes as strategic factors. Logistics has been seen as a competence whose return diminishes with future investment. In the past, especially in the biopharma environment, the focus was on research, development, sales, and marketing (see also (Booth, 1999)) rather than logistics processes.

Our results refute these earlier assumptions, as they clearly show that distribution and logistics costs represent a significant proportion of total company costs and must become a focus area in the future. The study conducted by Rossetti et al. (2011) also shows that manufacturers have increased their inventory levels to ensure a high level of service, which is an important selling point for customers. Our analyses and research results have shown that storing finished products and raw materials along the value chain is a critical success factor for companies and contributes to short delivery times. However, whether this strategy applies to different companies must be considered and weighed up, as higher inventory levels along the value chain lead to higher costs. The stability and continuity of the entire supply chain, from suppliers to production, warehousing and distribution, must be much more strategically considered and optimised by companies now and in the coming years after the pandemic. To this end, we recommend using simulations to analyse, test, and implement these necessary strategic adjustments.

In this context, inventory management is of strategic and vital importance. One of the essential tasks of an inventory manager is to manage inventory and ensure that the right material is available where it is needed, in the correct quantity and quality. However, all too often, only one person is responsible for inventory in a supply chain organisation. Such structures often lead to myopic decisions without considering the entire supply chain. Goyal (1977) considered optimisation between a supplier and a manufacturer to determine the optimal lot sizes. Later, he optimised his model by decoupling the number of lots and associated shipments. A large number of authors used a model of Goyal (1988) to modify the constraints and design new policies (e.g., (Braglia and Zavanella, 2003; Cárdenas-Barrón et al., 2014; Perera et al., 2017b; Rajput et al., 2019)). Discussions with the partner organisation have shown that inventory holding cost management is treated at a single entity with a reorder point system. Our results show that the potential for cost savings is high when logistics is considered from the perspective of the entire supply chain rather than from the perspective of a single company or a site level.

A well-designed and forward-looking planning and scheduling process, as well as the use of supply chain simulations, are key strategies for optimising pharmaceutical supply chains. There continues to be a general trend of companies consolidating excess capacity from several smaller production facilities into larger ones. The aim is to have a few larger facilities and distribution centres centrally managed from a global supply chain and produce in the region for the region instead of a decentralised structure. The result, however, shows that consolidation leads to increased complexity in the supply chain, bringing complex coordination issues (Shah, 2004). This, in turn, implies that logistics costs in this sector are very high (Booth, 1999), which our study also confirms. Therefore, understanding the dynamic behaviour of supply chains in the life science sector is considered even more important than ever (Shah, 2004).

Before we move on to the next chapter describing the problem, we would like to review supply chain complexity definitions and highlight that your work focuses on shortening the supplier chain. One of the earliest definitions of system complexity comes from Simon (1962), where a complex system consists of a large number of individual components that interact in non-simple ways. Yates (1978), on the other hand, extends this definition by suggesting that a complex system has one or more of the following characteristics: (1) interactions, (2) high number of components or interactions, (3) nonlinearity or interactions, (3) non-linearity, (4) broken symmetry, and (5) nonholonomic constraints. Waldrop (1993) adds to the above explanations dynamism that makes complex systems qualitatively different from static systems. Looking at these definitions of complex systems, it is understandable that a supply chain is complex due to the number of interfaces, products, processes between companies, communication and coordination, and therefore has a distinct supply chain complexity. Wilding (1998) was one of the first to define the term supply chain complexity by seeing supply chain complexity as a triangle consisting of deterministic chaos, parallel interactions and amplifications. Choi et al. (2001), on the other hand, defines supply chain complexity differently, in that complexity arises naturally from the extensive interconnectedness of supply networks, in which most suppliers are linked to numerous supply chains that ultimately deliver different products to different and often unpredictable groups of consumers. Based on the above definitions, it can be assumed that an increase in the number of connections and the interconnectedness of supply networks leads to greater complexity. Our approach is the other way around in that we want to reduce the complexity of the supply chain. Our work, therefore, focuses on shortening the supply chain.

Based on the review of relevant literature, there is a very limited body of research on supply chain reduction and optimisation in regulated markets.

2.3 Problem Description

In this chapter, our goal is to redesign the supply chain of a manufacturer of antibodies to enhance supply chain economic activities and to identify significant cost-saving opportunities.

The study investigates the manufacturing process of the BioProduction Division of a global company in the life science industry. We look at the Monoclonal Antibodies manufacturing processes from raw material procurement, extraction, selection, mass culture production, purification, and shipment to the end customer. The manufacturing process has several steps, including multiple production steps and production sites with corresponding storage and distribution until the purified antibodies are shipped from a central warehouse to the end customer.

Many companies in this environment must deal with strict regulations and guidelines (e.g., FDA). Antibody production is complex. It follows a production and distribution process imposed with high standards. Well-trained scientists carry out the complex manufacturing process and transfer the manufactured intermediates and final products to a specialised supply chain. Rapid support from auxiliary personnel, expediting processes, or outsourced processes to increase capacity cannot be applied in this case. Therefore, rapid scaling of production is only possible to a limited extent. In our case study, supply chain complexity acts on two levels: first, visible, tangible structural complexity, where supply chain complexity is justified by the fact that there are multiple production stages, and second, the interconnected and dependent supply chain that needs to be managed. These components increase transaction costs, communication costs, and supply chain costs. High entry barriers exist due to the necessary manufacturing know-how (e.g., patents) regarding invisible, intangible complexity. In addition, there is a close manufacturer-supplier relationship because the company successfully integrated the upstream production stages into its own company through backward integration. Another factor is the high entry barriers to achieving the high regulatory requirements (FDA, Good Manufacturing Practice (GMP), clinical trials, etc.).

Companies need more than building mutually beneficial long-term relationships to effectively manage such a complex supply chain in today's economy. It requires a detailed understanding of the tangible structural complexity of interconnected supply chains (Kim et al., 2015). The uniqueness of our study lies in the fact that the upstream production stages are subsidiaries of the partner company. They belong to the same business group in the BioProduction Division. This makes the company a very good research object for practical and theoretical analyses in the supply chain context - in particular, the often cited mutually beneficial long-term relationships are already established in the analysed company. For this reason, our study addresses supply chain complexity and, in our case, explicitly addresses complexity reduction in the regulated life science environment.

The tangible structural complexity is the main focus of our research. Our essay considers the in-depth analysis and understanding of the structural complexity. One of the main questions of the partner company was what impact reduced complexity has on the firm's financial performance. However, a supply chain reduction also means that the interactions, processes, and procedures managed by the 'extracted' company during the supply chain reduction phase must be taken over by the company to which the processes and procedures are transferred. Here, it is essential that the 'extended' company node can absorb this new complexity and not add more cost and complexity. In addition to the operational and financial benefits, it must also be considered that the newly created complexity may have to be absorbed at an additional cost.

The motivation for the study is manifold. First, our goal is to create a digital twin of the complex and cost-intensive antibody manufacturing process so that the globally structured company can run various scenarios, including the following issues. Second, we examine how costs and processing times develop over time. Third, we analyse individual manufacturing locations' cost structures, delivery times, and manufacturing times. Fourth, we aim to identify improvement opportunities in the logistics steps (storage and distribution). Therefore, through the study, many different problems will be analysed, discussed, and measures will be derived. In addition, a wide variety of analyses can be performed. The focus of the study, agreed with the company, is clearly on the cost benefits and general reduction in complexity of the reduced case for the company. Furthermore, this study addresses supply chain theory problems, which the company has identified as pain points, although they are not the subject of our analysis. These already recognised problems are only marginally touched upon here and will enable us to conduct further studies in the future.

2.3.1 Supply Chain for Antibodies Base Case

The simulation model allows us to represent the dynamic behaviour of the antibody supply chain and assess the total cost of the supply chain for different configurations of the supply chain. The total supply chain cost is given by the sum of the following costs: processing, logistics, transportation, and inventory holding costs. The manufacturing and purification process for antibodies is complex. Additional performance indicators have been identified to measure the efficiency and effectiveness of an alternative supply chain design. These indicators include the processing times, the logistics and transportation times, and the end-to-end lead times.

This study aims to redesign an existing supply chain and evaluate its impact on costs and lead times. Figure 2.1 shows the base model (AS-IS), and Figure 2.2 shows the simplified model (TO-BE).

Our model is a simplified digital twin of an antibody production and purification process through multiple stages of a world-leading manufacturer in the life science industry. Re-engineering a supply chain in such a business environment requires detailed planning considering new challenges and broad contingencies faced by a global, highly regulated, cost-pressured industry. Figure 2.1 represents the schematic base case business processes in the supply chain for antibody production, purification, order processing, order handling and distribution.

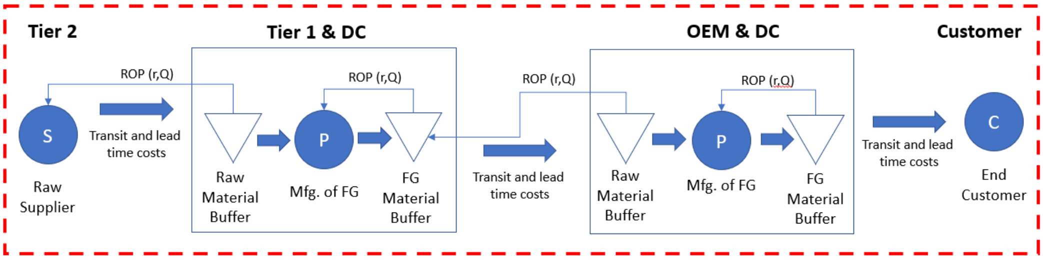

Figure 2.1: Base Case Business Process Model Antibody Manufacturing

The process starts at the cold chain distribution centre (Distribution Center (DC)), which is based in Frederick (Maryland, United States of America (USA)). Customers order purified antibodies online, over the phone, or through a company representative. Customer orders are served immediately from the finished goods level at the DC or count as lost sales if not sufficient finished goods stock is available to meet the customer demand. The DC then uses a standard Reorder Point (ROP) Policy where a replenishment order is triggered if the available finished goods stock drops below the trigger point. The DC demand is replenished by a Original Equipment Manufacturer (OEM) production facility close to the DC in Frederick. All replenishment orders for the DC are added to a manufacturing queue at the manufacturing plant. The manufacturing plant purifies the bulk-produced hybridomas into isolated antibodies. The purified antibodies are kept in bulk and then bottled in smaller finished good batches. The production cycle takes an average of two weeks and is transferred in 3-5 days to the DC.

The OEM in Frederick orders raw materials, also using a ROP Policy, from a company-owned subsupplier (Tier 1) located in Eugene (Oregon, USA). The Tier 1 is specialised in conjugating antibodies. The conjugation process takes up to two weeks. The Tier 1 produces semi-finished products and stores them in its DC. The chemicals and liquids are then shipped with a two-week transit time to the Frederick production facility.

The Tier 1 is ordering the necessary raw materials from an external Tier 2 supplier located in Boston (Massachusetts, USA), also using a standard ROP Policy. The Tier 2 supplier is specialised in mice injection with antigens. Harvesting the ordered volume of hybridomas can take between 6 to 9 weeks. The transit time is approximately two weeks to the Tier 1 location. The tier 2 supplier is not part of the corporate structure.

Most antibodies are commodities. However, manufacturing requires high regulatory standards, cold chain storage, and transportation. Nowadays, antibodies are sold online 24 hours a day, seven days a week. A researcher can order antibodies online whenever he wants to conduct an experiment. The ordered volume or weight is in the millilitre or micro-gram range. Antibodies are shipped worldwide from the central cold chain storage location in Frederick on the east coast of the USA.

All processes, from receiving customer orders, ordering raw materials from the different stages in the supply chain, packaging, storing, and distribution, must comply with high regulatory standards according to the company's regulatory certification.

2.3.2 Supply Chain for Antibodies Complexity Reduced Case

The redesigned model was derived from the base case model and reduced in complexity accordingly. We aim to reduce the manufacturing depth from a supply chain with eight stages to a supply chain with six stages. The complexity-reduced model in Figure 2.2 contains all the information, manufacturing, and general processes required to manufacture, store and distribute antibodies.

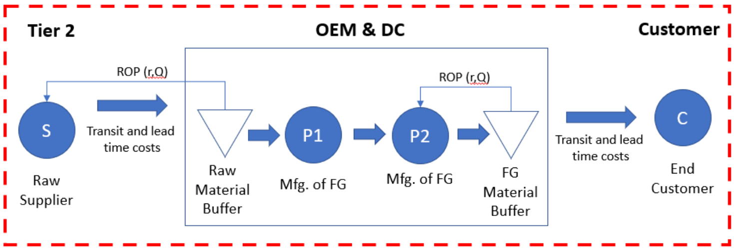

Figure 2.2: Complexity Reduced Model for Antibody Manufacturing

The customer ordering process of the redesigned case follows the same processes as in the base case. Namely, the cold chain DC based in Frederick (Maryland, USA) receives customer orders for purified antibodies. Customer orders are fulfilled from the finished goods inventory or counted as lost sales if there is insufficient finished goods in the DC. The DC then uses a standard ROP Policy to trigger a replenishment order if the available finished goods stock drops below the trigger point. The DC demand is then replenished by a production facility located in Eugene. All replenishment orders for the DC are added to a manufacturing queue at the manufacturing plant. The conjugation process takes up to two weeks. The conjugated semi-finished product is stored in a buffer stock for further processing. Chemicals and liquids are then transferred to the purification step to isolate antibodies, which takes up to two weeks. The purified antibodies are kept in bulk and then bottled in smaller finished good batches. The finished product is then shipped to Frederick DC with a lead time of two weeks.

Eugene orders the necessary raw materials from an external Tier 2 supplier in Boston, also using a standard ROP Policy. The Tier 2 supplier is specialised in mice injection with antigens. Harvesting the ordered of hybridomas takes between 6 and 9 weeks. The transit time to the next production stage at the Eugene site is two weeks.

2.4 Simulation

We developed a discrete event simulation using the SIMAN language and its visual interface Arena 16.10 to compare the As-Is (base case) and To-Be (reduced case) models. The partner organisation already uses the simulation software Arena Rockwell Automation. For this reason, we used the same system for collaboration. As a result, the company can access the database and perform separate analyses.

Due to the complexity of the manufacturing process and the scheduling rules, we chose the simulation approach. There are many trigger factors in the process, such as the arrival of raw materials, storage, and distribution of finished products, as well as the back-ordering process and the arrival of customers, respectively, ordering the final product.

Semi-structured interviews with the BioProduction Division senior management team helped to determine the problem description and the assumptions behind the simulation model. The parameters and data of the model, including production processes, ordering and processing information, and supply chain processes, are based on actual data from the industrial example.

At this point, we would like to discuss the unique features of the antibody supply chain and show how these unique features are modelled in the simulation. In principle, it is not easy to compare antibody production with classic production methods, such as assembly line production in the automotive industry. Nevertheless, the activities involved in antibody production can be operationalised and viewed as a production step. In the following, we will look at three antibody-specific production steps and how these were modelled in the simulation. The first step, which we will briefly explain, is called hybridoma technology. The hybridoma technology is a method for the large-scale production of monoclonal antibodies. It involves fusing antibody-producing B-lymphocytes from an immunised animal with myeloma cells. The resulting hybridoma cells have the ability to both produce antibodies and replicate continuously. These hybridoma cells are then selectively cultured and screened for their ability to produce the desired monoclonal antibody (Köhler and Milstein, 1975). The process step mentioned here represents the tier 2 supplier in our model who provides this item as raw material for our production process at the tier 1 location and is not part of the company. Therefore, modelling the production process in our simulation is not required as the hybridoma cells are a purchased item. The hybridoma cells are modelled with a triangular delivery lead time. However, we have included the explanation to give the reader a better end-to-end understanding of monoclonal antibody production. The second process step, antibody conjugation, is carried out in the tier 1 location with the hybridoma cells provided. Antibody conjugation refers to the process of attaching or linking antibodies to other molecules, such as fluorophores, enzymes, radioactive substances or drugs. This conjugation allows the targeted detection, visualisation or manipulation of specific cells or substances in various experimental, diagnostic or therapeutic applications (Thomas et al., 2016). In our case, the process time to chemically conjugate antibodies is usually two weeks. According to consultations with the scientists at the Tier 1 plant, the processing time for the conjugation of antibodies is 12 to a maximum of 17 days. In order to take this process time into account, we have modelled the production step in our simulation model with a triangular distribution of a minimum of 12 days, with a most likely value of 15 days and a maximum value of 17 days. The third step in our antibody production is the purification of the conjugated antibodies at the OEM plant. Antibody purification refers to the process of removing impurities that may have been introduced during the production or isolation of antibodies. These impurities may include proteins, nucleic acids, lipids or other unwanted substances. Antibody purification is essential to obtain highly pure and functional antibodies for various experimental, diagnostic or therapeutic applications (Li et al., 2010). Analogous to the previous step, we have modelled this production step in our simulation model with a triangular distribution. After consultation with the team of scientists at the site, we were also given a production time of a minimum of 12 days, most likely 15 days and a maximum of 17 days for this process step. The final product of the Tier 1 and the OEM plant is stored in a warehouse from which the downstream production step is supplied with a corresponding delivery time which we have modeld in our simulation.

For confidentiality reasons, some of the data had to be excluded. Instead, we have scaled the available data to be used in the simulation process. A panel of an academic and company practitioners from different departments verified and validated the simulation model.

2.4.1 Base Case Simulation Model

In the following, we show the simulation flow chart for the base case. The flow chart captures all the main processes of the simulation.

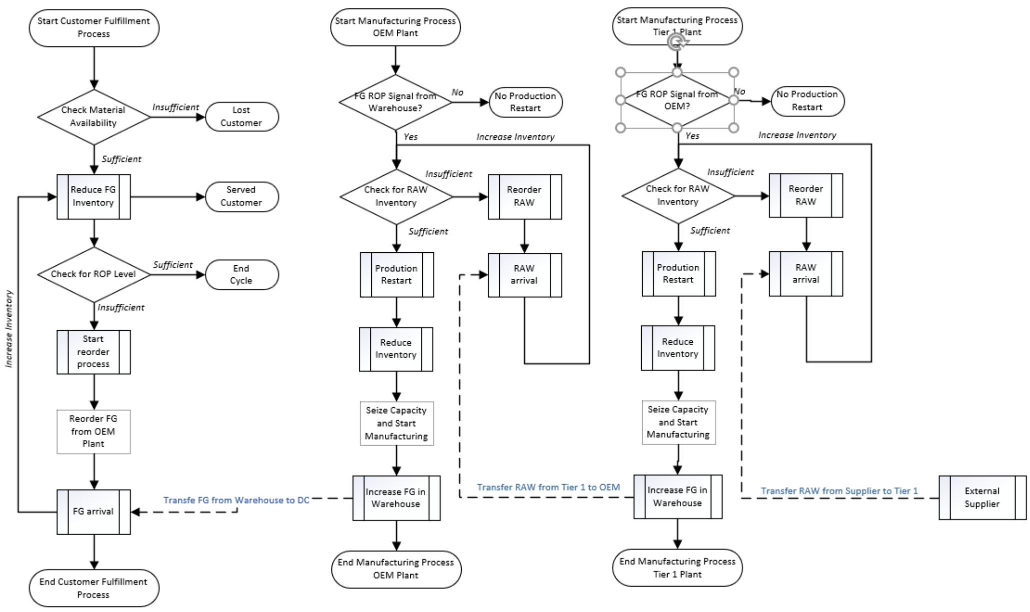

Figure 2.3: Flow Chart Base Case Model for Antibody Manufacturing

The process cycle starts with a customer arrival and a finished goods demand generation. In the simulation flow, only two options are considered. The demand is served immediately with a corresponding delivery time from a finished goods stock, or the order is not placed if the required volume is unavailable. Partial shipments or backordering is not considered in our model. If the finished goods level at the DC drops below the ROP a replenishment order is triggered. The replenishment order is placed at the OEM manufacturing plant and is fulfilled immediately from the finished goods stock with the corresponding delivery time. Partial shipment is not foreseen, but backorder is incorporated in the simulation if not enough finished goods are available at the OEM plant.

The OEM plant in the real world constantly produces goods and delivers them to the finished goods stock to level load production and maximise utilisation. In coordination with the partner organisation, the OEM plant in our simulation model will start production only if a signal triggers production. Reproduction is triggered if the finished goods level in the OEM plant drops below the ROP for finished goods. The reason to set up the system in this way is first to reduce the complexity in the simulation and second to analyse idle times depending on the changing end customer demand in a potential future research project. The production process will only start if sufficient raw material is available to produce finished goods. If the raw material is unavailable, the system will be idle until the ordered raw material is delivered. The raw material replenishment process follows a ROP Policy. If raw material drops below a ROP at the OEM plant, a replenishment order will be triggered at the Tier 1 supplier. The Tier 1 supplier immediately fulfils the OEM order from his finished good stock with a corresponding delivery time. Partial shipment is not foreseen, but backorder is incorporated into the simulation if not enough finished goods are available from the Tier 1 supplier.

The production and replenishment process for the Tier 1 plant is similar to the OEM plant. The Tier 1 manufacturer will only start production if sufficient raw material is available. The Tier 1 manufacturer orders his raw material from an external Tier 2 supplier if the raw material ROP level is met. The external supplier always has sufficient raw material to fulfil all orders with a corresponding lead time from the Tier 1 plant. The parameters for each process step for the base case will be discussed in Section 2.4.3

2.4.2 Complexity Reduced Simulation Model

Next, we present the simulation flowchart for the reduced case in Figure 2.5. The flow chart captures all the main processes of the simulation.

The main difference between the base and complexity-reduced cases is that the OEM manufacturing plant was 'eliminated', and all processes were integrated into the Tier 1 manufacturing plant. In our simulation model, key manufacturing and supply chain processes have been transferred to the Tier 1 site.

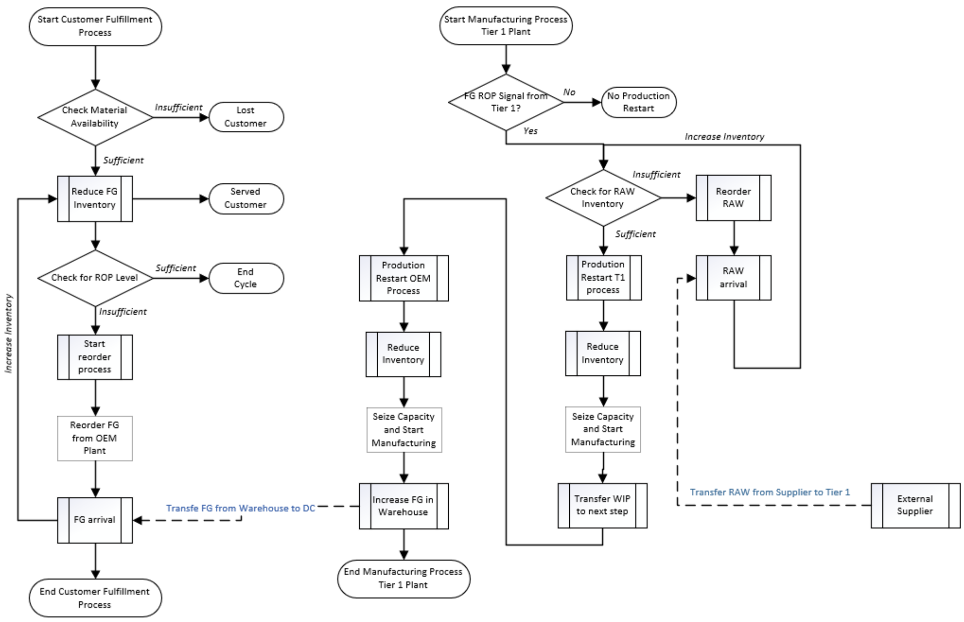

Figure 2.4: Flow Chart Complexity Reduced Model for Antibody Manufacturing

The basic structure is described as follows: A customer arrives and places an order that is fulfilled from a finished goods stock at the DC. Demand is served immediately with a corresponding delivery time from a finished goods stock, or the customer will not place an order if the required volume is unavailable. Partial shipment or backordering is not foreseen. A replenishment order will be triggered if the finished goods level in the DC drops below a ROP. The replenishment order is placed at the Tier 1 manufacturing plant and is fulfilled immediately from a finished goods stock with a corresponding delivery time. Partial shipment is not foreseen, but backordering is incorporated in the simulation if insufficient finished goods are available at the Tier 1 plant.

If the finished goods level in the Tier 1 plant drops below the ROP, a replenishment signal will trigger the start of production. The production process starts if sufficient raw material is available. If the raw material is unavailable, the system will be idle until the ordered raw material is delivered. The raw material replenishment process follows a ROP Policy. The Tier 1 manufacturer will order his raw material from an external supplier if the raw material ROP is triggered. The external supplier always has sufficient raw materials to fulfil all orders with a corresponding lead time. In the reduced case model, the material travels from one manufacturing step (former Tier 1 process) to the next manufacturing step (former OEM process) in the same Tier 1 plant due to the consolidation and reduction of complexity of the supply chain.

The parameters for each process step for the reduced case will be discussed next.

2.4.3 Key Parameters and Variables of the Model

Various metrics and variables are required, generated, and recorded in complex end-to-end order entry and production processes. In our simulation model, we agreed on a few main variables and parameters with the partner company for our research. The selected variables represent the decision variables for the company to make certain strategic and medium-term decisions in a supply chain context.

The two models were run with consumer demand data for the standard product until an approximate steady-state situation was achieved. Data were derived from data recorded in the Enterprise Resource Planning (ERP) system of the partner organisation for one year. The experiments were run on a computer mounted on an Intel Core i5-8365U at 1.60 GHz and 8 GB of RAM.

For the model, we used a confidence interval of 95%. The simulation was first performed with 100 replications to determine the number of required replications and obtain a high confidence interval precision of < 1,5%. After carrying out the 100 replications, high robustness could be seen by the relation of the half-width to the average. The precision of the confidence interval for all variables except inventory costs was < 0.8%. For inventory costs, in the base case, it was at 8.1%; in the reduced case at 4.5%. Since the 100 replicates did not give us the value we wanted, we used the following formula, substituting the values we have already obtained, to find the solution to meet our confidence interval precision requirement of < 1.5%.

$$n = t^2_{n-1,1-\frac{a}{2}}(\frac{S^2}{h^2})$$

We need to solve the equation for n (number of replications). The equation cannot be solved because the values t (t values for confidence intervals) and s (sample standard deviation) depend directly on n. Instead, we used the following formula for an approximation.

$$n = n_0(\frac{h_0^2}{h^2})$$

We decided to use the same number of replications for both models. For n_0 and h_0^2, we used the output value of the 100 replications. For h^2, we used the desired half-width value < 1,5%. Since the half-width deviation in inventory costs was higher in the base case than in the reduced case, we substituted h^2 from the base case into the formula. The result was 2904.2 replications needed for the base case model, rounded up to 2905 replications for our model. The same calculation for the reduced case model led to 894,9 (rounded to 895 replications). With 2905 replications for both models, we could reduce the precision of the confidence interval for all outcome variables below 1.45%, indicating a high precision of the results.

Next, we tested whether there was a statistically significant difference between the two models in the 95% confidence interval for the key decision variables. We use the Arena output analyser to compare the means of the decision variables (paired-t comparison of standards). For all decision variables, the means are not equal at the 0.05 level, which implies that the reduced case model is statistically significantly different from the base case model. We can draw a valid conclusion for the business from the results. The individual variables will be described in more detail in the following.

Key Variables	**Scope**
Processing time in production	Manufacturing time for the different necessary production steps in creating antibodies
Cost in production	Hourly rate in $ for each manufacturing step during the production process
Processing time in logistics & transportation	Processing time in logistics & transportation
Costs in logistics & transportation	Hourly rate in $ for each logistics step in the end-to-end supply chain
End-to-end processing time	Summation of all necessary time in production and supply chain activities to serve the customer
End-to-end processing costs	Summation of all spend value in production and supply chain activities to serve the customer
Inventory holding costs	Costs associated with storing finished goods and raw materials from an end-to-end view.

Table 2.1: Decision Variables and their Scope

Processing time in production:

The processing time in production is counted in days as the manufacturing and incubation process takes several days to complete. The production process includes the pure manufacturing and incubation times and the upstream and downstream quality management processes. These processes are particularly interesting in our analysis because antibody production must meet high regulatory requirements. We have simulated the necessary processes in our model with a triangular distribution.

According to the partner organisation, as the processes are not simple manufacturing processes, such as joining a piece of sheet metal together, there is a variation in the processing time. Process times were adopted based on actual work schedules.

Processing costs in production:

In our discrete event simulation, we modelled an hourly rate in $US assigned to the manufacturing processes according to the processing time. The exact $US amount for each process step was extracted from the work plans of the partner organisation and extrapolated with the necessary overhead costs (e.g., quality costs) to obtain a $US amount close to reality. In consultation with the partner organisation, the same $US amount was booked for the idle time during a regular operation to find out where there could be future potential for optimisation.

Processing time in logistics and transportation: The processing time in logistics and transportation comprises the components of picking, loading, unloading, and transport time on a truck. As the processing time consists of various components, it takes several days to pick, pack, load, transport, and unload the goods. Our modelled processing time also considers the different processing times in the different production facilities and transport distances, as the production facilities are far apart. We have received exact hourly rates from the corresponding warehouse and logistics managers at the sites and have transferred them into our model. The transport times represented when a truck left a plant, and the goods were unloaded and booked to the ERP system at the next plant. The company's ERP system verified the data.

Processing costs in logistics and transportation:

Processing costs are allocated to the respective processes at the different sites. The hourly rate is embedded in the overhead manufacturing cost structure and extracted from the ERP system. There is also an idle time in transport, for example, when a truck is being loaded or waiting at the loading ramp. In this case, a lower rate for idle time was included in the simulation because the costs during the journey were higher (tolls, fuel costs, etc.). Transport costs were determined based on invoices from the transport service provider.

End-to-End processing time:

End-to-end processing time is the summation of all production, logistics, and transportation processing times captured in the discrete event simulation.

End-to-End processing costs:

End-to-end processing costs are the summation of all processing costs in production, logistics, and transportation captured in the discrete event simulation.

Inventory holding costs:

The value of inventory, whether finished goods or raw materials, can be seen as tied-up capital and waste. However, storing finished goods and raw materials is necessary to offer short delivery times to the end customer and keep the manufacturing running. We have chosen to calculate the inventory value on hand for finished goods and raw materials as imputed costs of capital and show this value separately and not included in the end-to-end processing cost consideration due to its high importance for the partner company and our research.

It should be noted that the process times and costs mentioned and described here occur in both simulation models, the base case and the complexity reduced case. However, in order to represent the reduced complexity case in a simulation model, it was necessary to include all required processes, and thus the corresponding costs, in the complexity reduced model. For example, it would usually be necessary to add production line or expand a site to accommodate the additional processes or materials required in a shortened supply chain. These costs are not included in our model and were not programmed into the simulation. We are, therefore, looking at and comparing two different simulation models but using the same processes to produce the same end product. However, in order to answer this question, we will use a scenario analysis that shows in what conditions the reduction of stages makes sense to the company.

The base case and reduced case model were developed, refined with the partner organisation over several months, and validated step by step until the partner company could confirm an excellent approximation to reality based on the simulation results.

2.5 Analysis and Results

The simulation intends 1) to show the direct impact on costs and processing time between the base case and the reduced case, 2) to conduct a sensitivity analysis of the base case and 3) to conduct a robustness test with the Taguchi method.

2.5.1 Direct Cost Comparison of the Base Case and Complexity Reduction Model

Reducing an essential link in a complex supply chain and manufacturing process has significant implications for the business. Table 2.2 presents the results for the base case and the reduced case. The simulation results suggest that the complexity-reduced model significantly positively affects total production costs, processing time, and inventory holding costs.

Key Parameters	**Impact**
Processing time in production	17.02% reduction
Cost in production	54.74% reduction
Processing time in logistics & transportation	7.98% reduction
Costs in logistics & transportation	7.98% reduction
End-to-end processing time	10.41% reduction
End-to-end processing costs	45.47% reduction
Inventory holding costs	27.55% reduction
Sum of end-to-end processing costs and inventory holding costs	37.97% reduction

Table 2.2: Processing Time and Cost Comparison Base Case and Reduced Case

Consolidating complex manufacturing processes leads to a 17.02% reduction in the total manufacturing time to produce antibodies. This outcome is driven by the proximity of the downstream manufacturing processes and the streamlined product flow through the single manufacturing facility. More important is the overall reduction in production cost of 54.74% in our analysis. The main driver here is the significantly lower hourly rate in the Tier 1 plant (consolidation point). Our study used the fully burdened labour costs from routings in the partner organisations' ERP system. The fully burdened labour costs include the hourly salary and additional costs such as taxes, benefits, and supplies.

The processing time in logistics and transportation has not reduced much compared to the overall reduction in manufacturing processing time. The reason for this is that although the reduction eliminates certain logistics activities, the majority of logistics activities remain, particularly the long transport time. The reduction in logistics and transportation costs is significantly lower than in production costs. Here, too, the smaller reduction is due to the previously mentioned cause.

The end-to-end view for processing time and processing costs is the weighted sum of the production, transportation, and logistics activities. The overall processing time savings for production and supply chain activities were calculated with a reduction of 10.41%. The impact of complexity reduction appears relatively small on processing time if that reduction requires moving an entire production operation from one location to another in a regulated environment. However, in our example, it must be remembered that relocation cannot eliminate or reduce many processes. The production of antibodies requires a certain amount of processing time. However, we were able to show that a significant total cost reduction of 37.97% could be achieved through complexity reduction. Imputed inventory holding costs could be significantly reduced by 27.55% by eliminating one distribution centre and the efficiencies gained by reducing complexity and duplicate warehouse activities at two locations.

The analysis above compares the cost structure and process times of the two cases modelled. In the following, however, we would like to analyse how the return on investment changes due to the required investment costs and consider a change in the business environment. Based on restructuring projects already conducted in similar cases, we derive the necessary investments and restructuring costs to shorten a supply chain.

The following cost categories are major drivers of restructuring investments:

- **Transition Costs**: This includes expenses related to project management, consulting fees, and employee training to adapt to new processes and technologies.
- **Infrastructure Costs**: If the new supply chain strategy involves changes to manufacturing or distribution locations, there could be costs associated with building or modifying facilities. This includes expenses related to construction, equipment purchases, and facility upgrades.
- **Employee Costs**: Changes in the supply chain structure may lead to workforce adjustments. There could be costs related to retraining existing employees, hiring new staff with different skill sets, and potential severance packages for those affected by organisational changes.
- **Legal and Compliance Costs**: Adapting to a new supply chain model may involve legal considerations and compliance requirements, particularly in regulated markets. Costs could arise from legal consultations, regulatory compliance assessments, and ensuring that new processes align with relevant laws and standards.

Based on the cost categories and projects already executed, we assume investment costs of 1 million Euro for scenario one (low), 3 million Euro for scenario two (medium) and 5 million Euro for scenario three (high). Our scenario analysis also considers three different business environments. A situation where market conditions remain unchanged and meet planned expectations, deteriorates by 50% or increases by 50%. In our analysis, we look at the return on invested capital by comparing the investment required with the expected savings we generate by shortening the supply chain. The result is a number that indicates after how many years the invested capital will pay for itself. We compare the system costs of our base case and the complexity reduced model to perform the analysis. We do this by taking into account production costs, logistics and transport costs, and inventory costs that are already known in our two models for a time span of one year. We assume that 30% of these costs are fixed and 70% are variable, based on our experience and the breakdown of costs in our two models. In our scenarios, the fixed costs are not dependent on volume, but the variable costs are fully dependent on volume. In other words, a reduction in volume would cut variable costs in half or increase them by 50% in the two models while leaving fixed costs unchanged.

	Scenario Low - 1m€ Investment	**Scenario Medium - 3m€ Investment**	**Scenario High - 5m€ Investment**
No change	1.22 years	3.66 years	6.10 years
Reduction by 50%	1.88 years	5.64 years	9.39 years
Increase by 50%	0.92 years	2.75 years	4.58 years

Table 2.3: Scenario Analysis: Return on Investment to shorten the Supply Chain

A return on invested capital of less than 5 years is usually expected for similar investments in the business environment in which the partner company operates. Our scenario analysis shows that if market conditions remain on the projected trajectory, shortening the supply chain would require an investment of between 1 million Euros and 3 million Euros in order to be executed. If, on the other hand, the market volume were to fall by 50%, the investment would only be worthwhile at a cost of around 1 million Euros. On the other hand, if the market were to develop positively, restructuring would be lucrative for the company, even with a high investment of 5 million Euros.

A sensitivity analysis showed that these results are quite robust.

2.5.2 Sensitivity Analysis of the Base Case and Complexity Reduction Model

In our sensitivity analysis, we show the effect of value changes of specific key parameters on the system's total costs in the base case and the reduced case with the changes in parametric values from -50%, -25%, to +25% and +50%.

Percentage Change - Base Case	**-50%**	**-25%**	**+25%**	**+50%**
Cost in Production OEM	-17%	-8%	8%	17%
Cost in Production Tier 1	-6%	-3%	3%	6%
Total Production Costs	-23%	-12%	12%	23%
Cost in Logistics & Transportation DC-Customer	0%	0%	0%	0%
Cost in Logistics & Transportation OEM-DC	0%	0%	0%	0%
Cost in Logistics & Transportation Tier 1-OEM	-1%	0%	0%	-1%
Cost in Logistics & Transportation external Supplier-Tier1	-4%	-2%	2%	4%
Total Costs in Logistics & Transportation	-6%	-3%	3%	6%
Inventory holding costs finished goods DC	-19%	-10%	10%	19%
Inventory holding costs raw material OEM	-1%	0%	0%	1%
Inventory holding costs finished goods Tier 1	-1%	0%	0%	1%
Inventory holding costs raw material Tier 1	0%	0%	0%	0%
Total inventory holding costs	-21%	-10%	10%	21%

Table 2.4: Sensitivity Analysis Base Case Model

Table 2.4 presents the base case sensitivity. For the base case, the system is more sensitive to the total production costs and second to the total inventory holding costs. A primary contributor to the overall costs in the base case is the high labour costs at the OEM manufacturing plant. The second main driver is the imputed costs of finished goods and raw material inventory. The costs are justified because warehousing and logistics costs are relatively high since the finished product and the raw material must be stored under particular climatic conditions.

Percentage Change - Reduced Case	**-50%**	**-25%**	**+25%**	**+50%**
Cost in Production OEM	-11%	-5%	5%	11%
Total Production Costs	-11%	-5%	5%	1%
Cost in Logistics & Transportation DC-Customer	0%	0%	0%	0%
Cost in Logistics & Transportation OEM-DC	-1%	0%	0%	1%
Cost in Logistics & Transportation external Supplier-OEM	-4%	-2%	2%	4%
Total Costs in Logistics & Transportation	-5%	-3%	3%	5%
Inventory holding costs finished goods DC	-14%	-7%	7%	14%
Inventory holding costs raw material OEM	0%	0%	0%	0%
Total inventory holding costs	-14%	-7%	7%	14%

Table 2.5: Sensitivity Analysis Reduced Case Model

The sensitivity in the reduced case model in Table 2.5 is significantly different from the base case sensitivity results. The system is most sensitive to the total inventory holding costs and second to the total production costs. This is because, by reducing the complexity of the manufacturing process, personnel costs are significantly reduced compared to the base case. However, warehousing, logistics activities and physical warehouse show comparatively small changes in overall processing time, directly impacting costs. The model also shows that a greater distance between the new production facility and the finished goods warehouse increases the delivery time, increasing the inventory to compensate for the longer delivery time in a ROP system. The results show that the company should invest in a complexity reduction project and re-design the entire end-to-end supply chain.

Next, we will examine whether similar savings can be achieved if the company could significantly reduce its current cost structure in the base case model. The main reason for this question is that high costs are associated with site transfers in the regulated market environment. Therefore, we analysed whether a significant cost reduction of the current structure could lead to similar results as demonstrated in the reduced case model. Table 2.6 shows the results.

Cost Parameters - Percentage approximation to the Reduced Case				
Percentage Cost Improvement Base Case	**Manufacturing Costs Approximation**	**Transportation & Logistics Costs Approximation**	**Inventory Costs Approximation**	**Total Cost Approximation**
5%	9.1%	62.6%	18.1%	13.2%
7%	12.8%*	87.7%	25.4%	18.4%
15%		187.9%	54.4%	29.7%*
25%		313.2%	90.7%	43.8%*
40%		501.1%	45.2%	64.8%*
65%		814.2%	235.9%	100%*

Table 2.6: Results Base Case Model Cost Reduction Analysis and Results

On the left, we show the amount of cost improvement against which we compare our results "Percentage Cost Improvement Base Case". For example, if our partner organisation managed to reduce manufacturing costs by 5% in the base case, it would only achieve 9.1% of the total savings in our reduced case model. On the contrary, this means that 90.9% of the potential savings from a complexity reduction project are not realised. For the transport and logistics costs, on the other hand, 62.6% of the cost savings can already be achieved with a 5% cost optimisation in the base case compared to a full complexity reduction implementation. For inventory costs, it would still be 18.1% of the costs. Overall, a 5% reduction in all three cost factors would only achieve 13.2% of the potential savings that would have been possible with a complete complexity reduction project. The percentages also show the weighting of each cost and where the most significant potential for savings lies. The partner organisation has drawn our attention to the fact that the cost savings in manufacturing should be a maximum of 7% in our analysis, as the production of antibodies requires a certain processing time. Since the manufacturing cost approximation value does not exceed the improvement value of 7%, we have assumed the 12.8% value of the manufacturing cost approximation for the total cost approximation for the above percentage cost improvements for all improvements from 15% up to 65%.

To achieve a cost reduction as high as the result of the complexity-reduced case, the partner company would have to achieve a 7% cost reduction in manufacturing and a further 65% cost reduction in transportation, logistics and inventory costs to achieve the same effect. Disproportionately high savings would have to be achieved in transportation, logistics, and inventory costs, which are unrealistic from our point of view or that of the company.

In summary, if the company can realistically improve the cost structure by 7% in manufacturing and by 25% in Transportation & Logistics and Inventory, the company could generate 43.8% of the savings that a complete implementation of the complexity reduction would achieve. In total, the company would miss 56.20% additional savings without additionally considering the benefits of process time reduction here.

2.5.3 Taguchi Analysis Base Case and Complexity Reduction Model

A complete factorial design will be employed to fully investigate whether both systems, the base case and the reduced case, are robust to changes in various parameters. For the base case, we need to use the ten single unit costs, namely manufacturing costs in Tier 1, at the OEM, the transportation and logistics costs and inventory holding costs for raw and finished goods at the different storage locations. For the reduced case, we need to use six single-unit costs: manufacturing costs at the Tier 1, transportation, logistics, and inventory holding costs for raw and finished goods in the remaining storage locations. Furthermore, we want to investigate system changes to a low, medium, and high factor level. A low value considers a 7% reduction of costs, a medium value a 25% reduction, and a high value a 50% reduction of costs for the different parameters. A complete factorial design with ten parameters characterised by three levels would require 3^{10}, namely 59.049 experiments for the base case and 3^6, 729 experiments for the reduced case.

Taguchi's method (Roy, 1990) is an alternative to the factorial design that allows the analysis of many parameters without many experiments. Genichi Taguchi used a loss function. The loss function is the difference between the experimental and target values. The value is converted into a Signal and Noise (S/N) ratio (Taguchi, 1987). S/N is the mean to standard deviation ratio. The signal represents the wanted value (mean), and noise is the response's unwanted value (standard deviation). Taguchi has divided the S/N ratio into three subcategories based on the requirements of the response: a higher-the-better value, a medium-the-better value, and a lower-the-better value. The end-to-end supply chain cost characteristics in the present study are lower the better. Using Taguchi's orthogonal arrays, only 27 experiments are necessary in both cases. After conducting the experiments, we computed for each factor j the value $j\ \Delta$, which in Taguchi's analysis is used to judge the importance of the factors. The factors are ranked from the highest $j\ \Delta$, having the highest contribution to the cost, to the lowest $j\ \Delta$, having the lowest contribution to the cost. Taguchi's formula for lower-the-better was used to calculate the S/N ratio and results. Taguchi analysis was performed using the Minitab 21.1 software tool and the means of S/N ratio plots and analysis of variance (ANOVA).

Signal to noise ratio for the smaller the better: $-10log\frac{1}{n}\sum(R)^2$

where

n = Number of observations

R = Observed data for each response

As the assessment of each experiment is based on the measure S/N, which directly considers the variance of the experiment, it is paramount that the number of runs is the same for each experiment. We set the number of runs to 2905 because this number should guarantee a confidence interval of 5%.

Table 2.7 shows the test evaluation of ANOVA for the two cases. The test is carried out with the above-mentioned levels: -7%, -25% and -50%.

Cost Parameters - Percentage approximation to the Reduced Case								
S. No	**Cost Factors**	**Sum of squares**	**Mean Square**	**-7%**	**-25%**	**-50%**	**∆ S/N Ratio**	**Rank**
1	Tier 1 Production Costs	1,039,777,746	519,888,873	-106.25	-106.02	-105.62	-0.6328	3
2	OEM Production Costs	7,391,985,504	3,695,992,752	-106.78	-106.09	-105.01	-1.7727	2
3	Logistics Cost ExtSupplier-Tier 1	483,680,178	241,840,089	-106.17	-105.98	-105.74	-0.4249	4
4	Logistics Cost Tier 1-OEM	13,430,400	6,715,200	-105.97	-105.99	-105.93	-0.0601	6
5	Logistics Cost OEM-DC	3,357,600	1,678,800	-105.98	-105.97	-105.94	-0.0340	9
6	Logistics Cost DC-Customer	2,927,382	1,463,691	-105.96	-105.97	-105.96	-0.0153	10
7	Inventory Holding Costs RAW Tier 1	1,728,402	864,201	-105.90	-106.00	-105.99	-0.0962	5
8	Inventory Holding Costs FG Tier 1	11,462,766	5,731,383	-105.99	-105.95	-105.95	-0.0397	8
9	Inventory Holding Costs RAW OEM	10,863,942	5,431,971	-105.97	-105.98	-105.94	-0.0409	7
10	Inventory Holding Costs FG DC	9,458,426,754	4,729,213,377	-106.90	-106.11	-104.88	-2.0126	1

Table 2.7: Signal and Noise Ratios for the Base Case

The lower, the better Taguchi approach, the delta of the S/N ratios indicates the cost factors. The lowest value in the table contributes the most to the total supply chain cost of the base case. Figure 2.5 below represents the main plot of the base case data.

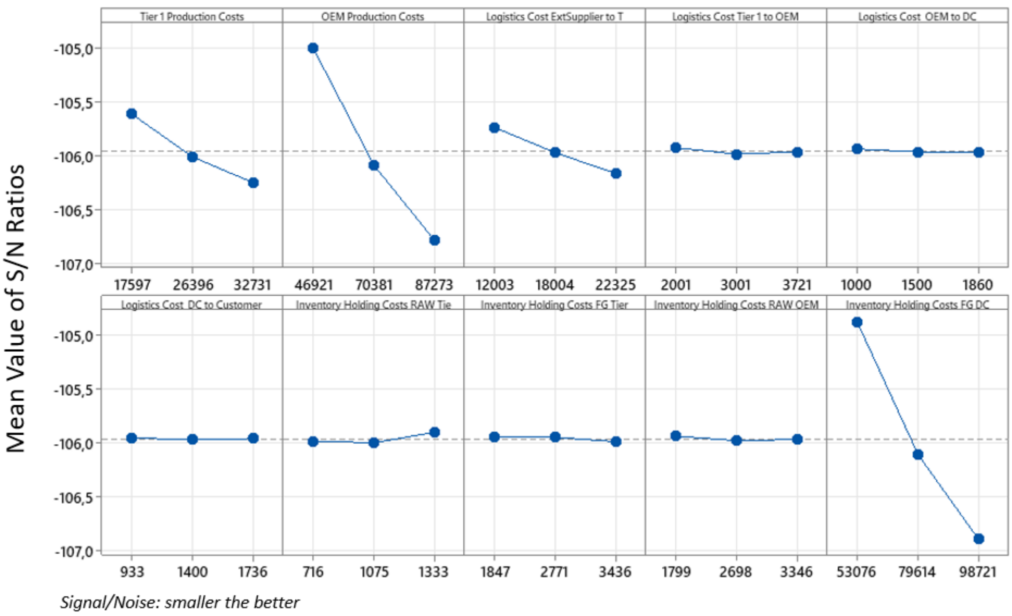

Figure 2.5: Main Plot for Signal and Noise Ratio Base Case

Table 2.8, analogous to the S/N ratio of the base case, shows the results of the Taguchi analysis for the reduced case. It can be clearly seen that the cost focus of both analyses is similar, indicating high validity.

Cost Parameters - Percentage approximation to the Reduced Case								
S. No	**Cost Factors**	**Sum of squares**	**Mean Square**	**7%**	**25%**	**50%**	**Δ S/N Ratio**	**Rank**
1	Tier 1 Production Costs	15.2296	7.6148	-102.48	-101.76	-100.65	-1.8253	2
3	OEM Production Costs	2.5231	1.2616	-101.98	-101.68	-101.24	-0.7443	3
4	Logistics Cost ExtSupplier-Tier 1	0.0379	0.0190	-101.68	-101.62	-101.59	-0.0897	5
6	Logistics Cost Tier 1-OEM	0.0033	0.0016	-101.62	-101.65	-101.63	-0.0249	6
7	Logistics Cost OEM-DC	0.0671	0.0336	-101.56	-101.68	-101.66	-0.1152	4
10	Logistics Cost DC-Customer	27.8277	13.9139	-102.77	-101.82	-100.30	-2.4651	1

Table 2.8: Signal and Noise Ratios for the Reduced Case

Figure 2.6 represents the main S/N plot for the reduced case. Graphically, the ranking can be detected much faster. The slope of the line shows the influence value.

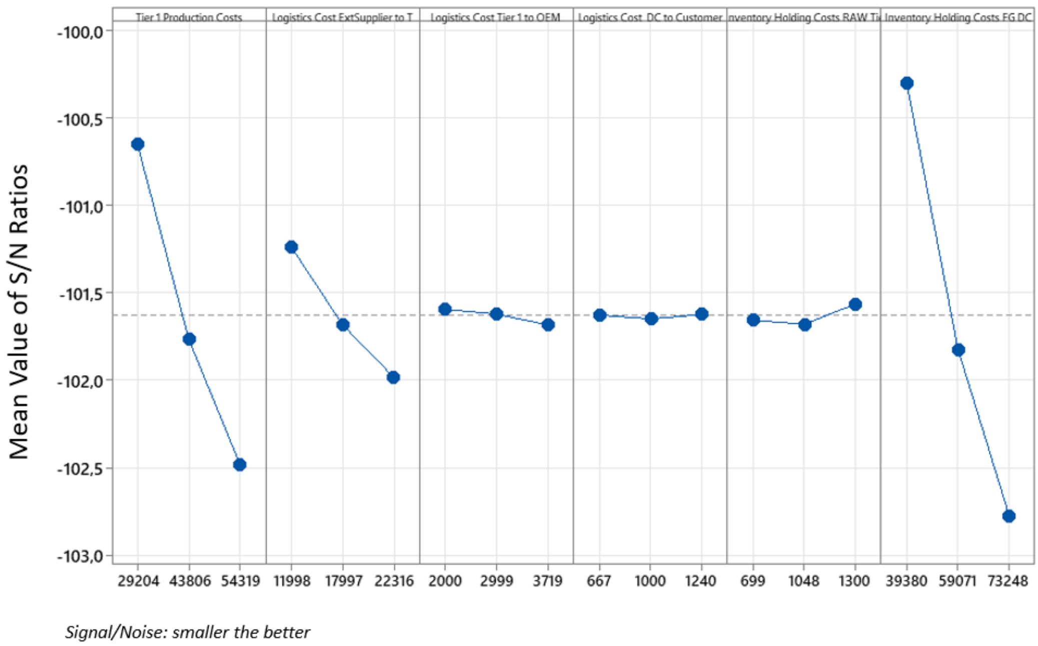

Figure 2.6: Main Plot for Signal and Noise Ratio Reduced Case

Figure 2.7 and Figure 2.8 below represent the summary of the information obtained above. For each factor j the value $j\ \Delta$ is calculated as the difference between the highest and lowest values of S/N for all parameters. The factors in Figure 2.7 and Figure 2.8 are ranked from the highest $j\ \Delta$, having the highest contribution to the cost of the end-to-end supply chain, to the lowest $j\ \Delta$, having the lowest cost contribution.

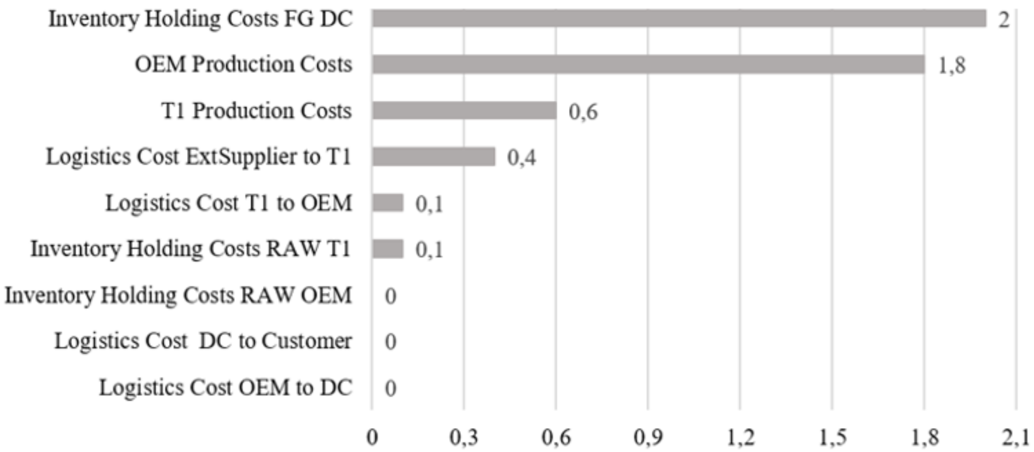

Figure 2.7: Taguchi´s method results Base Case

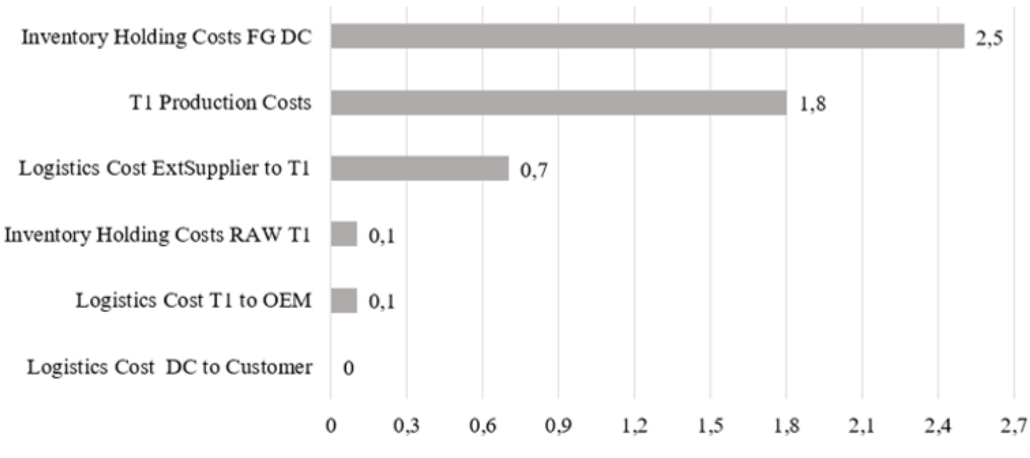

Figure 2.8: Taguchi´s method results Reduced Case

First, the above results show that the designed model is quite robust and correlates with the findings from the sensitivity analysis. The results of the Taguchi method are statistically significant. Second, both results show that inventory holding costs are the biggest contributor to supply chain costs for both models. In the base case, the production costs of Tier 1 and the OEM facility must be combined since the finished products must run through each site. Third, the analysis shows that the inventory holding costs for finished goods are a high-cost driver, even more so in the reduced case model, as more finished goods have to be stored in the DC.

2.6 Conclusion and Future Research

We provide a simulation model to reduce the complexity of the supply chain within the regulated life science industry.

The results suggest that companies operating under such supply and production conditions should focus on improving processing time and inventory holding costs. It was the first time the organisation used a digital twin to analyse the dynamic behaviour of the antibody supply chain and to evaluate multiple scenarios within a short time frame.

Changing a manufacturing process in a regulated market environment is difficult, time-consuming, and costly. The qualification and validation process to ensure the stability and validity of the process and the final audit by a regulated body are exhausting. In the past, it was challenging to assess the dynamic behaviour of market demands, supply chains, and manufacturing processes in detail. A system change in a regulated environment can have a significantly higher adverse effect on the business and customers than in an industrial setting. However, efficiency gains and cost savings are necessary in this sector to develop new products and treatments and to support customers to make the world healthier, cleaner, and safer. The model we present shows two distinct alternatives to modelling antibody manufacturing. Furthermore, the sensitivity analysis added an additional benefit to the analysis and the effects of efficiency gains in the base case.

According to the partner organisation, the performance indicators were highly valid. It was the first time the organisation had the opportunity to use a digital twin to model the dynamic behaviour of the antibody supply chain and to evaluate multiple scenarios in a concise time frame. In the future, we plan to model more complex manufacturing and logistics processes to replicate more sophisticated storage and manufacturing processes in the regulated market environment with a higher Stock Keeping Unit (SKU) depth.

The organisation was delighted with the results and plans to apply this approach to other settings.

Chapter 3

Supply Network Risk Spread in Regulated Markets

In the last ten years, the view of supply chains, from the beginning of manufacturing a product to the delivery to the customer, has changed significantly. The complexity of the downstream and upstream supply chains has increased. Researchers and companies have realised that more than the supply chain analogy is required to represent complex supply structures and multiple networks and ties within the entire value creation process. A new and improved form of representation increasingly establishes itself in research and practice. Complex supply structures are increasingly seen as deep networks that exchange tangible goods and intangible assets such as information and data. Over the last ten years, supply chain researchers have begun exploring ways to systematically analyse supply networks, as more than commonly used supply chain-relevant models were needed to represent this complex structural depth. Supply chain management researchers started using empirical social research methods and adapted them to the supply network analogy. With social network analysis, which has been known for more than 70 years, they found a way to analyse supply networks using key performance indicators and interpret the results in a completely new way.

In the following chapters, we apply social network analysis in a biotechnology company that produces PCR COVID test kits in a regulated environment to identify, analyse, and adapt network structures to increase supply network resilience. In our essay, we use key performance indicators and graphical representations to demonstrate the advantages of the social network concept in practice. Our results provide researchers and corporate decision-makers with the means to make far-reaching strategic corporate decisions to increase supply network resilience. Our research results and analyses represent a new way to sustainably improve the supply network resilience of a global biotechnology company.

3.1 Introduction

From the definitions of the supply chain (Chopra and Meindl, 2013; Christopher, 1998; Lee and Billington, 1992; Mentzer et al., 2001), it can be generally stated that the supply chain was born as a complex system through which it is possible to satisfy the request of a customer for a product efficiently. Supply Chain Management (SCM) includes all operations and their coordination that could promote this satisfaction, e.g., product manufacturing, handling, transportation and delivery. The SCM "domain" begins when a certain demand for a product arises while it ends with product delivery. In this sense, the classic SCM does not consider essential phases such as product concept design and collaborations with the development team. The first forms of the supply chains represented a collaborative short-term, goal-orientated network of enterprises (Camarinha-Matos, 2009), where the structural configuration and complexity act as a mechanism for competitive advantage and maximise the overall value generation process (Chopra and Meindl, 2013; Reeve and Srinivasan, 2005; Reid and Sanders, 2019; Sezen, 2008; Nel and Badenhorst-Weiss, 2010; Lambert and Cooper, 2000). Collaborations are essentially limited to that revenue maximisation goal, and since another one could conceptually replace its short-term nature, one member with the same skills.

Attracting increasing attention from both the academic and industrial world, supply chains started to evolve towards more complex medium-long-term collaborative networks (McCarthy and Golicic, 2002; McLaren et al., 2002; Horvath, 2001; Manthou et al., 2004; Naesens et al., 2009), to face global competition better.

First, some authors (Harland, 1996; Lamming et al., 2000) changed the supply chain term in supply network. This is because the supply chain model was linear and unidirectional (Lamming et al., 2000) and needed to evolve into a more network framework favouring cooperation between partners, as the name supply network demonstrates. Additionally, there was a significant increase in the number of discussions among researchers that a network perspective holds distinct advantages in supply chain management research (Wilding, 1998; Lazzarini et al., 2001; Choi et al., 2001; Lee et al., 2004). Supply networks are characterised by 'lateral links, reverse loop, two-way exchanges, etc.' (Lamming et al., 2000). The supply network framework is a more appropriate model today, as companies become increasingly complex systems through the outsourcing of processes (Chung et al., 2004).

Secondly, the interconnections between companies and the increasing complexity in the world of supply chains have led to the notion of the supply chain as a supply network. Generally, a network can be defined as a specific type of relation linking a defined set of events, objectives, or persons. This set of events, objectives, or persons comprised of the network is called actors or nodes (Mitchell, 1969). Since a supply network consists of events and objectives and people interacting with each other, interpersonal and social aspects are eminently important. SNA is a sub-field of social psychology and studies groups of individuals and their interconnectedness. The following definition describes a social network: "A Social Network consists of a finite set or sets of actors and the relation or relations defined on them", the relation can be seen as the defining element of networks and means a "collection of ties of a specific kind among members of a group" (Wasserman and Faust, 1994). The variable actor can be any branching point in a social network. SNA is considered a quantitative method to evaluate relational data consisting of actors and relationships (Wasserman and Faust, 1994). Network analysis is essentially determined by the definition of the actors of interest (nodes), relationships (ties), and the boundary specification of the network (Knoke and Kuklinski, 1982). The connections examined between social units vary depending on the research question and the unit under study (Jansen, 1999; Wasserman and Faust, 1994). Relationships can be directional or symmetrical, binary, or scored by intensity or frequency. SNA looks not only at the behaviour of individuals but also at how individuals interact and influence each other. SNA is modelled and analysed using graph theory, algebra, and statistics (Freeman, 2004).

Third, the definition of SNA between individuals can be applied to the analysis of supply networks. At the end of the 20th century, people were talking about supply chains; at the beginning of the 21st century, it was recognised that the supply chain is not a linear chain of upstream and downstream process steps but consists of extended supply networks divided into several levels between actors in an extended network (Lazzarini et al., 2001). Due to its complexity, a single supply chain manager can hardly control a supply network. Supply network participants must coordinate with each other in a collaborative relationship (Mueller et al., 2008). Moreover, the relative position of companies in a dense network to each other influences their behaviour and their strategy (Borgatti and Li, 2009). In this context, the relative position, the importance of each individual company and its broader relationship structure to each other are of imperative importance for future success and competitive advantage (DiMaggio and Louch, 1998; Borgatti and Li, 2009). As a result, SNA has recently gained high acceptance among researchers and academics in integrating this concept in the operations and SCM field with other branches of management theory (Carter et al., 2007; Autry and Griffis, 2008; Borgatti and Li, 2009). In particular, the network theory approach could be applied to the SCM domain to broaden the possibilities of analysing several supply chain phenomena, structures, and complexities (Borgatti and Li, 2009; Håkansson and Persson). One of the first contributions from a SNA perspective on a supply network was made by Kim et al. (2011). The material flow of three supply chains in the automotive industry was mapped. They researched the structural characteristics of the supply network and provided SNA metrics to supply network constructs and concluded that SNA can supplement and complement the analysis of supply networks. Borgatti and Li (2009) also found that SNA offers many more opportunities to study the underlying relationships in supply networks. Despite the aforementioned research and research findings in recent years, the high potential of SNA in a SCM context has been little explored in new studies (Wichmann and Kaufmann, 2016).Wichmann and Kaufmann (2016) state that "scholars are not yet entirely aware of the many possibilities the social network analysis approach offers to the supply chain management field." Therefore, there is still much research room to apply the new metrics in a wide variety of network studies and levels of analysis (Borgatti and Li, 2009; Wichmann and Kaufmann, 2016).

The purpose of our essay is three-fold. First, we analyse the network structure of a global biotech company that develops, produces and distributes SARS-CoV-2 PCR test kits. Next, we examine the structural complexity of the supply network. Finally, we test a risk mitigation strategy to increase the structural resilience of the supply network. The research method is quantitative modelling. We adopted the supply network perspective to fully characterise the structural configuration and complexity of the global biotech company's broad supply network in the regulated market environment. We will provide a broader set of key network metrics for comparative analysis and identification of key aspects and pinch points. Our study assumes that the main interest in studying a supply network structure and complexity is its effects on supply network disruption risk and resilience. In doing so, our objective is to empirically advance the supply network and SCM theories, showing the power of applying SNA in different levels of analyses to supply chain studies. Concerning managerial matters, we sought to characterise the structural complexity and, based on this, recommend structural changes to reduce disruption risk and increase resilience.

General solutions for the entire industry or other industries are beyond the scope of our study and should be addressed by further research in the same industries and other industries. The essay is divided into six sections. In the following section, we present the theoretical framework explaining the applicability of SNA for the characterisation of supply networks and the possibilities for network metrics for evaluating structural complexity. Next, we present the research methodology, detailing the techniques and procedures used in our data collection and analysis. The fourth section presents and discusses the results of the social network metrics. In the sixth section, we test a risk mitigation strategy applied to our network under investigation using MCS. The final section details the study's main conclusions, limitations, and suggestions for future research.

3.2 Literature Review

In the following literature review, we highlight not only the basic relevant literature but also the broader field of research in which our research focus can have a far-reaching impact.

3.2.1 Supply Networks

Today's supply chains are not just about aggregating supplier and customer relationships. SCM has adopted a holistic view of the chain analogy from the most upstream to the most downstream actor, including products, processes, and services (Sloane and O'Reilly, 2013). The researchers found opportunities to add value and reduce costs along the ties between the actors (Houlihan, 1988; Stevens, 1989; Cooper and Ellram, 1993; Cooper et al., 1997). The attention was focused on the vertical relationship of the supply chain actors and less on the diagonal and horizontal relationships. The increased awareness and research interest in such inter-firm links of diagonal and horizontal relationships has prompted scholars to consider such links from a social network theory perspective (Galaskiewicz, 2011).

Early contributions by social network scholars such as Burt (1982), Granovetter (1985), Galaskiewicz and Wasserman (1989), Powell et al. (1996) and Uzzi (1997) in the field of social network theory have framed our understanding of these concepts, the interdependence of actors, and how to use them in a supply network context (Sloane and O'Reilly, 2013).

Early supply chain studies focused on the supplier-buyer relationship revealed the importance of interdependence and that an indirect relationship (e.g., a customer's relationship with other suppliers) can affect the focal firm (Håkansson and Snehota, 1989). The interconnected business environment highlights the fact that the action of an individual firm can affect not only other actors in a network but also the network itself (Sloane and O'Reilly, 2013). A shock effect in one part of a supply network has lasting effects on other parts of the network (Galaskiewicz, 2011). Buffers and inventory levels can compensate for a disruption in the supply network. However, downstream actors must rectify the situation quickly if environmental degradation or labour abuses, airwaves, and social movements occur upstream (Bartley, 2007). The interdependence, the associated knowledge flow, and the critical role of the network position of companies prompted the view of the business network on supply chains (Håkansson and Snehota, 1989; Holm et al., 1999; Johanson and Vahlne, 2011). Thus, SNA in a SCM context emphasises the pressing need to incorporate the network analogy and focus the firm's attention on gaining better performance, operational efficiency and sustainable competitiveness (Corbett et al., 1999; Dyer and Nobeoka, 2000; Kotabe et al., 2003; Sloane and O'Reilly, 2013).

Some researchers used simulation models to study hypothetical supply networks (Kim et al., 2015; Pathak et al., 2007), others used real-world examples applying the case study approach (Jarillo and Stevenson, 1991; Choi and Hong, 2002) and others focused on developing taxonomies of supply networks (Harland et al., 2001; Lamming et al., 2000; Samaddar et al., 2006). There is a lack of research with a theoretical framework that connects the theory of social networks to the dynamics of the supply network and the comprehensive application of SNA to study supply networks (Kim et al., 2011).

3.2.1.1 Supply Network Design

Supply Network Design (SND) is a long-term strategic management decision problem that must be made under various uncertainties and the anticipation of future activity levels. Top management and board members must answer questions such as the following: What is our target market, what is the price point, is it a make-to-order or make-to-stock market, what is the right amount of production and distribution facilities, where should they be located, and what transportation methods should be used, etc.? Additional internal operational (e.g., the complexity of the manufacturing process, material handling, etc.) and external (exchange rates, transfer prices, tariffs, tax regulations and trade barriers (Devika et al., 2014; Martel, 2005) questions must be answered, contributing to the complexity of SND models. In addition, parameter and performance metrics must be installed to assess the long-term performance and quality of the network design in the long run. Uncertainty is the last variable that must be incorporated in SND. Most models in SND research are static and deterministic. These variables are in an extended planning horizon, not deterministic, but dynamic (Klibi et al., 2010). Scholars have considered multiple random variables to optimise network design and used static one-year models for decisions such as the size of warehouses and manufacturing facilities, as most of the literature suggests. Facility location models are a major research topic in SND and can be characterised into four types: continuous, network, analytic, and discrete (ReVelle et al., 2008). The typical approach of such models is to determine locations, the number of facilities, capacities and sizes of facilities, technology and area allocation for the production and process of products at different facilities, selection of suppliers, etc. (Simchi-Levi et al., 2003). The common approach to identifying the optimal SND uses discrete location models (Melo et al., 2009). Large manufacturing facilities, such as in the automotive or aviation industry, are built to last several years, and static models are far from suitable for SND decision making in such an environment. Moreover, most decisions in SND have been made on random variables (demand patterns, price points, exchange rates, etc.) without considering disruptions or ripple effects such as terrorist attacks or natural disasters that seriously affect the entire supply network. Thus, uncertainty modelling becomes essential for more realistic SND (Klibi et al., 2010). The presentation of a network structure, in combination with the SNA approach and the opportunities identified by it, can add considerable value to SND.

3.2.1.2 Increase Resilience in Supply Networks

Globalisation, horizontal, vertical, and diagonal expansion of supply networks, increasing product complexity, customisation of mass-produced goods, just-in-time concepts, and the buyer's market have led to a highly complex and vulnerable supply network of companies, which was not only reinforced during the pandemic but also exposed these vulnerabilities. Disruptions in such a complex and dynamic business environment may disable some actors at the local supply level and even amplify their impact on the global supply network (Rice and Caniato, 2003; Chopra and Sodhi, 2004; Hendricks and Singhal, 2009). The resilience of a supply network can be seen as a measure of how vulnerable a system is to disruption. It can be defined as the supply network's ability to return to its original or more favourable condition after a major disruption (Elleuch et al., 2016). It is an important task for supply chain leaders to improve the resilience of today's complex and global supply networks (Kleindorfer and Saad, 2009; Wu et al., 2007). Disruptions are infrequent, unexpected, and huge deviations from regular operations such as labour strikes, earthquakes, floods, bankruptcy, fire, etc. (Chopra et al.; Kleindorfer and Saad, 2009) and transportation disruptions due to closure of national borders due to wars, terrorist attacks, sanctions, strikes at ports, or extreme weather conditions (Wilson, 2007).

Dynamic adjustment and proper allocation of resources along the network are necessary for network recovery (Ivanov et al., 2017). Proactive risk mitigation strategies can be used to increase the resilience of the supply network, such as redundancy (e.g., multiple sources, safety stocks) and robust strategies (e.g., reroute in the network) (Gupta et al., 2015; Tomlin, 2006; Singhal et al., 2011).

The highly dynamic global supply network environment makes it challenging to implement suitable contingency plans for all unexpected disruptions (Macdonald and Corsi, 2013). Real-world networks have complex topologies that are significantly different from random or lattice graph structures, and they can be easily disconnected during a disruptive event (Xia, 2020). Thus, topological research has been introduced into the resilience of supply networks (Thadakamalla et al., 2004). If a link between two network nodes is disturbed, a node rewiring approach can improve resilience (Zhao et al., 2011). A necessary condition for the rewiring approach is the self-organisation repair behaviour of old and new nodes in a supply chain network (Geng et al., 2013).

3.2.2 Supply Networks and Epidemic Outbreaks

Epidemic outbreaks can be classified as a special case of supply network risk characterised by a long-term disruption and unpredictable scaling, a ripple effect along the whole network, and simultaneous disruptions in supply, demand, and logistics infrastructure. Today's companies have a global supply network and have implemented lean concepts (e.g., Just-in-Time) during the last decades. Such lean manufacturing strategies and lean supply chains have explicitly become prone to epidemic outbreaks (Ivanov, 2020). Fortune Magazine reported that 94% of the Fortune 100 companies have been affected by the COVID-19 outbreak (Fortune, 2020). Actors in a dense supply network have a series of common questions, such as how long it takes until the supply network recovers, how long the network can sustain an epidemic supply network disruption, what is the most efficient supply network operating policy to cope with disruptions at different levels of severity of the epidemic dispersal (Ivanov, 2020)? The literature on epidemic outbreaks and their effect on supply networks is scarce. An article by Johanis (2007) was concerned with a pandemic response plan that Toronto Pearson International Airport has developed following the consequences of the SARS epidemic outbreak.

The SARS outbreak of 2002/2003 has not yet reached the magnitude of COVID-19, but it has affected the airline industry greatly. 30% of Taiwan's international flights were cancelled in 2002/2003 (Chou et al., 2004). At the beginning of the millennium change in 2000, the degree of globalisation and the role of China as a global manufacturing melting pot differed from the current situation. The overall impact of SARS on the global supply network was relatively low (Ivanov, 2020). In a white paper, the British Standards Institution reported in 2014 that the Ebola virus outbreak negatively impacted global logistics (BSI, 2014). After conducting a lesson learnt during the Ebola outbreak Büyüktahtakın et al. (2018) detected the need for a decision support framework to predict the negative effect on supply networks and to improve operational and logistics problems during the crisis. Newspapers and companies reported a drastic decline in operational performance related to the COVID-19 outbreak. The German Post logistics provider declared earnings before interest and taxes reduction between 60-70 million euros (Reuters, 2020). In late February 2020, the COVID-19 outbreak caused 9% of the container shipping fleet to be inactive. Furthermore, Chinese manufacturers reported reaching the lowest production volume since the Great Recession (Unglesbee et al., 2020).

3.2.3 Social Network Analysis

Social network structures can be investigated using network and graph theory. A network consists of nodes and ties. The nodes can be companies or persons that influence decision-making. Ties between the nodes connect these nodes. SNA analyses the patterns between the ties of a network. One primary use of SNA is identifying the key social network actors (Tichy et al., 1979; Wasserman and Faust, 1994). Originally, SNA has been used to study friendship (e.g., online social networks) or community structures (e.g., households/neighbourhoods) (Kumar and

Chandra, 2010), communication patterns (Zack and McKenney, 1995), it can be used to study the spread of diseases (Klovdahl, 1985) and the diffusion of innovation (Abrahamson and Rosenkopf, 1997; Greve, 2009; Valente, 1996). Later, scholars applied the SNA concept to analyse individual firms' performance (Ahuja et al., 2009; Burkhardt and Brass, 1990; Uzzi, 1997).

SCM and operations management scholars have recognised the potential of SNA to understand better supply networks, the importance of the position of each individual firm and how the network structure itself affects the individual firm and the performance of the whole network (Kim et al., 2011). Choi et al. (2001) postulated using the SNA perspective to analyse and study complex networks. Ellram et al. (2007) stated that the social network theory could be a practical model for analysing the influence on supply chains. Borgatti and Li (2009), Carter et al. (2007) and Ketchen and Hult (2007) named SNA as a key research and analysis methodology to advance the field of SCM and logistics. Complex and dense supply networks are more than a traditional buyer-supplier relationship and consist of multiple interconnected parties such as n-tier suppliers, OEM, service providers, and customers (Bellamy and Basole, 2013). More recently, SNA and graph theory were applied to research questions such as sustainability and resilience in a supply network context. Lu et al. (2018) analysed how the social network influences the implementation of sustainable supply chains in a Confucianist society. Hard and soft ties are essential to increase capabilities and collaboration in environmental investments in the supply chain. His findings support the notion that the social network is complementary in creating environmental and social responsibilities in supply networks. Nuss et al. (2016) analysed how SNA can be applied to identify potential supply constraints using scenario analysis for high-end (turbine blades) and low-end products (batteries). The information collected and analysed can be used for risk assessment and countermeasures to increase supply network resilience. Despite the multiple fields of potential applications, scholars emphasise the many methodological challenges associated with the use of SNA methodology in a supply network context (Wichmann and Kaufmann, 2016). Data collection and access to the wider network is challenging if a network consists of more than two actors (Kim et al., 2011). In a complex network, identifying relevant and irrelevant entities is essential and can have a significant effect due to the interdependent nature of social networks (Butts, 2008). Moreover, collecting relevant network-level data is imperative for operations and SCM to be integrated with other management disciplines (Kim et al., 2011). Finally, an unspecified network boundary can cause misleading results (Marsden, 1990) and therefore, researchers conducting SNA must specify the boundaries of the analysed network (Butts, 2008). Thus, systematic adoption of SNA in the field of supply network management will be instrumental in exploring the behavioural mechanisms of whole supply networks (Borgatti and Li, 2009).

A snowball concept can be applied if the boundaries of a network are unknown. A key set of actors is asked to identify other actors with whom they have a specific connection, who in turn are asked to identify the next set of actors, etc. The process ends if the focal group cannot identify any more actors. This approach can lead to biased identification and misleading metrics on a network level if the initial actors only identify actors in their related network and not in the entire network (Carpenter et al., 2012; Marsden, 1990). The snowball concept is widely used in SNA research and is excepted as a form of egocentric sampling (Carpenter et al., 2012). The sociocentric sampling approach aims to identify and analyse all actors in a known network. This approach improves the reliability of network data (Marsden, 1990) and is useful when actors are pre-defined, such as employees in a company (Carpenter et al., 2012). Data and information collection is another challenge because organisations often have data protection policies in place, and SNA researchers cannot link actors in a network (Borgatti and Molina, 2003; Hollenbeck and Jamieson, 2015). An actor's missing or incomplete response has far-reaching effects on the quality and a potential rippling effect (Butts, 2008; Kossinets, 2006). Researchers often face access problems to gather the necessary information, and a high workload is needed to collect and analyse the data (Halinen and Törnroos, 2005). In addition to collecting information and data, researchers face analytical challenges such as structural autocorrelation and endogeneity (Carpenter et al., 2012). Structural autocorrelation occurs when actors are related, which is a precondition in a social network tie. Consequently, the network data are not independent and violate the assumption in the regression analysis (Carpenter et al., 2012). Endogeneity can emerge if measurement errors occur (Carpenter et al., 2012), for example, if the network is not correctly linked due to missing survey responses (Kossinets, 2006).

3.2.4 Network Metrics

The ties between actors (or nodes) can be soft (knowledge transfer, information flow, trust, etc.) and/or hard (material flow, money flow, transportation, etc.). The SNA approach leads to an analysis of the structural characteristics (hard ties) and the relationships (soft ties) between the actors of a supply network (Hollenbeck and Jamieson, 2015; Kim et al., 2011). Network metrics were developed to analyse and measure social networks at the node and network level (Everett and Borgatti, 1999; Freeman, 1978; Krackhardt, 1990; Marsden, 1990). From the individual actor's perspective, the node-level metric measures how an actor is embedded in the structural network. The metrics commonly used at the node level are degree, closeness, and betweenness centrality. Network-level metrics measure how the overall structural network ties are organised from the perspective of the observer. The commonly used metrics on a network level are network density, centralisation, and complexity (Kim et al., 2011).

3.2.4.1 Node-Level Metrics

Identifying key actors in a network is one of the main goals of network analysis (Tichy et al., 1979). The importance of a central position of an actor can be measured with the centrality value. A high centrality value has been associated with power (Coleman, 1973), social status (Freeman, 1978) and prestige (Burt, 1982). Three important centrality values are to be distinguished: degree centrality, closeness centrality, and betweenness centrality (Everett and Borgatti, 1999; Krackhardt, 1990; Marsden, 1990). The more ties a node has - a greater connectedness - the higher its central position in a network, and thus the node has a high degree centrality (Freeman, 1978; Marsden, 1990). Closeness centrality measures a node's proximity to all other network nodes beyond the nodes it is directly linked to. A high closeness centrality value indicates that a node can quickly reach all other nodes in the network with indirect ties (Kim et al., 2011). A high value implies greater autonomy and independence, and the node becomes less reliant on other nodes in the network (Freeman, 1978; Marsden, 1990). A node with a high betweenness centrality value lies on the shortest path between all combinations of pairs of other nodes and connects nodes that would otherwise be disconnected. The node acts as an intermediary between groups of nodes, and the dependence of other nodes to gain access makes the node central in the network (Kim et al., 2011). This central betweenness position gives node influence or control over other nodes (Marsden, 1990) and can constrain or facilitate interactions between nodes in the network (Freeman, 1978).

3.2.4.2 Network-Level Metrics

Network density measures the connectedness of relative ties to the number of potential ties in a network. If all nodes were connected to all other nodes in a network, the network would have a density of one (Scott, 2000). Network centralisation measures the overall connectedness around particular nodes in a network (Freeman, 1978). In a star structure, where an actor lies in the middle and is linked to all other nodes and these other nodes are not connected to each other, this structure has the highest possible network centralisation (Kim et al., 2011). A highly centralised network implies high power and control across the network. A network with a high density reflects a wide distribution of control and cohesiveness (Kim et al., 2011).

The complexity of a network depends on the number of relations within a network, the number of nodes, and the degree to which they are connected to each other (Frenken, 2000). High complexity in a supply network context is related to a large number of highly interconnected actors in a system, implying high coordination costs (Choi and Krause, 2006b), the high collective operational burden for the members (Kim et al., 2006), and high interdependence between the members on the supply network level (Kim et al., 2011). On the network level, complexity is related to network centralisation and density. High coordination costs are required in an exceptionally centralised network where actors are highly interconnected (Pudlák et al., 1988). A supply network with a high-density value requires more effort to build and maintain (Marczyk and Deshpande, 2010).

3.2.4.3 Cliques and Subgroups

Identifying a cohesive substructure within the network is another meaningful measure of SNA (Wasserman and Faust, 1994). Subgroups can be identified bottom-up or top-down. The bottom-up method starts with the identification of a single node. The goal is to find tightly connected sets of nodes around that node. These sets of nodes are called cliques, cores, clans, or plexes. Cliques identify network regions with a marked intensity of ties and the connection between these subgroups (Richards and Rice, 1981). The top-down method looks at the whole network and identifies specific nodes (cutpoints) where the network subgroups would break apart if that node were removed (Harary and Frank, 1969; Wasserman and Faust, 1994). Cutpoints play an important role in a network structure as a gatekeeper for the product or information flow (Sloane and O'Reilly, 2013).

3.3 Research Methodology

A classic social network in the sense of relationships among social entities and human beings, usually does not have a natural boundary. Therefore, it is essential to carefully specify the boundaries they impose on a network, as it is an important but also challenging task to include the right nodes and entities in the research question (Butts, 2008). Not precisely specified or not strictly defined network boundaries can lead to a wrong interpretation of the results (Marsden, 1990). Our research goal is to perform a complete network analysis of a company in the biotech sector. Therefore, it is important to define the exact boundaries in advance. For this reason, we use sociocentric sampling in our analysis.

The goal of sociocentric sampling is to identify all actors in an entire network that significantly enhances the reliability of the network data (Marsden, 1990). This method can be used when actors in a network can be precisely determined (Carpenter et al., 2012). A commonly used sociocentric sampling method is the whole network design approach. We can use this method in our essay because we can access company data. Thus, we can identify the entire set of actors and gather data with respect to the whole network.

3.3.1 Data Source

The research is carried out in cooperation with a biotech company. For this purpose, the company has assured us of its cooperation and provided the database for our research. The company operates in a regulated medical field and manufactures SARS-CoV-2 PCR test kits and various applications. Because the study was conducted during the height of the COVID pandemic, the goal of building a resilient and stable supply network to meet the demand for SARS-CoV-2 PCR test kits is even more important. The network includes several delivery stages between the production plants manufacturing the final product and the subsuppliers up to the

2nd delivery stage. The final product is a PCR test to detect the SARS-CoV-2 virus.

Figure 3.1: Example of a PCR Master Mix COVID Test Kit

The topic is of great research importance since for the first time in human history it was necessary to massively increase the production volume of PCR test kits due to the immense global demand. Many of the individual components needed experienced delivery bottlenecks and difficulties during the production ramp-up phase. From the raw plastic to the outer packaging of the test kits. Since the delivery structure corresponds to a network instead of a straight-line delivery structure, we use SNA and graph theory to analyse the delivery network.

An extract from the company's ERP system represents the database. The different supply structures are visible in the extract on the basis of a bill of material. Before the planned investigation and analyses can be performed, the existing raw data that the company provided in an Excel spreadsheet was brought into a manufacturer-supplier relationship level. By relationship, the level means between which companies a supply relationship exists to produce the final products. So, which company sends the assemblies, subassemblies, high-level assemblies, and raw materials from one node to another?

3.3.2 Data Processing

To create a network, it was necessary to review each line item and link the material flow from one node (company) to the next node (company), and so forth. Of the 4,999 lines extracted in the full bill of material, we identified 255 distinct companies throughout the supply network. 11 of the nodes could be identified as partner companies Manufacturing Facilities (MFG) and 244 nodes as the supply base. The remaining line items were either process steps or other necessary routings in the partner company's ERP system to plan and execute the production of the test kits. For data privacy reasons, we have anonymised the names of the suppliers and the partner organisation.

x0	x28	x59	x90	x120	x151	x180	x210	x238
x1	x29	x60	x91	x121	x152	x181	x211	x239
x2	x30	x61	x92	x122	x153	x182	x212	x240
x3	x31	x62	x93	x123	x154	x183	x213	x241
x4	x32	x63	x94	x124	x155	x184	x214	x243
x5	x33	x64	x95	x125	x157	x185	x215	x244
x6	x35	x65	x96	x126	x158	x186	x216	x245
x7	x36	x66	x97	x127	x159	x187	x217	x246
x8	x38	x68	x98	x128	x160	x188	x218	x247
x9	x39	x69	x99	x129	x161	x189	x219	x248
x10	x40	x70	x100	x130	x162	x190	x220	x249
x11	x41	x71	x101	x131	x163	x191	x221	x250
x12	x42	x72	x102	x132	x164	x192	x222	x251
x13	x43	x73	x103	x133	x165	x193	x223	x252
x14	x44	x75	x104	x135	x166	x194	x224	x254
x15	x45	x76	x105	x136	x167	x195	x225	x255
x16	x46	x77	x107	x137	x168	x196	x226	x256
x17	x47	x78	x108	x138	x169	x197	x227	x257
x18	x48	x80	x109	x139	x170	x198	x228	x258
x19	x49	x81	x110	x142	x171	x199	x229	x259
x20	x50	x82	x112	x143	x172	x200	x230	
x21	x51	x83	x113	x144	x173	x202	x231	
x22	x52	x84	x114	x145	x174	x203	x232	
x23	x53	x85	x115	x146	x175	x205	x233	
x24	x54	x86	x116	x147	x176	x206	x234	
x25	x55	x87	x117	x148	x177	x207	x235	
x26	x56	x88	x118	x149	x178	x208	x236	
x27	x58	x89	x119	x150	x179	x209	x237	

Table 3.1: Anonymised Supplier Nodes in the Network

Next, it was necessary to find the link between the individual nodes in the supply network and put them into an orderly structure. With the support of the partner company and preliminary work, we were able to connect the individual nodes gradually. Supply chain networks with interfirm relationships are commonly modelled using undirected links (Perera et al., 2017a). We adopted this approach for our research because, in a partnership network, there is not only a unidirectional flow of materials from one company to another but a bidirectional financial and communication link.

Label	**Category**	**Loccation**
SG31ABI	MFG	Singapore A
SG33ABI	MFG	Singapore B
US01	MFG	Grand Island
US02	MFG	Frederick
US03	MFG	Carlsbad
US04	MFG	Madison
US15	MFG	Eugene
US21ABI	MFG	Housten
US24ABI	MFG	Austin
US26ABI	MFG	San Francisco
US34	MFG	Rochester

Table 3.2: Anonymised manufacturing sites and the site location

To visually represent the connection of the individual nodes, the connections were transferred to Gephi. Gephi is software to explore and understand graphs. The software user can manipulate the structures, shapes, and colours to reveal hidden patterns in a network. According to the software provider: “The goal is to help data analysts make a hypothesis, intuitively discover patterns, isolate structure singularities or faults during data sourcing. It is a complementary tool to traditional statistics, as visual thinking with interactive interfaces is now recognised to facilitate reasoning. This is a software for Exploratory Data Analysis, a paradigm that appeared in the Visual Analytics field of research.” (Gephi, 2002).

3.3.3 Network Topology and Structure

Before starting with the network analysis, we begin with a general overview of network topologies and structures.

The following three network topologies are widely regarded as a benchmark (Perera et al., 2017a):

- Random graphs
  - Nodes are randomly connected to each other
  - Modelled using the Erdos-Rényi model (Erdos and Renyi, 1960)
- Small-world networks
  - The nodes are not connected directly to one another but can be reached from every other node within a small number of connections
  - Modelled using the Watts–Strogatz model (Watts and Strogatz, 1998)
- Scale-free Networks
  - Their degree distribution follows a power law
  - Modelled using the Barabasi-Albert model (Barabási and Albert, 1999)

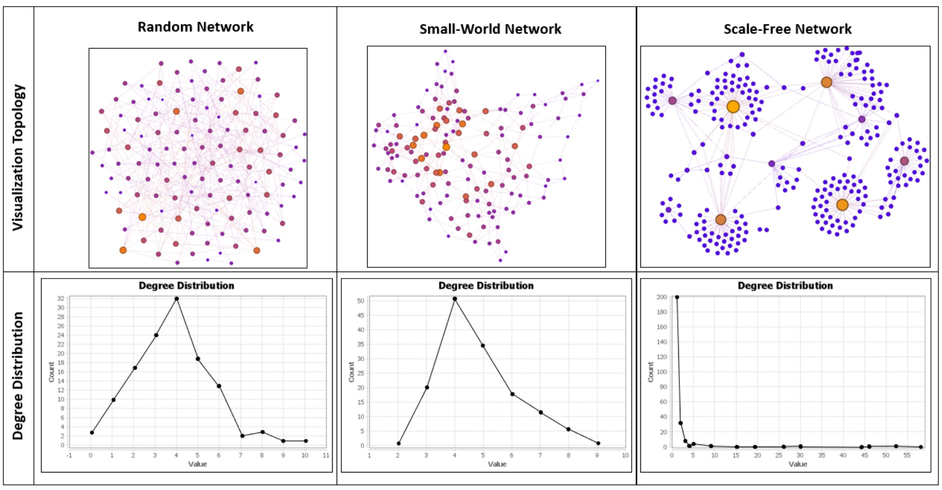

Figure 3.2: Graphical representation of the network topologies

In Figure 3.2, the different typologies can be easily recognised. In the random and small-world model, there are no or hardly any focal points that serve as hubs between various other nodes. On the other hand, a Scale-Free network has focal, highly connected hubs that can be viewed as network nodes. These network nodes play a prominent but critical position in a network as they make it very vulnerable to attacks, for example.

A network in social science is often presented in a graphical representation as shown above. However, this graphical representation is based on a data set that resembles a matrix or vector form. In the following, we briefly introduce these structural data to help the reader better understand the graphical representation and the matrix structure. The adjacency matrix is the most common data representation format in an empirical context. The matrix is represented by an n x n relation, whose *ij-th* cell is equal to *1* if node i send an edge to node j, and *0* otherwise. For an undirected graph G with an adjacency matrix A, $Aij = Aji$. This is generally not true if G is a digraph. If G is simple, then all elements of the diagonal of A will be identical *0*. Otherwise, $Aii = 1$ node i has a loop.

	A	B	C	D	E	F	G	H	I
A	–	1	1	1	0	0	1	0	1
B	1	–	1	0	1	0	1	0	0
C	1	1	–	1	1	1	1	0	0
D	1	0	1	–	0	1	0	0	1
E	0	1	1	0	–	1	1	1	1
F	0	0	1	1	1	–	1	0	0
G	1	1	1	0	1	1	–	1	0
H	0	0	0	0	1	0	1	–	1
I	1	0	0	1	1	0	0	1	–

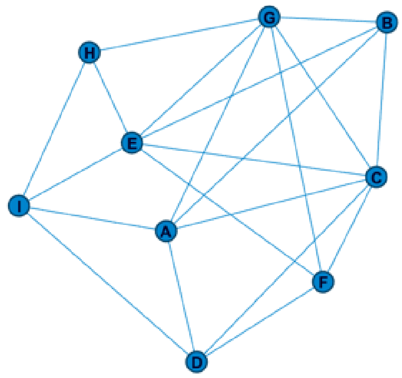

Figure 3.3: Example of an adjacency matrix and a corresponding network graph

Measurement of the structure of a network attempts to make inferences explicitly on the properties of a network. They are mainly limited to the number of nodes to which the network is connected but also to individual attributes of these nodes and/or the existence of ties between them. The "gold standard" of network analysis is to build a detailed reconstruction of a holistic network. These networks are usually referred to as global networks or whole networks. The analysis of such networks allows us to analyse the global but also local properties of a network. Most studies in small groups and organisations are designed to build a whole network and replicate it with data (Butts, 2003). The core analysis of this study is the whole network.

3.3.4 Graphical representation of the network

We begin with an overview of the network generated from the adjacency matrix. Figure 3.4 shows the entire network of SARS-CoV-2 PCR test kits generated with the Gephi software using the Yifan Hu graph layout (Hu, 2005). The Yifan-Hu graph layout is an algorithm that combines the advantages of force-based algorithms and a multilevel algorithm to reduce the complexity of the algorithm. This algorithm works very well for large networks and visually clusters strongly related subgroups of nodes toward the centre.

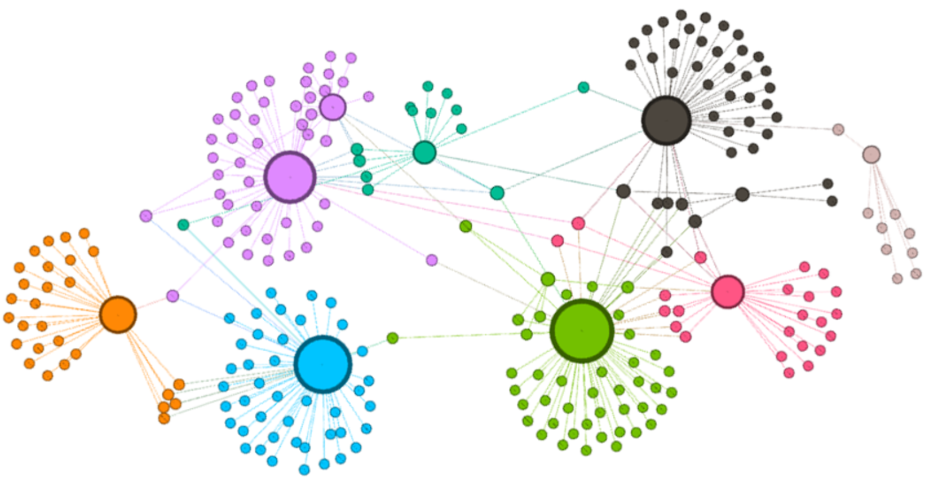

Figure 3.4: SARS-CoV-2 PCR test kits network overview

Without deeper analysis, only rudimentary conclusions can be drawn from the graph. For example, weak ties could be identified in the network shown. Weak ties are connections that provide the only link between two companies or clusters. This and other analysis techniques can be used to determine not only the resilience but also the robustness of the network. More detailed statements about the structure or important properties of individual nodes cannot be derived. However, the first cores and peripheries can already be recognised from the graphic, and subgroups can be formed. For a better visual representation, we had the software colourise the subgroups. The graphic represents the degree of interconnectedness or centrality (size of the bubbles) and the affiliation of the suppliers with the same colour represented by smaller circles to the respective manufacturing sites.

The illustration gives a first impression of the network density to be studied and underlines the high potential of SNA when applied to supply networks. In the next chapter, a more in-depth SNA analysis is performed to gain better insight into the actors' interrelationships and identify the critical key positions of the individual nodes and subgroups.

3.4 Analysis and Results

A key point is the analysis of the network using graph theory. Graph theory is used to calculate specific values with which specific statements about the network can be made. This and other results of the calculation are specially designed network metrics.

The most important network metrics are degree, closeness, betweenness centrality, network density, and centralisation. In particular, the SNA metrics size and density of the SNA metrics are of outstanding importance in characterising the complexity of the supply network. The network metrics also allow us to ask certain questions about the network's resilience. The results and significance of the global network metrics for the entire network are discussed below, followed by the specific nodes and their significance in the network. For the following analyses, we will draw on the network metrics already discussed in Chapter 3.2.4, which are calculated as follows.

Important graph theoretical concepts for network-level metrics include:

No.	Property	Equation	Observations
1	Size	*G=(N,E)*	(1) G is the graph consists of N nodes and E edges connecting the nodes to one another; the size of a network is equal to the number of nodes.
2	Density	$d(G)^u = \frac{m}{\frac{n(n-1)}{2}} =$ $mx\frac{m}{n(n-1)} = \frac{2m}{n(n-1)}$	(2) For undirectional networks D is the network density; n is the number of nodes; m is the number of existing relations in the network (Scott, 2000)
3	Centra-lization	$C_D = \frac{\sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]}{max\sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]}$ $\mathrm{C}_D(n_i) = \sum_j x_{ij} = \sum_j x_ij = x_{i+}$	(3) C_D is the network-level degree centralization. (4) $C_D(n_i)$ the node-level degree, $C_D(n^*)$ is its maximum value in the network x_{ij} in the binary variable equal to 1 if there is a link between n_i and n_j, but equal to *0* otherwise (Freeman, 1978).
4	Diameter	$d(G) = max\{d(G; u, v) : u, v \in V(G)\}$	(5) *d(G)* is the maximum distance between any two nodes in *G:d(u,v)* is the length of the shortest path joining them (Xu, 2001).
5	Average Path Length	$W(G) = \sum_{(u,v)\subseteq V(G)} d(u, v)$ $\mu(G) = \frac{W(G)}{n(n-1)}$	(6) *W(G)* Wiener Index sum of distances d between all nodes u and v of G (Wiener, 1947). (7) $\mu(G)$ the average number of edges on the shortest path between any given node of the network (Calero Valdez et al., 2012).

Table 3.3: Global Network Properties and Formula

Important graph theoretical concepts for node-level metrics include:

No.	Property	Equation	Observations
6	Degree Centrality	$C_D(n_i) = \sum_{j=1}^{n} xij_{(i \neq j)}$	(8)$C_D(n_i)$ is the node-level degree centrality xij$_{(i \neq j)}$ is the total amount of direct links with other nodes (Wasserman and Faust, 1994).
7	Closeness Centrality	$\mathrm{C}_c(n_i) = \frac{1}{[\sum_{j=a}^{n} d(n_i, n_j)]}$	(9) $\mathrm{C}_C(n_i)$ is the node-level closeness centrality d(n$_i, n_j$) is the total number of steps from node n to other nodes in the network (Wasserman and Faust, 1994).
8	Betweenness Centrality	$\mathrm{C}_B(n_i) = \sum_{j<k} \frac{m}{n(n-1)}$	(10) $\mathrm{C}_B(n_i)$ is the node-level betweenness centrality g$_{jk}$ is the total number of geodesics linking the two nodes g$_{jk}(n_i)$ is the number of those geodesics that contain (n$_i$) (Freeman, 1978).

Table 3.4: Node-Level Properties and Formula

3.4.1 Global SNA Metrics and structural configuration

The network size and density have 255 nodes and a total of 309 connections between each node.

The whole network centralisation can be calculated with the following global network centralisation formula from Table 3.3:

$$C_D = \frac{\sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]}{max \sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]}$$

The numerator in the formula is calculated using the node-level degree centrality values of the nodes in our network. In the following chapter, we will discuss the global network centralisation of specific networks in detail. To calculate the numerator, we need the node-level degree centrality value of each node in our network. First, we sort the values in descending order from the largest degree centrality value to the smallest. The Gephi software calculates and sorts each value. To compute the numerator, we need to find the difference between the largest degree centrality value, which in our case is the Austin site, and each of the remaining 254 nodes and add that together. The numerator has a value of 30.5114.

To calculate the denominator, we must find the theoretical maximum global centrality for a network of the same size and as many nodes. In a star network, the most central node connected to each other node has the highest degree centrality of 1. In Gephi, we programmed this theoretical network with 255 nodes connected to one central node. The central node has a degree centrality value of 1, and each other node in the network has the same value of 0.500986 (see the star shape network example in Figure 3.5). We perform the same calculation as above by calculating the difference between the largest degree centrality value in our network and each of the remaining 254 nodes, their corresponding degree centrality values, and add that together. The denominator in our example has a value of 126.7496.

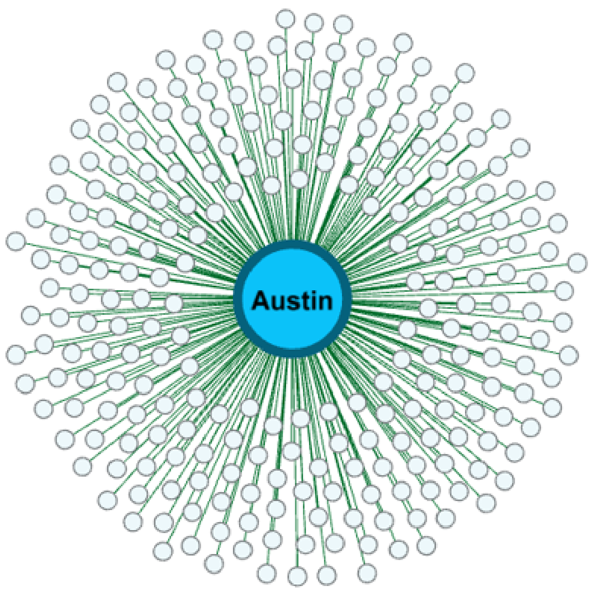

Figure 3.5: Figure 14 Star Shape Network

By putting both values in the global centralisation network formula we can calculate the centralisation value for our network under study:

$$C_D = \frac{30.5114}{126.7496} = 0.2407$$

Our network has the typology of a scale-free network. To put the global centralisation value in a better context, we performed the same calculation as above with the two other widely common network topologies, a random and a small-world network.

The following figure is a random network with 125 nodes and 246 edges. The centralisation value of the network is $C_D = \dfrac{9.4696}{61.2490} = 0.1546$.

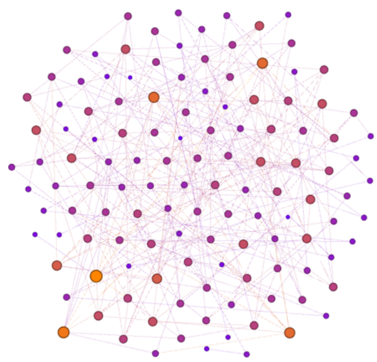

Figure 3.6: Random Network Example

The small-world network has 144 nodes and 357 edges. The network centralisation value is $C_D = \dfrac{9.9658}{71.2492} = 0.1399$.

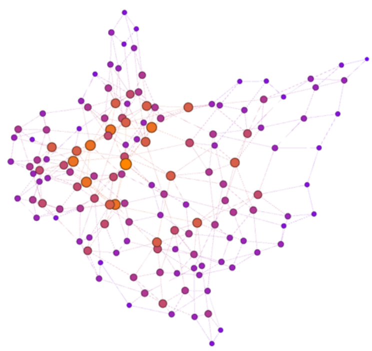

Figure 3.7: Small-World Network Example

We have applied the Yifan-Hu graph layout to the networks shown above to better demonstrate the network typology. The algorithms can be recognised that certain nodes are larger, and thus have more connections or when clusters form around certain nodes.

Our network has a value of 0.2407 which we interpreted as comparatively high in comparison to the other two calculated values for the random and small-world network. The centralisation score is important for our study because other studies have also shown a correlation between a high centralisation score and increased potential risk to a company's supply network (e.g., (Stergiopoulos et al., 2015; Nuss et al., 2016; Ledwoch et al., 2016; Lavassani and Movahedi, 2021)). Next, we calculate the diameter and average path length values to complete the global network parameters.

The diameter value $G : d(u, v)$ is the largest shortest path distance that connects two nodes. In a simple supply chain-related notion of a "transportation network," the diameter gives a value for how far a vehicle must travel from one node to another in the worst case. The result for our network using the formula for the diameter calculation (see Diameter Formula Table 3.2) is 8. In a star-shaped network with one centre node and one node at the periphery, the calculation is rather simple as one can reach every node within two steps. The diameter value is not meaningful and must be put into context. No derivation to the compactness of a network can be derived based on a high diameter value. It may be that a network has only a few nodes and the connection between the nodes is low, as seen in the following example in Figure 3.8, which has the same diameter as our biotechnology company with a network diameter of 8.

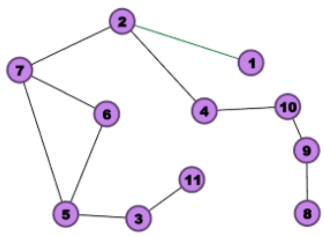

Figure 3.8: Example high Diameter low number of nodes

Therefore, for a quantitative assessment, the diameter value must be considered in the context of the size and density of a network. However, a low diameter value indicates that the nodes are close together and that the graph is compact.

The average path length $\mu(G)$ is the average number of edges on the shortest path between any given network node. The average value can be more informative than the pure diameter value since it can be regarded as a general indicator of the "navigability" of a network. This can be deduced from the fact that a high average distance indicates that the nodes tend to be farther away from each other, and thus the graph is less compact. In contrast, a low average distance implies that nodes are close together and have better "reachability". However, the total number of edges and nodes should also be included here in a quantitative consideration. The significance of the value increases accordingly if there is a low average distance between the nodes in a network with many hundreds of nodes. For a supply network, the average path value can therefore be interpreted in a way that makes it easier for the participants in the network to coordinate and communicate. For our network, the average path length is 4.0635. This means that, on average, each node can be reached within 4 steps considering the entire network.

The final metric for global network values is density. Density is explained by how many connections there would be in the network if every node were actually connected to every other node. We use formula 2 from Table 3.3 for this purpose. We need to calculate two values for this. The numerator is twice our example's current connections (2 * 309 = 618). The denominator is the number of potential connections of all nodes ((255 * (255-1) = 64.4770)). The network density is 0.0095. This number means that just 0,95% of the potential connections are utilised in the network.

In summary, using the Gephi software and the defined global network properties and formulas, we could present a comprehensive picture of the global network structure of the SARS-CoV-2 PCR test kits.

3.4.2 Node-Level SNA Metrics

This chapter looks at the node-level SNA metrics. The sociogram in Figure 3.9 shows the first metric that we would like to investigate in more depth, the degree centrality of all nodes.

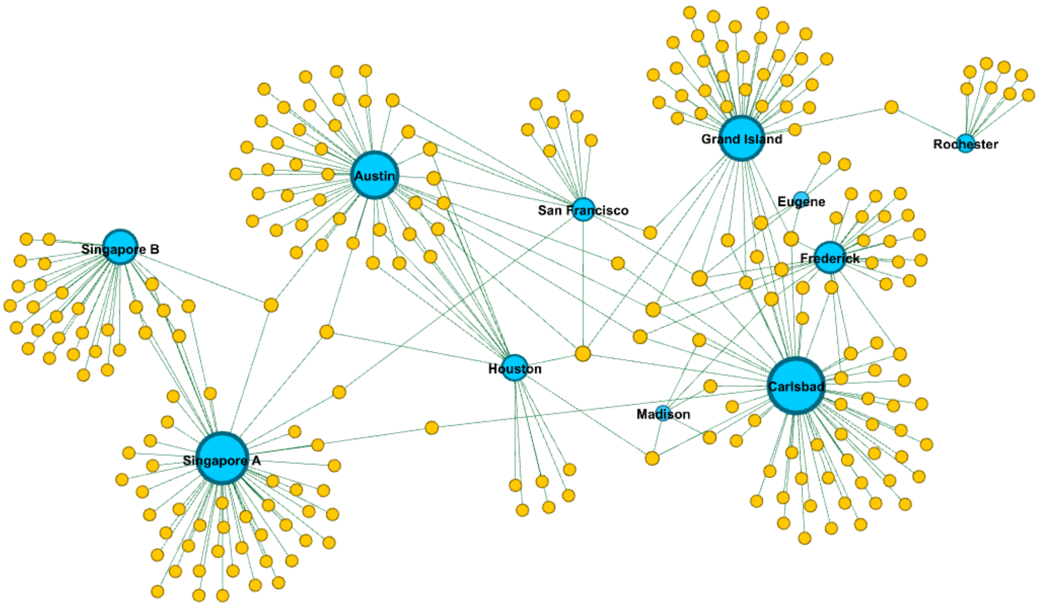

Figure 3.9: Overview of degree centrality based on the size of the circle

The degree centrality value at the node level is based on the number of links a node has with other nodes. Since a high-degree centrality value is considered to be of great importance in a network, we will discuss the individual values in the network in this chapter and work out their importance and criticality in our example.

The blue circles represent the manufacturing sites owned by the partner company and their location (city name) of the main components, respectively, the final product of the SARS-CoV-2 PCR test kits. Orange circles represent the various suppliers that deliver raw materials and assemblies to the biotechnology companies' production sites. With Gephi, we can graphically display each node's degree centrality value with the circle's size. This illustration clearly shows that the production sites have a significantly higher degree centrality than the suppliers.

The reason for this is that in the production environment of biotechnology companies, contracts are often concluded with one supplier, or only one supplier can deliver the corresponding materials. Accordingly, we can already derive a risk for the company from the presentation of degree centrality that the production sites are the focal points. In particular, the focus is on the large sites. This is indicated not only by the degree centrality value but also by the size of the locations in reality.

The following table shows the degree centrality values for the production sites and suppliers with more than 3 connections.

Name	**Node Category**	**Degree-Centrality Value**
Carlsbad	Manufacturing	58
Singapore A	Manufacturing	52
Austin	Manufacturing	46
Grand Island	Manufacturing	43
Singapore B	Manufacturing	30
Frederick	Manufacturing	26
Housten	Manufacturing	19
San Francisco	Manufacturing	15
Rochester	Manufacturing	9
x202	Supplier	5
x258	Supplier	5
Madison	Manufacturing	5
Eugene	Manufacturing	5
x70	Supplier	4
x227	Supplier	4

Table 3.5: Degree Centrality value for nodes with more than 3 connections

The production sites have the highest degree centrality values. However, it is still interesting to see that there are suppliers with several links to other nodes as well.

Next, we look at the closeness centrality of the individual nodes. Closeness centrality measures a node's proximity to all other network nodes beyond the nodes it is directly linked to. This value is particularly interesting in a scale-free network as it highlights nodes that not only have many individual connections points to another node (cluster nodes – in our examples, the manufacturing sites) but can quickly reach all other nodes via these connection points. We first present the results graphically and then the 15 highest values in Table 3.6. The circle size reflects the high of closeness centrality value.

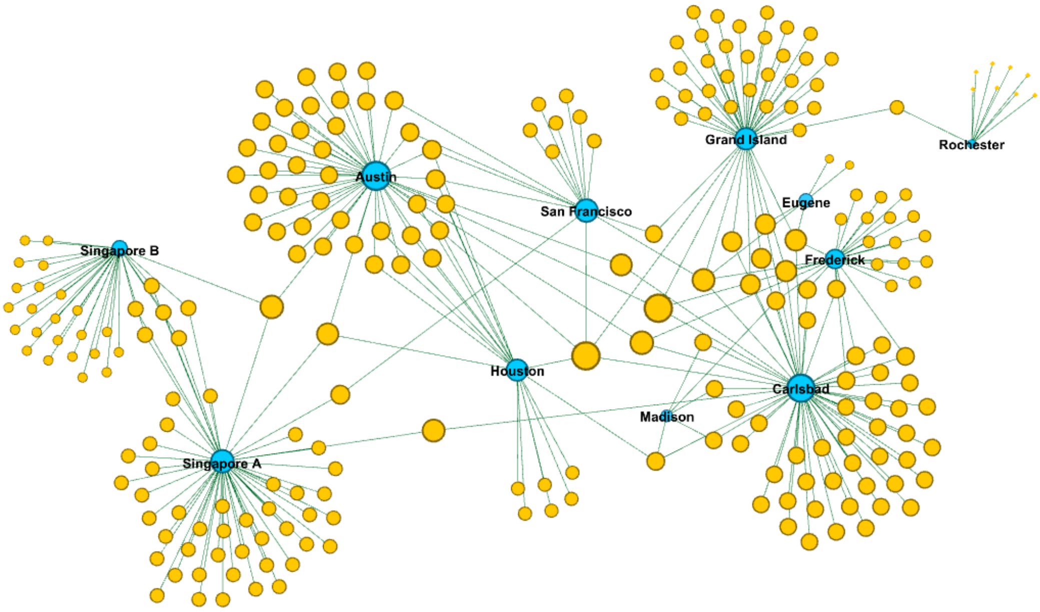

Figure 3.10: Overview of closeness centrality based on the size of the circle

The top 15 nodes include six manufacturer locations and nine supplier locations. The closeness centrality sociogram above shows a completely different picture in comparison to degree centrality. Suppliers have a significantly higher influence on this analysis and act as connection points between individual production locations on the network. This result also becomes clear in the further examination of the node-level metrics when we look at the values for betweenness centrality.

Name	**Node Category**	**Closeness-Centrality Value**
Austin	Manufacturing	0.370
x70	Supplier	0.362
x258	Supplier	0.362
Carlsbad	Manufacturing	0.362
x225	Supplier	0.322
x223	Supplier	0.322
San Francisco	Manufacturing	0.322
Singapore A	Manufacturing	0.321
x129	Supplier	0.316
x202	Supplier	0.316
Grand Island	Manufacturing	0.312
Houston	Manufacturing	0.311
x229	Supplier	0.310
x50	Supplier	0.309
x227	Supplier	0.306

Table 3.6: Node-Level Closeness Centrality

In Figure 3.11, we present the sociogram for betweenness centrality. Again, the circle size represents the height of the betweenness centrality value. A node with a high betweenness centrality lies on the shortest path between all combinations of pairs of other nodes. A high betweenness gives the node influence or control over other nodes and can constrain the interaction (e.g., supply of parts) between other nodes.

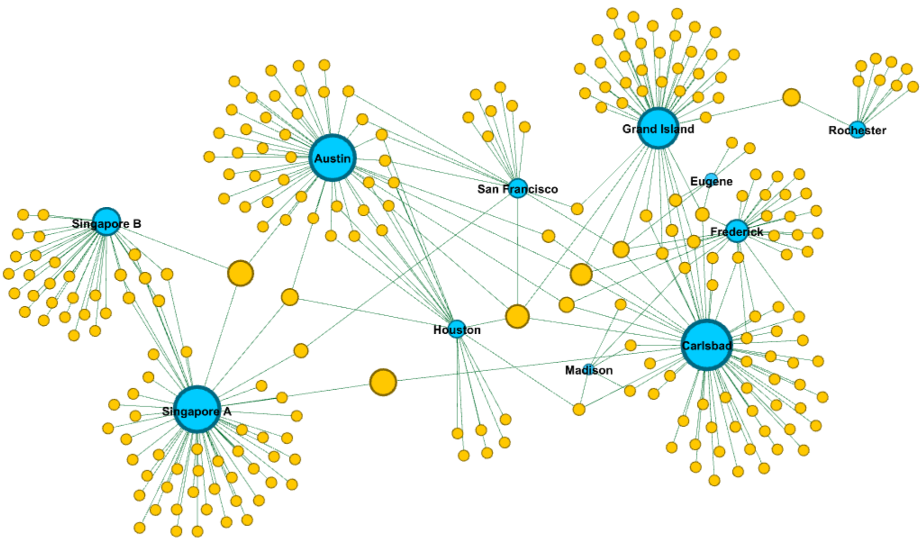

Figure 3.11: Overview of betweenness centrality based on the size of the circle

The top 15 values are summarised in the table below. The values presented below correlate with the physical nature and size of the partner company sites.

Name	**Node Category**	**Betweenness-Centrality Value**
Carlsbad	Manufacturing	0.411
Singapore A	Manufacturing	0.371
Austin	Manufacturing	0.369
Grand Island	Manufacturing	0.313
Singapore B	Manufacturing	0.177
x129	Supplier	0.164
x223	Supplier	0.154
x258	Supplier	0.132
Frederick	Manufacturing	0.125
x70	Supplier	0.114
San Francisco	Manufacturing	0.088
Houston	Manufacturing	0.072
x33	Supplier	0.069
x227	Supplier	0.064
Rochester	Manufacturing	0.062

Table 3.7: Node-Level Betweenness Centrality

We conclude the chapter with a summary of the values presented and their significance for our study and for the company.

Name	**Node**	**DC**	**Name**	**Node**	**CC**	**Name**	**Node**	**BC**
Carlsbad	Manuf.	58	Austin	Manuf.	0,370	Carlsbad	Manuf.	0,411
Singapore A	Manuf.	52	x70	Suppl.	0,362	Singapore A	Manuf.	0,371
Austin	Manuf.	46	x258	Suppl.	0,362	Austin	Manuf.	0,369
Grand Island	Manuf.	43	Carlsbad	Manuf.	0,362	Grand Island	Manuf.	0,313
Singapore B	Manuf.	30	x225	Suppl.	0,322	Singapore B	Manuf.	0,177
Frederick	Manuf.	26	x223	Suppl.	0,322	x129	Suppl.	0,164
Houston	Manuf.	19	San Francisco	Manuf.	0,322	x223	Suppl.	0,154
San Francisco	Manuf.	15	Singapore A	Manuf.	0,321	x258	Suppl.	0,132
Rochester	Manuf.	9	x129	Suppl.	0,316	Frederick	Manuf.	0,125
x202	Suppl.	5	x202	Suppl.	0,316	x70	Suppl.	0,114
x258	Suppl.	5	Grand Island	Manuf.	0,312	San Francisco	Manuf.	0,088
Madison	Manuf.	5	Houston	Manuf.	0,311	Houston	Manuf.	0,072
Eugene	Manuf.	5	x229	Suppl.	0,310	x33	Suppl.	0,069
x70	Suppl.	4	x50	Suppl.	0,309	x229	Suppl.	0,064
x228	Suppl.	4	x228	Suppl.	0,306	Rochester	Manuf.	0,062

Table 3.8: Summary of Node-Level values

Table 3.8 summarises the values for degree centrality (DC), closeness centrality (CC), and betweenness centrality (BC). The table shows that a few nodes have emerged as key nodes on the manufacturer and supplier side and are of corresponding importance.

The analysis of the node-level values has clearly shown the potential of applying SNA on supply networks. In this chapter, we gained important insights for our study. We were able to identify the critical nodes for production and suppliers. The calculated values measured the importance and criticality of the nodes. Since production facilities are of outstanding importance to the company SNA was able to confirm the importance of strategic locations with the key figures presented. These are, in particular, the Carlsbad site as the largest and the Austin site. Two suppliers also play an important role. x258 supplies the labels that are essential for the end product. x70 supplies chemical base materials such as nuclease or sodium hydroxide.

The final analysis is the identification of subgroups. We start with the top-down method. In the top-down method, we look at the entire network and try to identify the cut points. Cut points are nodes with outstanding significance. If these nodes disappear, the network will structurally break up into different sup-groups without a connection to each other. The cut points allow us to draw conclusions about the structural holes of the network and where they exist. In the following diagram, we illustrate the concept.

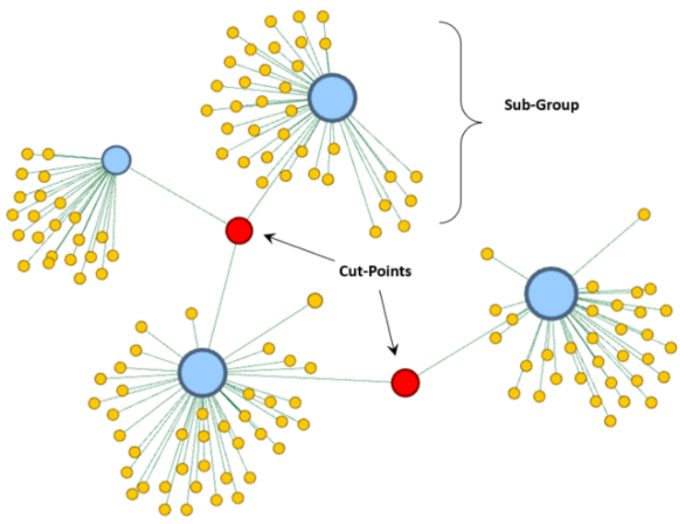

Figure 3.12: Example of cut-points and sub-groups

For analysis and better illustration, we first removed the nodes with only one connection in the network, since the cut-point must have at least two connections. The complexity-reduced network is shown in Figure 3.13. On the left side, we detected one cut point after eliminating the nodes with one connection. The blue dots represent supplier sites with two connections. The picture on the right-hand side shows the disconnected subgroup in an entire network view.

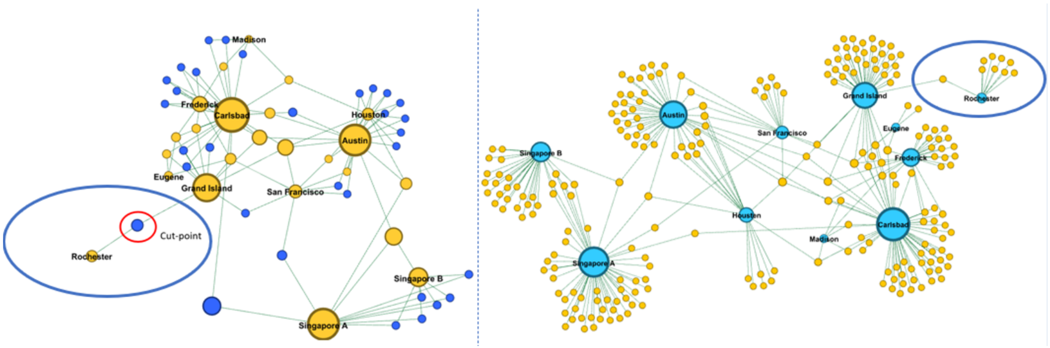

Figure 3.13: Left the complexity reduced network; right the basic network

The subgroup analysis showed one actual cut-point in the network that would "cut off" Houston production from the rest of the network.

In a further step, we use the bottom-up method. Our goal in this method is to find tightly connected sets of nodes around a specific node. These groupings are also called cliques. Cliques identify network regions with a marked intensity of ties and the connection between these subgroups. In our analysis, we were able to identify eight subgroups. Figure 3.14 presents the subgroups in detail. The figure shows that specialised suppliers have formed around the respective production sites. Therefore, a clear clique formation is recognisable, which we have coloured for better presentation.

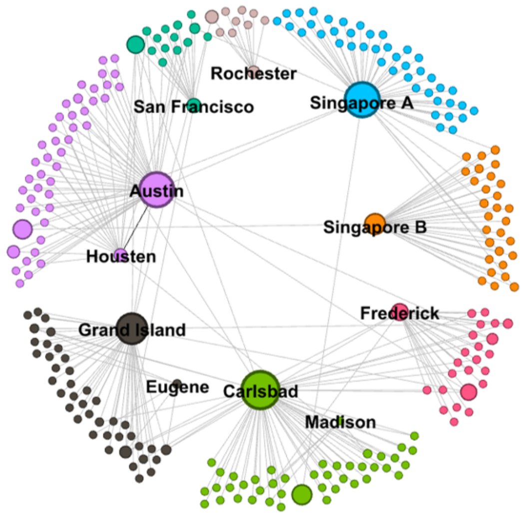

Figure 3.14: Sub-groups in the Supply Network

The size of the nodes in Figure 3.14 reflects the betweenness centrality value. We were able to identify suppliers in the clique formation with a high betweenness centrality. These suppliers tend to be larger companies, and thus supply products to various manufacturing locations.

3.4.3 Network Structure and Structural Complexity

Based on our supply network research, we can draw the following conclusions: The network structure is a scale-free network. The network contains 255 nodes with 309 connections. The global centrality value is 0.2407. The network's diameter is 8, which means that in the worst case, each node can be reached within 8 steps. The average path length is 4.0635, meaning that each node can be reached in 4 steps.

The results of the node-level metrics provide important information based on standardised social network metrics and give important information about the specific node in the context of a supply network. By analysing the three-core metrics, we identified the critical nodes and, thus, the critical production sites or suppliers. The critical production sites based on the three metrics are Carlsbad and Austin. The critical suppliers are x258 and x70. This result also correlates with the results we collected in practice and in coordination with the partner company. Both sites are of outstanding importance in the production of COVID test kits. Suppliers are critical because they supply specific materials to multiple production sites and therefore have a high value and criticality in practice.

Then we checked whether there were certain cut-points that would divide the network into different subgroups. Our analysis identified one such cut-off point that would separate the Rochester site and its suppliers from the remaining supply network. After analysing the cut point and identifying the Rochester site and its suppliers as a subgroup, we took a detailed look at the site. The Rochester site is a comparatively large site with approximately 1000 employees. The site produces COVID test kits for the company and as an original equipment manufacturer for other companies. Therefore, the site was included in our analysis since it could take over the production of the company's own test kits as an additional site. Finally, we analysed the subgroups in the entire network and identified 8 different subgroups.

In the following, we have summarised the main metrics for a better overview:

Property	**Equation**	**Results**
Size	$G=(N,E)$	255 nodes; 309 connections
Density	$d(G)^u = \frac{m}{\frac{n(n-1)}{2}} =$ $mx\frac{m}{n(n-1)} = \frac{2m}{n(n-1)}$	0.0095 density
Centra-lization	$C_D = \frac{\sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]}{max\sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]}$ $C_D(n_i) = \sum_j x_{ij} = \sum_j x_i j = x_{i+}$	Global Centrality Value is 0.2407
Diameter	$d(G) = max\{d(G; u, v) : u, v \in V(G)\}$	The max worst network length is 8
Average Path Length	$W(G) = \sum_{(u,v)\subseteq V(G)} d(u, v)$ $\mu(G) = \frac{W(G)}{n(n-1)}$	In average each node can be reached in 4.0635 steps.
Degree Cent-rality	$C_D(n_i) = \sum_{j=1}^{n} xij_{(i\neq j)}$	Top 3 nodes with the highest Degree-Centrality: • Carlsbad: 58 • Singapore A: 52 • Austin: 46
Closeness Centrality	$C_c(n_i) = \frac{1}{[\sum_{j=a}^{n} d(n_i, n_j)]}$	Top 3 nodes with the highest Closeness-Centrality: • Austin: 0.370 • x70: 0.362 • x258: 0.362
Between-ness Centrality	$C_B(n_i) = \sum_{j<k} \frac{m}{n(n-1)}$	Top 3 nodes with the highest Betweenness-Centrality: • Carlsbad: 0.411 • Singapore A: 0.371 • Austin: 0.369

Table 3.9: Network Properties and Formula

3.5 Risk Assessment and Mitigation using Monte Carlo Simulation

Our subsequent research is based on our discussions with the partner organisation. Especially in an uncertain time such as the COVID pandemic and with the production of a product that is essential for the fight against the virus worldwide, it was of great importance for the global management team to identify vulnerabilities as well as risks in the supply network and to be able to derive measures. Such uncertainty of leadership teams has been confirmed in previous research. Harland et al. (2003) found that less than 50% of the potential risks in their supply network were known to the companies studied. The potential risks to their own company were mostly only identified in their own functions. Furthermore, the visibility of global supply chain leaders outside their own functions decreased significantly with increasing globalisation. Therefore, the possibility of identifying potential risks in the entire supply network also decreased massively (Vilko and Hallikas, 2012). Jüttner (2005) pointed out at the beginning of the twentieth century that supply chain vulnerabilities must be identified within the company and with partner organisations and where there are links between the different organisations in the global supply network structure.

In the following, we present a new approach to how companies can identify vulnerabilities and risks outside their own corporate functions, define countermeasures, and hypothetically test them in conjunction with social network metrics and MCS. We chose MCS because it provides very fast results compared to other analysis or estimation methods.

We show that MCS in combination with SNA can be used to analyse a network with respect to vulnerability and risk mitigation measures can be derived. The results are compared with the original network using the scenarios' respective SNA metrics. This makes it possible to use large amounts of data to determine how resilient the network is.

In the following, we present the theory and calculation example underlying the experiment before we turn to our network underlying the thesis.

3.5.1 Application of Monte Carlo Simulation in combination with Social Network Metrics

One of the key factors in risk identification is the visibility of the supply network, as many authors acknowledge (i.e., (Basole and Bellamy, 2014a; Caridi et al., 2010; Al-Mudimigh et al., 2004)). Graphical network representation software can first generate visibility and second help to analyse the network structures. A graphical network presentation shows the suppliers and the links between the suppliers and the manufacturing companies. SNA further offers, as discussed in detail in the previous chapters, the important SNA metrics that provide a supply chain practitioner and upper management with quick and easy-to-understand and advanced information to derive actions that are not used this way in the normal supply chain environment. These metrics are novel to the supply chain world and are slowly entering the literature and vernacular.

In the supply chain literature, the number of publications related to applying SNA to supply networks has increased significantly over the last 10 years (i.e. Sloane and O'Reilly (2013); Kim et al. (2011); Borgatti and Li (2009)). In these analyses and research supply networks were explored using SNA, the metrics were discussed and academic and managerial contributions were described. The results and contributions were related to the structural design and the individual SNA metrics of the investigated supply networks in different industries and areas. In recent years, researchers have become more aware of SNA metrics and realised that these metrics could be used not only in social (interpersonal) networks to detect vulnerable and risky nodes or links but can also be applied to supply networks. The researchers started investigating the structural complexity, network and node-level metrics and combined the SNA metrics data with a risk management approach (Ledwoch et al., 2016; Nuss et al., 2016; Basole and Bellamy, 2014b; Mizgier et al., 2013). The approach is particularly interesting when not all of the required information from the supply network is available to make specific assumptions related to risk. However, potential risks can already be identified if the links between the different nodes are available.

Multiple applications were identified to use degree centrality in vulnerability assessment since the height of the value represents the number of connections to other nodes (Chopra and Khanna, 2014). The degree centrality value can be seen as a good indicator of the node's exposure to what flows through the network (i.e. (Kuzubaş et al., 2014; Wang et al., 2010)). Betweenness centrality is another suitable measure for systematic risk assessment, as a node with a high betweenness centrality value can be seen as an intermediary passing semifinished and finished goods along the supply chain to the final customer. These nodes act as intermediaries and control the flow of goods and information (Kim et al., 2011). Closeness centrality is also an SNA metric that can be used to describe the importance of a specific node in a network. The higher the closeness centrality value of a node, the more embedded the node in the network, and the smaller the average distance to the other node of the network. A high-centrality node can be classified as a navigator in a supply network (Kim et al., 2011).

Degree and closeness centrality are also good values for risk analysis and could be used for our application. However, the information content of the degree centrality value is limited, as it only partially reflects the network topology (Mizgier et al., 2013). Additionally, the content of the information is relatively low and other values can be better used for risk analysis (Niu et al., 2015). The closeness centrality value considers all nodes in the network, including nodes with only one connection to another. This is generally valuable information, but we are particularly interested in nodes with at least two connections.

In order to make a risk measurable and subsequently derive risk minimisation measures, it is not only necessary to be able to identify the nodes in a network but also to recognise the critical nodes that have a significant influence on the network risk (Basole and Bellamy, 2014b; Mizgier et al., 2013; Bezuidenhout et al., 2012). Various SNA metrics can be used to analyse the structural significance of networks and individual nodes (Kim et al., 2011). Betweenness centrality has been identified as a particularly good measure of structural importance. Companies with a high betweenness centrality value are considered particularly important because if the node disappears or production is disrupted, this would affect many more companies than a disruption of a company with lower betweenness values (Borgatti and Li, 2009). For this reason, we use the betweenness centrality value for our next analysis using the MCS.

However, our method of calculating network risk differs from the existing literature. The authors Basole and Bellamy (2014b) also use the betweenness centrality value to express a node's structural importance. However, for their analyses, they use inventory variability as operational risk and the Altman Z-score for financial risk to calculate supply network risk. Ledwoch et al. (2016) uses the Katz centrality and the physical distance of companies (nodes) to determine risk exposure in the physical supply network. In his study of physical distance, he analyses the speed of disruption spread in the material network. The authors Yildiz et al. (2016), on the other hand, do not calculate a risk but the reliability of a supply network, which is based on delivery risks and costs of available capacity to fulfil demand. They also analyse an increase in the network's reliability when additional nodes are added to the network. The authors Qazi et al. (2018) use a more traditional approach to manage the supply chain risks by analysing and treating potential risks, such as process and supply risks, with a risk management process and then analysing the result. Our approach, on the other hand, uses the Word Risk Index (WRI) and the corresponding risk indices of the state for each node, the betweenness centrality value of the node and a factor for risk diversification so that we can use the MCS for assessing the node and network-level risk. In chapter 3.5.3 we illustrate the method with a numerical example.

3.5.2 Simulation Design

We used the Crystal Ball Suit Microsoft Excel add-in version 11 from Oracle for our investigation. Since the application is not a standalone solution, we use Microsoft Excel 365, on which Crystal Ball is installed. Next, we transferred the data already obtained from the analysis in Gephi for the betweenness centrality values into Excel. The data fields we used are the anonymised nodes' ID and the respective betweenness centrality value for that node. In our investigation, we focus only on the supplier nodes and not on the manufacturing sites. Furthermore, we only include the nodes with at least two connections to other nodes. As a result of these necessary restrictions, the number of supplier nodes was reduced from 244 to 45.

Based on the preceding research provided, we can assume that a high betweenness centrality value can be associated with a high risk. Since we know the betweenness centrality values of the individual suppliers through the network analysis, we can present a ranking list of the high-risk suppliers sorted in descending order. Already this information is very valuable for a company because it is possible to identify the most critical suppliers already by a comparatively simple SNA. However, the betweenness centrality is a static value. It does not change after the SNA calculation. Since supply networks have become much more volatile due to internationalisation, especially COVID, a probabilistic value should be used. MCS allows us to simulate multiple future events and draw conclusions. Thus, each possible future event can be tested not only once, but also based on different probabilities and forecasts multiple times.

Regulated products are subject to a special level of protection to ensure that customers and other stakeholders are protected from any potential risks. Companies are required to implement appropriate quality management systems for regulated products in their end-to-end supply chain to minimise potential risks. Various external bodies, such as the FDA, periodically audit and verify compliance with the required measures in the various companies. These activities and measures can be considered supply chain compliance, which combines adherence to relevant industry regulations and requires transparency and traceability in the supply chain, especially in pharmaceutical industries (Klueber and O'Keefe, 2013). A company operating in this market must, therefore, take appropriate measures. Modelling and simulation analysis in the context of supply chain management in regulated markets provides insights into compliance, risk management, efficiency, and strategic decision-making. Simulation models can incorporate the specific compliance requirements imposed by regulatory bodies on supply chain operations. This includes product safety standards, transportation regulations, and environmental guidelines. Simulation analysis identifies and assesses these risks, helping organisations develop strategies to mitigate potential disruptions. Furthermore, regulatory compliance often extends to suppliers and vendors. Simulation models can help assess the impact of regulatory requirements on supplier relationships, evaluate alternative suppliers, and ensure that the entire supply network complies with relevant regulations. However, it should also be noted that regulatory environments are dynamic, and changes can significantly affect supply chains. Simulation models allow organisations to conduct scenario analysis to understand how potential changes in regulations could affect the supply chain, enabling proactive decision-making and adaptation. The key issues and potential risks outlined above represent different application areas where our modelling and simulation analysis can be used to mitigate risk. However, due to the wide range of possible applications, we have focused on one potential network risk in the regulated market sector, which can be represented by our method and reduced using the below-mentioned measure. Our analysis and simulation focus lies in regulated markets that may require supply networks to have robust emergency response plans, like a vaccine manufacturer or, as in our example, COVID test kits. Our presented approach can help organisations test and refine risk minimisation plans to ensure the efficient and compliant handling of emergencies, such as pandemic outbreaks or regulatory crises.

Since we have only a static betweenness centrality value for each node, we had to model the occurrence of the risks under consideration using a distributions function. Therefore, we assign a risk value to each node. The risk value is based on the World Risk Index of 2022 (WorldRiskIndex, 2023). To apply the risk value to our study, we had to determine the country of origin for the nodes, respectively, the suppliers. Together with the partner company, we identified the shipping address. We then assign the risk value from the WRI for the respective node as 'the' risk value. Taiwan is not listed in the report. Due to proximity to China (risk value 28.7) and the Philippines (risk value 46.82), we have taken an average value of both countries for Taiwan. In addition, we incorporate probability into the risk factor. We made the following assumptions. (1) With specific proactive risk mitigating measures, the company can improve the actual risk factor by 5%. (2) Do nothing and accept the actual risk defined by the WRI report. (3) Face an increase in the risk factor by 20% with the emergence of a global disruption. We had to make these assumptions, as WRI does not incorporate supply chain volatility or potential improvements over time. We used a triangular distribution for the risk factor with a deviation of -5%, 0%, and +20%. The positive value can be associated with a disruption in the delivery situation that increases the network risk accordingly. On the other hand, a negative value reduces the risk of the network. The software Crystal Ball calculated 10,000 times a potential future risk factor by the corresponding betweenness centrality value of the respective node and the probability distribution for the WRI. The confidence interval for our calculation was set to 95%.

Table 3.10 shows the values sorted in descending order according to the betweenness centrality value:

Table 3.10: Summary of Node-Level Data required for the Monte Carlo Simulation

Anonymised Supplier-ID	**Betweenness Centrality**	**Country**	**WRI Factor**	**Risk Factor (-5%)**	**Risk Factor (+20%)**
x7	0.009439	Singapore	0.81	0.77	0.97
x15	0.001147	United States	22.73	21.59	27.28
x16	0.016814	United States	22.73	21.59	27.28
x23	0.011135	United States	22.73	21.59	27.28
x24	0.035107	United States	22.73	21.59	27.28
x33	0.068625	United States	22.73	21.59	27.28
x48	0.003714	United States	22.73	21.59	27.28
x50	0.018574	United States	22.73	21.59	27.28
x64	0.001147	United States	22.73	21.59	27.28
x70	0.114256	United States	22.73	21.59	27.28
x75	0.009439	Singapore	0.81	0.77	0.97
x76	0.009439	Singapore	0.81	0.77	0.97
x78	0.005465	United States	22.73	21.59	27.28
x84	0.001147	United States	22.73	21.59	27.28
x85	0.001108	United States	22.73	21.59	27.28
x94	0.001108	United States	22.73	21.59	27.28
x98	0.005821	United States	22.73	21.59	27.28
x99	0.00918	United States	22.73	21.59	27.28
x115	0.003003	United States	22.73	21.59	27.28
x129	0.16447	United States	22.73	21.59	27.28
x133	0.001147	Singapore	0.81	0.77	0.97
x136	0.009439	Singapore	0.81	0.77	0.97
x147	0.001147	United States	22.73	21.59	27.28

ID	**Betweenness Centrality**	**Country**	**WRI Factor**	**Risk Factor (-5%)**	**Risk Factor (+20%)**
x150	0.011135	United States	22.73	21.59	27.28
x173	0.003714	United States	22.73	21.59	27.28
x181	0.001147	Ireland	3.1	2.95	3.72
x189	0.003714	United States	22.73	21.59	27.28
x190	0.012083	United States	22.73	21.59	27.28
x202	0.056599	United States	22.73	21.59	27.28
x206	0.009439	Singapore	0.81	0.77	0.97
x211	0.003714	United States	22.73	21.59	27.28
x212	0.001108	United States	22.73	21.59	27.28
x219	0.011135	Taiwan	37.76	35.87	45.31
x223	0.154008	Singapore	0.81	0.77	0.97
x225	0.045087	United States	22.73	21.59	27.28
x227	0.001147	United States	22.73	21.59	27.28
x228	0.028216	United States	22.73	21.59	27.28
x229	0.063641	Lithuania	2.24	2.13	2.69
x230	0.001147	United States	22.73	21.59	27.28
x233	0.003003	United States	22.73	21.59	27.28
x234	0.009439	Singapore	0.81	0.77	0.97
x251	0.003714	Lithuania	2.24	2.13	2.69
x252	0.005465	United States	22.73	21.59	27.28
x254	0.021271	United States	22.73	21.59	27.28
x258	0.131612	United States	22.73	21.59	27.28

The last step was to transfer the data into an Excel format, set up Crystal Ball, and run the simulation.

3.5.3 Simulation and Risk Minimisation

Before we go into the individual results of the simulations and present the figures of the analyses, we would like to present a simple numerical example of our calculation method of the potential risk of a node, and then we demonstrate the calculation of the risk spread of the network. To do this, we first select the node x258 from our network. The node has a betweenness centrality value of 0.1316, a WRI factor of 22.73, a WRI factor reduced by 5% of 21.59 and a WRI factor increased by 20% of 27.28. These three WRI values are important for calculating the risk distribution of a single node using the betweenness centrality value. We use a triangular distribution based on the reduced 5% WRI factor (minimum value), the WRI factor (most likely value) and the increased 20% WRI factor (maximum value). The Monte Carlo application randomly selects on the basis of the triangular distribution of one of these values and then multiplies the value with the betweenness centrality value of the node. By iterating the 10,000 replicates, the multiplier changes according to the random triangular distribution. As a result, the product of the triangularly distributed WRI value (minimum - most likely - maximum) and the betweenness centrality value of the node is almost always different. This implies that the risk spread we have defined for node x258 will change throughout each iteration and will move between the minimum value of 2.8412 (0.1316 * 21.59 = 2.8412) and the maximum value of 3.59 (0.1316 * 27.28 = 3.59). The application computes the standard deviation of all the calculated values from the 10,000 iterations for our node x258, passing it to the MCS for graphical representation. This calculation is carried out in the same way for each of the nodes. In order to obtain a scatter in the histogram, the calculation was recorded by the Monte Carlo application, and then the standard deviation of all nodes was determined to create a holistic histogram of the supply network risk spread.

The data was transferred to Excel, and 10,000 repetitions were set in Crystal Ball. Based on the triangular distribution of the risk factor values and inclusion of the betweenness centrality value, the following results could be obtained from Crystal Ball for the base case.

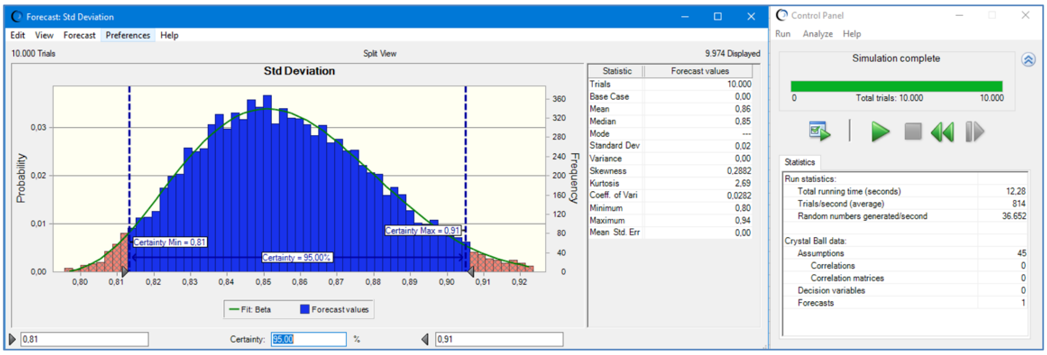

Figure 3.15: Probability Histogram actual Supply Network

In total, more than 36,500 random numbers were generated per second, and the simulation could be completed in 12.28 seconds. Here, the advantages of the MCS become clearly visible.

The histogram in Figure 3.15 represents the distribution of the standard deviation value, the probability, and the frequency during 10,000 repetitions. The mean value is 0.68, the mean standard deviation of all the values calculated in that run. With a certainty of 95%, the standard deviation of the calculated values will be between 0.81 and 0.91.

We call this calculated value Supply Network Risk Spread (SNRS). The SNRS gives the company a quick and easy-to-calculate risk ratio for the entire supply network under consideration. A high value in this context equals higher risk in the network. The goal of a company must be to reduce this value. Identifying SNRS is the first step. In the second step, measures must be derived and implemented to reduce SNRS. With the sensitivity analysis built into Crystal Ball, we can determine which node in the network has the greatest impact on SNRS. In our case, we were able to identify three important nodes, which are shown in Figure 3.16.

The nodes with the highest contribution to variance correlate with our previous evaluations of closeness centrality and betweenness centrality. Our results show

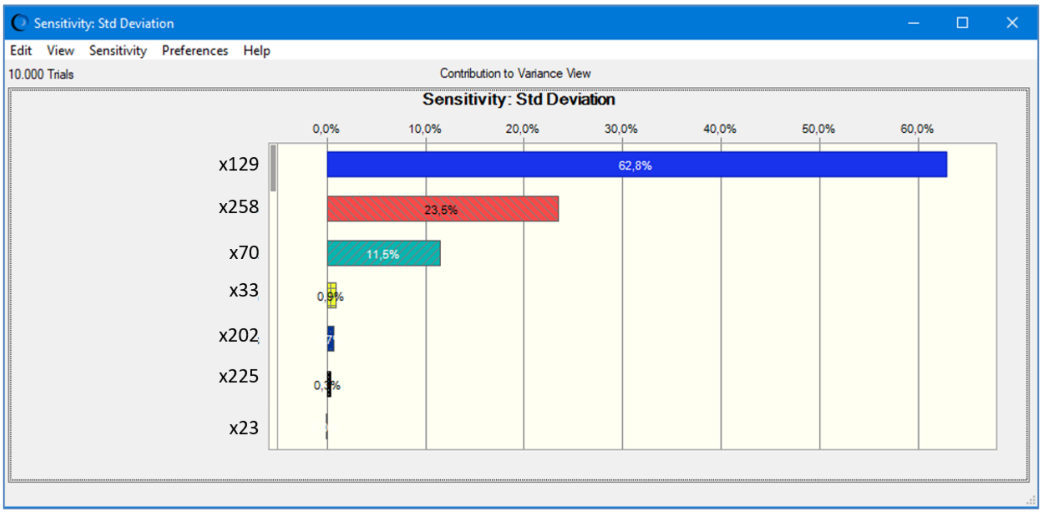

Figure 3.16: Sensitivity Analysis Contribution to Variance

that all three nodes have a comparatively high betweenness centrality. Due to the high level of contribution of these nodes to the SNRS, we apply one of the 'classic' risk mitigation strategies in supplier management, dual sourcing.

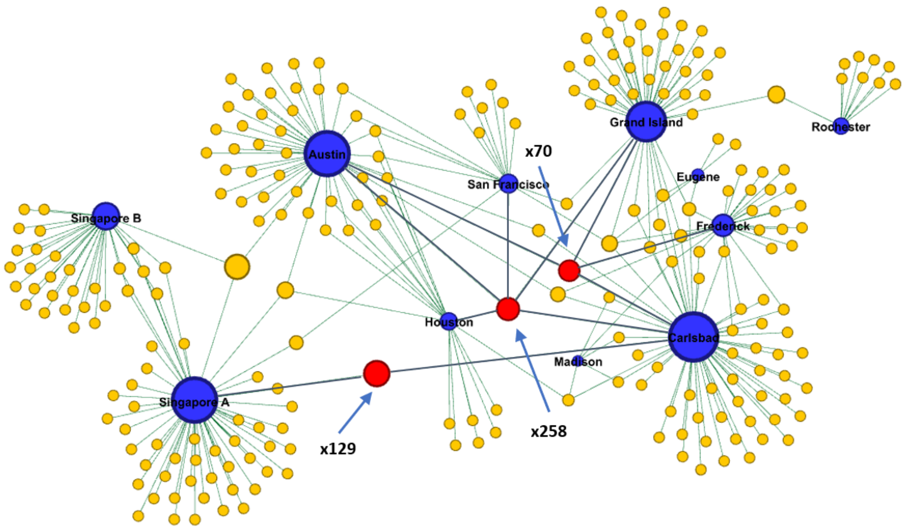

Figure 3.17: Network Graph with red marked nodes with the highest contribution to sensitivity

Figure 3.17 shows the three identified nodes with the highest contribution to variance coloured red. For the purposes of the following analysis, only two of the three identified nodes, the x129 supplier and the x258, will be considered as dual sourcing. To conduct the analysis, we need to duplicate the original x129 node first. This means that we create a new node, "xx129" and establish the connection between the production sites in Singapore and Carlsbad, as shown in Figure 3.18.

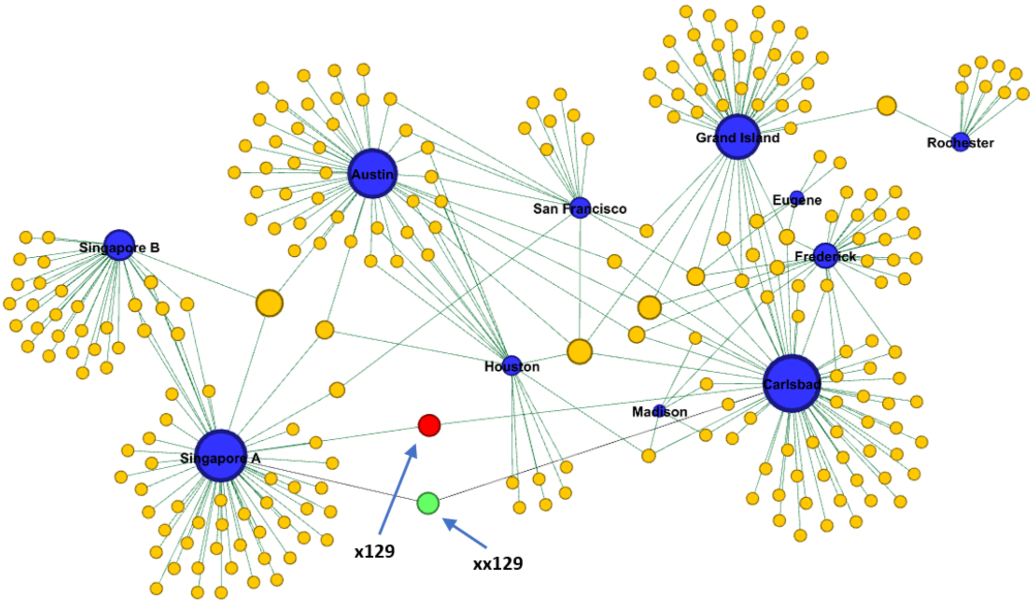

Figure 3.18: Adjusted Supply Network with Dual Sourcing for Supplier x129

Adding a node to a supply network changes all social network node-level metrics, which we need to recalculate. Our results show that dual sourcing has significantly changed the previously calculated betweenness centrality value of x129. The original betweenness centrality value in the base case was 0.16447. In the dual-source case, the value was reduced to 0.093022. The betweenness centrality has reduced by 43.45%, which already implies a significant risk reduction. We transferred the new values of all nodes to Excel and ran Crystal Ball again with 10,000 repetitions at a confidence interval of 95%.

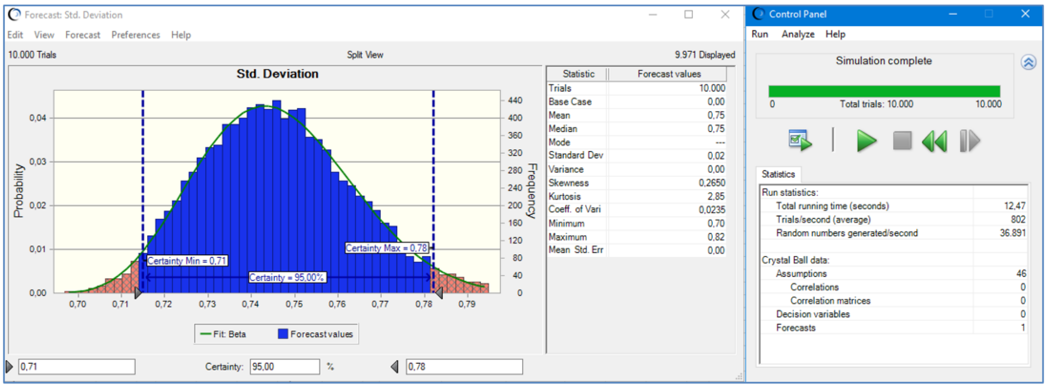

Figure 3.19: Probability Histogram with Dual Sourcing for Supplier x129

Dual sourcing has significantly changed the standard deviation and the mean value of the standard deviation in a positive direction. The mean value dropped from 0.86 to 0.75, a reduction of 12.79%. The min and max values of the 95% certainty dropped from min0.81 – max0.91 to min0.71 (-12.35%) – max0.78 (-14.29).

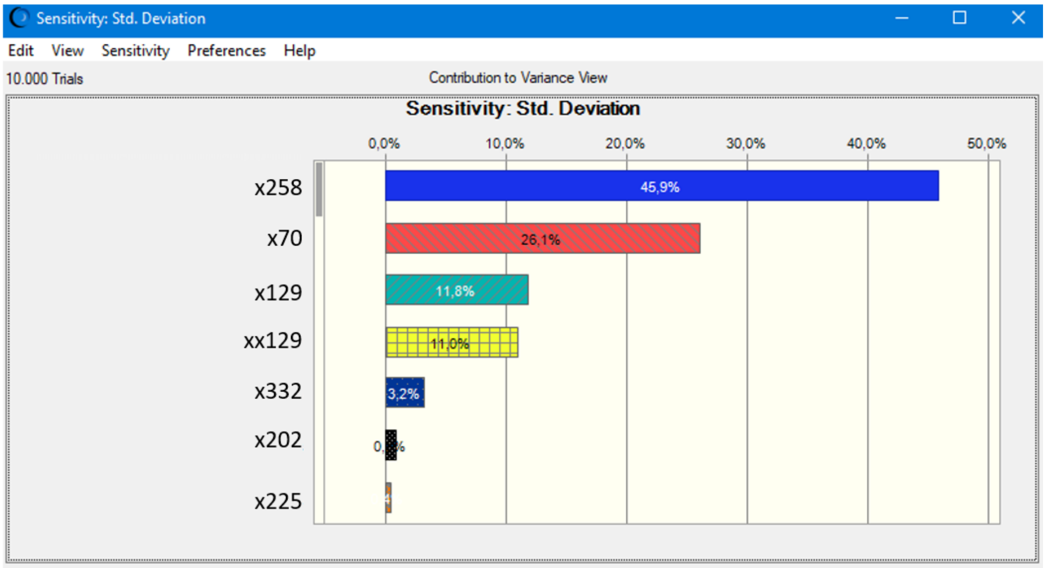

Figure 3.20: Sensitivity Analysis with Dual Sourcing for Supplier x129 and Contribution to Variance

The contribution to the variance of the standard deviation changed, and x258 and x70 replaced x129 as the top two contributors. The dual-sourcing site xx129 is in place four. The contribution to x129 variance changed from 62.8% to 11.8% for the original source and was 11% for the dual source node.

In the second iteration step, we implemented dual sourcing for x258.

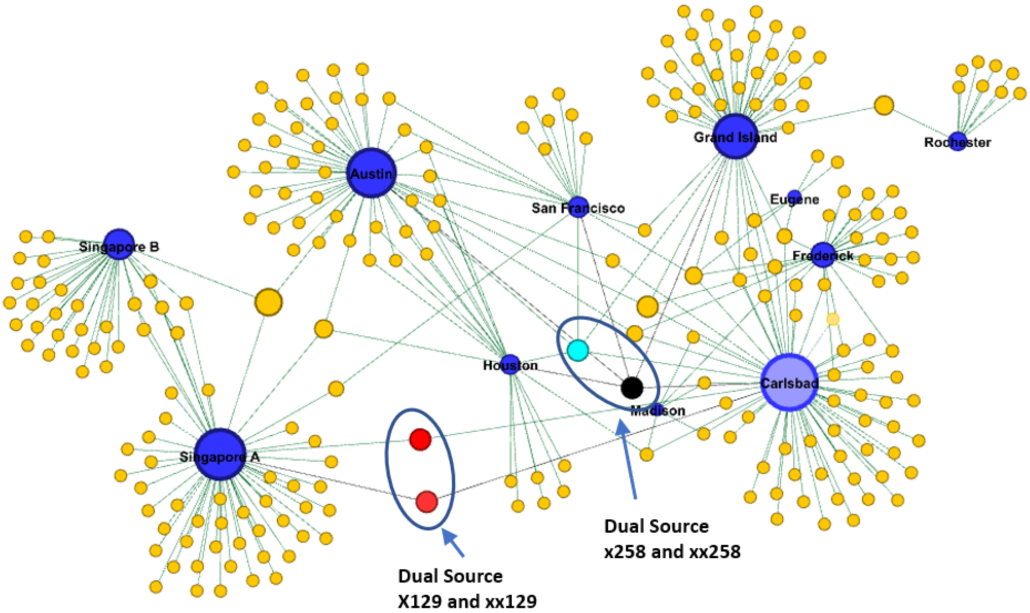

Figure 3.21: Additional Dual Sourcing for Supplier x258

The node-level values were also determined in the second iteration and then transferred to Excel and Crystal Ball. We then performed the calculations with Crystal Ball. By adding another node to the network, all betweenness centrality values have changed again, as expected.

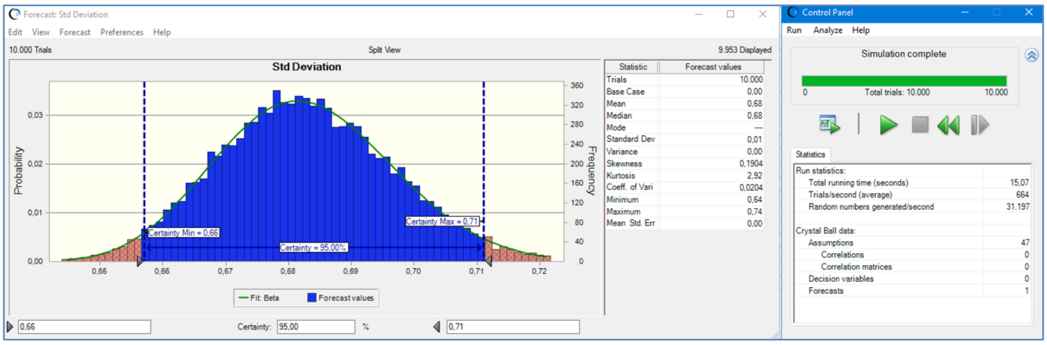

Figure 3.22: Probability Histogram with Dual Sourcing for Suppliers x129 and x258

The dual-sourcing approach positively changed the standard deviation and mean value again. The mean value dropped from 0.75 to 0.68, a reduction of 9.33%. The min and max values of the 95% certainty dropped from min0.71 – max0.78 to min0.66 (-7.04%) – max0.71 (-8.97%).

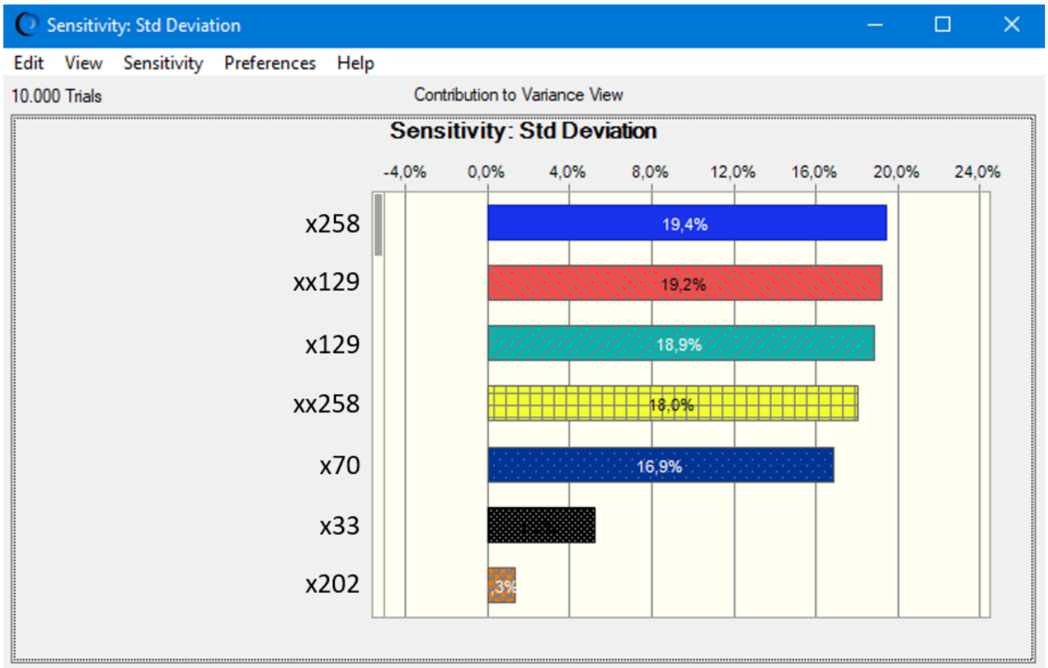

Figure 3.23: Sensitivity Analysis for Dual Sourcing for x129 and x258 Contribution to Variance

It can also be seen in this second iteration that the contribution to variance in x258 has been significantly reduced. Interestingly, the values did not drop as much as in the first iteration.

3.5.4 Chapter Summary and Results

In the previous chapters, through our analysis and simulation, we demonstrated that MCS combined with SNA metrics is a simple way to analyse a supply network for risk and quickly test possible risk mitigation scenarios. The following table summarises the calculated values:

	Base Case	**Iteration 1**	**Improvement Iteration 1**	**Iteration 2**	**Improvement Iteration 1 ->2**	**Improvement Iteration 0 -> 2**
Betweenness Centrality x129	0.16447	0.093022	43.44%	0.089309	3.99%	45.70%
Betweenness Centrality xx129		0.093022		0.089309	3.99%	
Betweenness Centrality x258	0.131612	0.125233	4.85%	0.08934	28.66%	32.12%
Betweenness Centrality xx258				0.08934		
Std. Deviation Mean	0.86	0.75	12.79%	0.68	9.33%	20.93%
Std. Deviation Minimum	0.81	0.71	12.35%	0.66	7.04%	18.52%
Std. Deviation Maximum	0.91	0.78	14.29%	0.71	8.97%	21.98%

Table 3.11: Node-Level Betweenness Centrality

Based on the values in Table 3.11, a risk reduction approach, such as dual sourcing, significantly reduces the risk. Combining the SNA metrics, we were able to prove in a calculative way the impact of dual sourcing on the betweenness centrality value of each node in the context of the entire supply network. It is also interesting to note that including another supplier reduces all betweenness centrality values of the nodes.

However, the betweenness centrality values are point-in-time values. We were particularly interested in analysing the influence of a dual source approach in relation to a risk index WRI and a risk spread. Here, too, we were able to prove by calculation that dual sourcing reduces the risk of the supply network. Furthermore, we were able to prove and show in the simulation how high the network risk would be for a company with a 95% confidence interval. We call this value the SNRS. We could show that in a future scenario with a dual source approach for x129 and x258, the SNRS is on average 20.93% lower than without a dual source approach.

3.6 Conclusion and Future Research

The adaptation and application of SNA and graph theory in supply network research has increased significantly in recent years. Creating transparency in the end-to-end supply network and identifying critical nodes has become a research focus, especially during the Covid pandemic. The representation of the network in graph form with the combination of the SNA metrics offers a powerful way to understand the complexity of the dense network and recognise the critical dependencies. The SNA allows us to evaluate critical nodes. This fact is of great importance because, based on the metrics obtained, measures can be derived to increase the resilience of a supply network. Our empirical research shows that the combination of SNA, network graph visualisation, and MCS represent a valuable systematic approach that improves decision-makers ability to identify and manage risks in a supply network and derive risk mitigation strategies. We illustrate our approach with an essential real-world example of a supply network of SARS-CoV-2 PCR test kits on the regulated market. Our study has several important implications for creating value for both supply network researchers and practitioners.

First, we would like to emphasise that supply chains have to be transferred to supply networks, and companies must develop supply network intelligence capabilities. Even before the Covid pandemic, supply networks were very complex due to growing globalisation. Therefore, the management of the supply network became increasingly important. Therefore, the identification of optimisation and savings opportunities, as well as the identification of risks in the supply network, became much more challenging. In addition, very few companies have visibility into their supply network beyond the first-tier supplier or know to develop and visualise such a network graphically. Our study shows that the graphical visualisation brings considerable added value and allows a systematic analysis of nodes, especially in the context of the interconnectedness of all nodes that create a global network view. In particular, the visualisation of the network in conjunction with the SNA metrics and, thereby, the graphical representation (size, colour, etc.) of each node leads to an essential capability of the supply network that allows the mapping of suppliers and potential risks. Based on these underlying data and the integration of a scenario simulation, in our example MCS, companies can develop and create new risk metrics such as our defined SNRS. Organisations that use our analytical approach are able to analyse the current state of the supply network risk and to quickly and easily perform a scenario comparison. Additionally, graphical visualisation and presentation of easy-to-understand metrics support the process of recognising critical nodes and linkages in the context of the entire network. At the same time, the visualised network raises decision-makers' awareness about the vulnerable network structure of their supplier network. We are convinced that our approach adds significant value to companies and should be one of the first steps in building a supply network intelligence capability in the enterprise.

Second, we use graph theory to perform the mathematical calculation of the global supply network. We improve the understanding of supply network theory and decision support tools through the graphical representation of global supply networks. Although SNA and graph theory have been used in social research to capture and analyse social relationships and social networks for half a century, supply network research has only begun to address these aspects in detail in recent years. Furthermore, companies and researchers explored alternative supply network risk management frameworks that have received great urgency and attention in the post-COVID era. Our research thus contributes to the supply network research community and to the existing pool of decision support models by presenting a novel approach to combine social network analysis, graph visualisation, and MCS that provides a holistic view and enables companies and researchers to study supply risk factors that shape supply networks in a scale-free network.

Third, suppose the intensive preliminary work is carried out, and the supply network with the different nodes is known. In that case, the approach presented will be introduced quickly and easily in the company. The calculated metrics and our presented decision support tool are essential elements in the daily operational risk mitigation work and guide decision-maker's strategic activities across a company's entire supply network. The decision-makers have to monitor the network continuously to keep it up to date to derive the appropriate actions. Therefore, many companies require a rethink, especially in supply chain and sourcing organisations. Thy myopic culture that often prevails in these areas has to be left, and an end-to-end view should be practised. New incentive strategies have to be created in these organisational units to enable a change of focus.

Finally, in times of limited resources, where the fast pace of our world, and the volatile circumstances in the post-Covid era, have to be considered, it is important to support and improve the focus process of decision-makers. With the help of our study and the visual structural analysis provided, we help decision makers maximise opportunities in their supply network while mitigating the impending risks. Our investigation is based on actual and new information collected during the Covid pandemic. We were able to support the company in a vulnerable time and helped to provide risk reduction measures.

Our study is not without limitations. The accuracy of the results in empirical studies depends on the quality of the input data. Therefore, we have taken all necessary precautions to validate the database and the structural and risk data. We acknowledge that we used only one type of risk - WRI - in our analysis, which predominantly assumes social, infrastructure, and environmental risks. We did not consider possible supplier risks (insolvency, late deliveries, quality risk, etc.). Betweenness centrality is recognised as an indicator of risk but cannot be used as a risk metric in its own right. Therefore, several risk types should be included, calculated, and visualised for further research. Our study concentrates on one possible risk mitigation measure: dual sourcing. We did not further investigate the cost-benefit ratio, here is potential for future research. Although we consider dynamic data in our study with the help of MCS, the object of the study - the supply network - is a static consideration and follows a base case and a risk-optimised case.

Future research should emphasise the evaluation of more interactive tools and focus on dynamic simulation. Due to our study, there are multiple opportunities for future research.

Chapter 4

Simulation optimisation for an inventory problem with expediting

Stable and predictable delivery times in the pre-Covid years meant that certain supply and inventory management strategies, such as just-in-time or optimised order point policies that significantly reduced inventory, gave companies a competitive advantage. After the outbreak of the Covid pandemic and the shift from predominantly deterministic to stochastic delivery times, many supply and inventory management strategies did not prove to be optimal in volatile markets. Consumer and business needs have also changed and are now more unpredictable than ever before. Therefore, companies should review and reevaluate their supply and inventory management strategies in light of stochastic demand and delivery times. We consider this market change in the following chapters by examining two specific cases. Case (1) is a model with stochastic demand and deterministic lead time with the option to expedite orders, and case (2) is a model with stochastic demand and stochastic lead time with the option to expedite orders. We seek to find four optimal inventory policies under defined service-level expectations for each of these two cases. We then conduct a sensitivity analysis and compare the first case with stochastic demand, a deterministic lead time, and the possibility to expedite orders with our second case with stochastic demand and stochastic lead time and the possibility to expedite orders under the four distinct inventory policies. The simulation results provide interesting and novel results for research and practice.

4.1 Introduction

Inventory management and optimisation are now integral to manufacturing companies and are performed by specialised departments. Inventory is a double-edged sword. On the one hand, inventory is necessary to meet customer demand, provide a high level of customer service, and generate profit for the company. On the other hand, inventory is capital tied up, and the company cannot invest in other, more lucrative areas. A balanced inventory with the lowest possible capital commitment while delivering the highest customer service is the goal of every company. Customers who cannot be served with existing inventory generate additional backorder costs, or the company loses the targeted sales profit altogether (lost sales), as the customer can purchase the goods from a competitor. Thus, an inventory manager whose task is to monitor and optimise inventory assumes an essential role in the company. Research has also shown that too high inventory stocks hurt the firm's long-term return rate (Koumanakos, 2008).

Two main factors play an essential role in inventory management. One is the level of demand for the goods in a given period, and the other is the delivery time to replenish the inventory so that enough goods are in stock for the existing demand. In addition to the main objective that goods should be in stock to satisfy immediate customer demand, inventory is also increased by a certain factor to protect the company against uncertainties in the supply chain. The two main uncertainties in the manufacturing sector are the actual delivery time of a product and the actual customer demand in a period, which can be expressed by delivery time and demand volatility. In reality, both factors fluctuate throughout the year. The company must implement appropriate measures to minimise the negative impact of volatility.

The volatility of the markets can be balanced with different methods. One main method used for this purpose in the wide-ranging field of supply chain management is inventory management. The main tasks of an inventory manager are to maintain the inventory at an optimal level to maximise on-time delivery to achieve a high level of customer service and, at the same time, to minimise inventory costs to increase company profitability through optimal inventory management (Nirmala et al., 2022). A higher level of service implies higher inventory costs, as more inventory must be maintained to deal with possible uncertainties and market volatility. Inventory costs include ordering, carrying, and stockout costs (Porteus, 2002). Stockouts, in turn, lead to backorder costs or lost sales. Lost sales cost a company up to 30% more than backorder cost models (Zipkin, 2008). Backorder in this context means that no stock is available to fulfil the customer's demand, but the customer is willing to wait for his demand to be fulfilled. As a result, the inventory theoretically has a negative value. The customer waits until the product has been replenished and the physical stock level is sufficient to meet the backordered demand. The company is credited with a theoretical backorder penalty cost corresponding to the customer's waiting time in such a case. In the event of lost sales, the inventory does not take on a negative value. The inventory value remains at zero, and the customer demand is booked directly as lost sales with the corresponding product value. In many practical applications, studies have shown that most of the original demand can be considered lost (Bijvank and Vis, 2011).

Various inventory policies, some of them complex, have been developed in the literature and are available to companies today to manage customer demand and replenish inventory. Today, companies have access to sophisticated digital systems that apply complex inventory policies in the enterprise resource planning system on a global level for all product types to improve customer service performance in the volatile market environment, thus increasing the competitiveness and profitability of their own company. In essence, the different inventory policies and systems consider the current customer demand, the free inventory available to meet the customer demand, when a replenishment order should be placed based on the assumed delivery time, and the orders already placed in previous periods. Inventory policies are based on mathematical formulas and models to determine, for example, the optimal order timing, the optimal replenishment volume or the optimal safety stock. Optimal inventory policies maximise a company's overall profitability by minimising inventory costs and maximising customer service.

Many of these models assume a comparatively regular demand based on historical data or a sales and operations plan for the coming periods. Replenishment lead times for the products sold were also very stable and often contractually fixed with the supplier. Many companies, especially automotive groups, introduced a just-in-time concept in which on-site inventory was kept to a minimum and the required material was provided just before it was needed. Many companies have grown and succeeded through these theories and concepts over the past several decades. With the onset of the first Covid-19 cases in late 2019 and the global pandemic in early 2020, comparatively stable global supply chains have collapsed in weeks. On the one hand, the demand for certain products has decreased significantly, while on the other hand, the demand for products (e.g., mouth masks) has increased sharply. Delivery times for certain articles have become unpredictable from one day to the next. Such demand and lead time variability present companies with major challenges in meeting customer expectations and operating profitably, even outside of a pandemic situation.

As we enter 2023, although the relevant pandemic and Covid-19 measures have expired in most countries and supply chains are easing, many inventory managers are still dealing with a very volatile market situation. Short-term replenishment decisions must be made with the hope that customer demand will increase and inventory levels will not become too high due to capital restrictions. Markets that suffered from demand during the pandemic phase must be revived. The "new normal" must arrive globally in the markets and in global supply chains.

We evaluated the expediting and reorder policies for a single-stage inventory system with stochastic demand and lead times based on a preliminary investigation.

Our study examines two cases: (1) stochastic demand and deterministic lead time model with expediting, (2) stochastic demand and stochastic lead time model with expediting. We conducted a simulation optimisation study to identify four optimal inventory policies for these two specific cases.

We explicitly opted for a simulation of the inventory control problem rather than traditional approaches to modelling inventory control problems such as stochastic dynamic programming. In our model, the reasons for using simulation over traditional approaches are as follows. Inventory systems can be highly complex, with numerous variables, such as demand variability, lead times, and order quantities. Simulation provides a realistic and dynamic representation of these complexities, allowing for a more accurate assessment of system behaviour under various conditions (Thierry et al., 2008). Incorporating random variables and stochastic processes can simulate dynamic scenarios, helping identify potential stock outs and backorder situations and assess the impact of variability on inventory levels and costs. A simulation model allows for testing different inventory control policies and strategies without disrupting operations. This helps optimise inventory management by assessing the performance of various policies under different conditions, facilitating the identification of the most cost-effective and efficient approach. Simulation provides a platform to replicate the day-to-day operations of an inventory system in a digital supply chain twin, considering factors such as order processing, lead times, and stock outs. This realistic modelling helps understand how parameter and policy changes affect overall system performance (Ivanov et al., 2019). Inventory managers often need to evaluate the impact of various scenarios on inventory levels and costs. Simulation allows for creating multiple scenarios, such as sudden changes in demand, supplier delays, or changes in order policies, helping managers make informed decisions and develop robust strategies. Implementing changes in a real-world inventory system can be costly and time-consuming. Simulation provides a cost-effective way to experiment with different strategies, helping organisations avoid unnecessary expenses associated with trial-and-error approaches in a live environment. A traditional approach, like dynamic programming, on the other hand, is based on a solid theoretical foundation and uses mathematical models to find optimal decision rules. This allows for clearly structuring and formulating the problem using probability distributions, allowing for accurate and formal solutions (Rust, 2019). Based on the advantages of the simulation approach over, e.g. dynamic programming, the simplicity of creating simulations in such programs today, and the suitability of the approach to our model, we decided to use simulation optimisation in favour of classical approaches to modelling inventory control problems.

Our research contribution is an intensive simulation optimisation with a focus on expediting and reorder policies for a single-stage inventory system with stochastic demand and lead times. A subsequent summary and analysis of the two different cases are provided in the related essay. In addition, we argue that the results should not only be treated in theory but offer practical insights for inventory managers, as the last three pandemic years have shown us.

There are nine sections in the essay. In the second section, we conduct a literature review, focussing on publications in expediting and reordering policies for an inventory system with stochastic demand and lead times. In sections 3 to 6, we conduct a simulation and optimisation study to find optimal policies for both cases. Next, we perform a sensitivity analysis based on our observations. Section eight interprets the results from a theoretical and practical perspective and discusses the results and limitations of our study. The final section details the main conclusions and suggestions for future research.

4.2 Literature Review

During the last 70 decades, numerous papers discussed optimal policies for different kinds of inventory and demand problems. The first publications focused mainly on inventory optimisation in a single installation with some demand pattern. The authors incorporated purchase, holding, and shortage costs into the mathematical equation. The named cost functions are considered linear homogeneous functions. The objective was to minimise the discounted value of all costs charged during purchasing decisions. Optimality has been achieved by calculating and determining optimal purchasing quantities with a stable lead time (Arrow et al., 1958). To achieve the optimality, not-real-world assumptions have been incorporated into the equation, e.g., supply was considered infinite for a static single-item, single-echelon with a fixed lead time model. Later, more sophisticated methods were developed to incorporate stochastic lead times with different stochastic demand patterns. The following chapters review the primary literature streams for the two simulation models under investigation.

4.2.1 Stochastic demand and deterministic lead time with expediting

Barankin (1961) and Neuts (1964) structure their model around an independent and identically distributed periodic demand with a fixed lead time of one period and the possibility of an emergency order with immediate delivery within the same period. They include shortage costs, backordering costs, holding costs, and additional costs for emergency orders in the analysis. The emergency order size is fixed for all periods and cannot be adjusted during processing. Normal orders will be placed at the supplier for each period with a pre-calculated optimised order size. Suppose the regularly placed order is insufficient to cover the demand and the inventory level drops below a prescribed emergency stocking level. In that case, the inventory manager can make an additional emergency order in this period. Barankin´s and Neuts´s model shows an optimal ordering policy for emergency stocking levels in certain cases. Fukuda (1964) extends the model analysed by Barankin (1961) and Neuts (1964) to a third supply mode. He proves optimality when an inventory manager can have an emergency order with instantaneous delivery in the same period and normal delivery in the next period, as analysed by

Barankin (1961). Fukuda implemented a third mode with delivery in two periods from now with lower costs than the previous two modes of delivery and showed an optimal ordering policy. Veinott (1966) reviewed the dual supply modes (expediting and normal lead time) as well as the multi-echelon problem formulated by Clark and Scarf (1960) and incorporated both models into an inventory optimisation problem and could provide a simplified proof of the Clark-Scarf model.

Compared to the literature mentioned above and its extensive mathematical and detailed analysis of specific cases, researchers Moinzadeh and Nahmias (1988) took a more general approach. The authors study a simple *(Q, r)* policy and extend the policy to a *(Q1, Q2, r1, r2)*. When the inventory level hits *r1* a standard purchase order will be placed for volume *Q1*. If the inventory level drops below *r2* before the standard purchase order arrives, an expediting order for volume *Q2* is placed. The authors show significant savings by simulating their approach without mathematical proof. Moinzadeh and Schmidt (1991) analysed *(s-1, S)* inventory systems with expediting. If the inventory hits $\hat{S}$ - which means that the inventory level is critical to achieving a specific service level - an expediting order will be placed. The authors calculate orders placed solely with regular orders, expediting orders, and a dual-supply mode. The simulation shows that the lowest overall cost is achieved by using a dual supply mode.

Lawson and Porteus (2000) extend the classic serial multi-echelon model by Clark and Scarf (1960) into a dual-supply mode model where expediting is allowed at each echelon in a finite and infinite planning horizon. The inventory manager can make dynamic lead time management decisions at each echelon per period. The decisions include an expediting possibility to the next echelon with instantaneous delivery, a regular flow with a one-week lead time, and detain units at the same echelon. The model implies that any inventory available at an echelon can be moved to the most downstream echelon instantaneously within the same period. The goal is to minimise the present value of the expediting costs, regular order costs, detained costs, inventory holding costs, and shortage costs. The authors show that a top-down base-stock policy is optimal when the upstream echelons' inventory manager ignores the downstream managers' decisions. Muharremoglu and Tsitsiklis (2003) follow a similar approach to the model studied by Lawson and Porteus (2000). However, in their model, the expedited orders do not have to pass each echelon until they reach the exogenous modulated Markov demand. They can be instantly transferred to any downstream echelon. The authors show that an extended echelon base stock policy for expediting decisions and standard echelon base stock policies for regular lead-time decisions can be applied.

Huggins and Olsen (2010) prohibit backordering and analysing a model in which the inventory manager makes periodic decisions to expedite orders to meet stochastic demand in the next period. The optimal expediting policy for the analysed model was a regular production policy of the form *(s, S)*. Sethi et al. (2003) incorporate a demand forecast into the periodic review inventory model with the possibility of expediting and fixed ordering costs. The authors show that the forecast updates impact the optimal ordering policy more than the inventory position in a specific period, and the forecast updates impact the *(s, S)* type optimal ordering policy positively. Feng et al. (2005) extend the model analysed by Sethi et al. (2003) with a third supply mode (fast, medium, and slow) and show that there is an optimal base-stock policy for fast and medium delivery with the mentioned high impact of forecast updates. No general optimal base-stock policy could be applied to the slow-delivery mode. However, the movement of units through the different models analysed is deterministic.

4.2.2 Stochastic demand and lead time with expediting

Compared to the three literature streams mentioned above and their large number of publications, the number of publications in the special case with stochastic demand and lead times with expediting is relatively small. The reason for this is, similar to the case with order crossing, the complexity of the models and the traceability of the state of the variables in a steady-state or dynamic simulation.

Moreover, differentiation from the previous models is also difficult since an earlier delivery can be considered an expedited order in the expediting case with deterministic lead times.

Mohebbi and Posner (1999) developed an exact lost-sales model with non-unit-sized demands where orders of sizes *Q1* and *Q2* are placed at reorder levels *s1* and *s2 (s1, Q1, s2, Q2)*, while previous research has been limited to *(s, Q)* or *(s, S)* policies where standard and expedited orders have been placed at reorder levels *s* and *zero*. They designed a continuous-review inventory system with compound Poisson demand and nonidentical exponentially distributed lead times. They were able to formulate two cost minimisation models with and without a service level constraint. However, due to the complexity of the cost functions, a four-dimensional numerical search appeared unpractical. In a complexity-reduced two-dimensional case of *s 2=0* and *Q2=s 1*, they were able to show that, in comparison to an *(s,Q)* model without expediting, expediting can be economical in circumstances involving high shortage cost or high service levels.

Korevaar et al. (2007) defined and derived a system for automobile spare parts companies with stochastic demand and lead times with expediting. The team aimed to bring the service level of over 100,000 SKU spare parts in the system under consideration to over 95% while minimising total logistic costs. Instead of expediting, the researchers used the terms rush and regular orders. The rush order is triggered when the on-hand inventory crosses a threshold. A rush order will be triggered when the probability is high enough to satisfy the demand is positively affected. This implies that the rush order must have a shorter lead time than the normal order. In their paper, the researchers do not provide any mathematical proof of their calculation but refer to heuristics and approximation of target values with the help of a simulation programme. In the practical example, it could be shown that the project objectives were achieved.

Schimpel (2010) dissertation is one of the most profound and far-reaching work on stochastic demand and lead times with expediting. His model is based on the work of Mohebbi and Posner (1999), with the *(s1, Q1, s2, Q2)* policy. Mohebbi and Posner (1999) used a Poisson demand and exponential lead times in their model. Schimpel (2010) extends the model of Mohebbi and Posner (1999) to include arbitrarily stochastic demand and stochastic lead times. In his dissertation Schimpel (2010) defined a model with one-order and two-order cycles. The one-order cycle is referred to as a more standard reorder-point scenario. If the reorder point *(R1)* is met, a replenishment order *(Q1)* is triggered. In this scenario, it is assumed that (1) demand does not reach the expediting reorder point *(R2)* and (2) if *(R2)* is reached, the replenishment order window is too small to trigger a replenishment order. In the two-order scenario, he formulates three different main scenarios. In the first scenario, the first order triggered by *(R1)* arrives first with order quantity *(Q1)*. Then *(R2)* triggers *(Q2)*, which arrives after the first order. In the second scenario, the second order *(Q2)* triggered by *(R2)* arrives earlier than the first order *(Q1)* triggered by *(R1)*. In the third scenario, both orders *(Q1, Q2)* arrive simultaneously while the trigger point *(R1)* and *(R2)* follow one after the other. However, Schimpel (2010) states that in a case where the lead times of both orders are continuous variables, the probability of such a case is zero. The author formulated exact formulas for the mentioned cases and applied his model to a warehouse based on a real-world case. He could show that an expediting option in a case where demand and all lead times are stochastic is beneficial.

4.3 Case description and Policy definition

This chapter presents the two cases to be investigated and the four different inventory policies with their respective characteristics before moving on to the actual optimisation simulation and analysis of the results.

4.3.1 Case 1: Stochastic Demand and Deterministic Lead Time with Expediting

The first case is a discrete-time series model in which the customer's arrival is constant with a known demand distribution that is independent and identically distributed. We chose a Poisson distribution because it assumes that events occur independently, which is essential for our analysis. The Poisson distribution is well suited for modelling count-based data, where the aim is to predict the number of events that will occur within a fixed interval. It is also widely implemented in statistical software and company ERP applications. We, therefore, consider the following Poisson distribution function to be very suitable for our study:

$$P(X = k) = \frac{e^{-\lambda}\lambda^k}{k!}$$

Where:

- X is a random variable following a Poisson distribution.
- k is the number of events which can take any non-negative integer value.
- $P(X = k)$ represents the probability of observing exactly k events.
- e is the base of the natural logarithm, approximately equal to 2.71828.
- λ is the rate parameter of the distribution, representing the average number of events that occur in the given interval.
- ! is the factorial function.

The lead time for regular orders is treated as a deterministic non-negative integer value with a fixed time lag between order placement and receipt of the goods. The lead time for expediting orders is zero, where the order placement and receipt are instantaneous, and the inventory is updated instantly.

4.3.2 Case 2: Stochastic Demand and Lead Time with Expediting

For our second case, we also use a discrete-time series model with a Poisson distribution function with a known demand distribution that is independent and identically distributed. Only the delivery time of the ordered replenishment material differs from the first case.

We have decided to use a triangular distribution for the lead time with non-negative integer values. The triangular distribution is a continuous probability distribution with a probability density function. We chose this distribution because it is easy to program and implement in the simulation software. Furthermore, the distribution function reflects reality since the delivery times of most products are not completely random. Rather, a high percentage of the originally promised delivery time is met. This results in deviations up or down, which shortens or lengthens the delivery time. The probability density function of the Triangular Distribution is:

$$f(x;a,b,c) = \begin{cases} \frac{2(x-a)}{(b-a)(c-a)}, & \text{if } a \leq x < c \\ \frac{2}{b-a}, & \text{if } x = c \\ \frac{2(b-x)}{(b-a)(b-c)}, & \text{if } c < x \leq b \\ 0, & \text{otherwise} \end{cases}$$

For expediting orders, the lead time is as in the first case zero, where the order placement and receipt are instantaneous, and the inventory is updated instantly.

4.3.3 Description and explanation of the four Inventory Policies

There are a number of commonalities between the inventory policies presented here, and these will be the subject of discussion first. There are three inventory-related parameters that are essential to our study and represent the core values of the four optimal inventory policies.

- Inventory Position (IP)
- Base Stock Level (BSL)
- Expediting Base Stock Level (E-BSL)

The IP is the respective inventory value of the material in the system on a given date. This value is not only necessary to calculate the different costs in the optimisation simulation, but this value is essential to trigger the material replenishment purchasing orders. The BSL value determines at which IP value a regular order is triggered. The E-BSL value, on the other hand, determines at which IP value an expediting order is triggered. The simulation process follows a fixed sequence:

1. Customer demand is generated at the beginning of a new period.
2. The system checks whether IP is higher or lower than BSL.
3. If the IP is higher than the BSL the demand is deduced from IP. The system calculates the holding costs at the end of the period. A new period starts.
3. Customer demand is generated at the beginning of a new period. If the IP is lower than the BSL but higher than the E-BSL a regular order is triggered according to the inventory policy. The ordering costs are calculated for the regularly placed order. The order is staged in the delay module according to the lead time. Then the customer demand is deducted from the IP and the holding costs are calculated. A staged regular order from a previous period may arrive and is added to the IP at the end of that period. A new period starts.
4. Customer demand is generated at the beginning of a new period. If the IP is lower than the BSL and lower than the E-BSL a expediting order and/or regular order is triggered according to the inventory policy. The expediting ordering costs are calculated. Potential regular order costs are calculated, and the regular order is staged in the delay module according to the lead time. The expediting order arrives instantly during the period and is added to the IP. Then the customer demand is deducted from the IP and the holding costs

and the potential backlog costs are calculated. A staged regular order from a previous period may arrive and is added to the IP at the end of that period.

In the following figures and the corresponding decision-making strands, we explain the differences between the four inventory policies. For this, we use the following notation and description:

- R_1: Reorder point for regular orders at the BSL value.
- R_2: Reorder Point for expediting orders at the E-BSL value.
- $Q_{BSL1}, Q_{BSL2}, ..., Q_{BSLn}$: reorder quantity regular orders.
- $Q_{EBSL1}, Q_{EBSL2}, ..., Q_{EBSLn}$: reorder quantity expediting orders.
- $t_0, t_1, t_2, ..., t_n$: regular spaced time intervals.
- t_c: duration between time intervals.
- lt_c: lead time for regular placed orders.

Figure 4.1 illustrates the decision-making process and the corresponding action to be taken at the beginning of each period for ***Policy 1***.

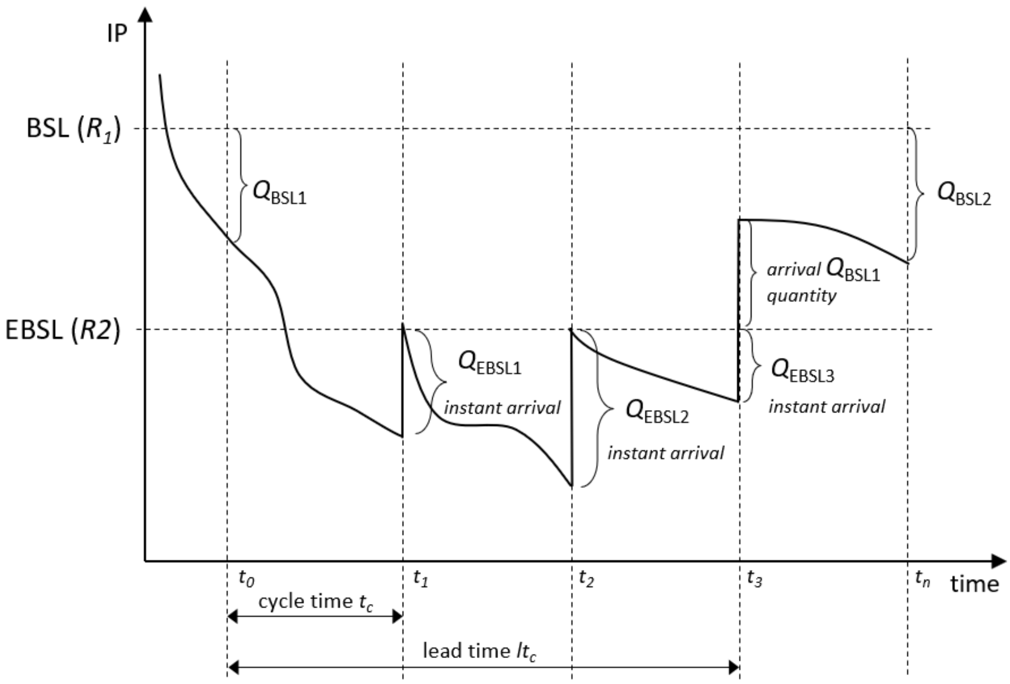

Figure 4.1: Policy 1: The exemplified cycle of the replenishment policy.

There are three decision-making strands for policy 1:

(1) If the IP is above the BSL at the beginning of the period, no action will be taken in this period.

(2) If the IP is below the BSL but above the E-BSL at the beginning of the period, a regular order is triggered. The volume of the regular order depends on the difference between the IP at the beginning of the period and the BSL.

(3) If the IP is below the E-BSL at the beginning of the period, an expediting order is triggered, which is delivered instantaneously in the same period. The volume of the expediting order depends on the difference between the IP at the beginning of the period and the E-BSL.

Figure 4.2 illustrates the decision-making process and the corresponding action to be taken at the beginning of each period for ***Policy 2***.

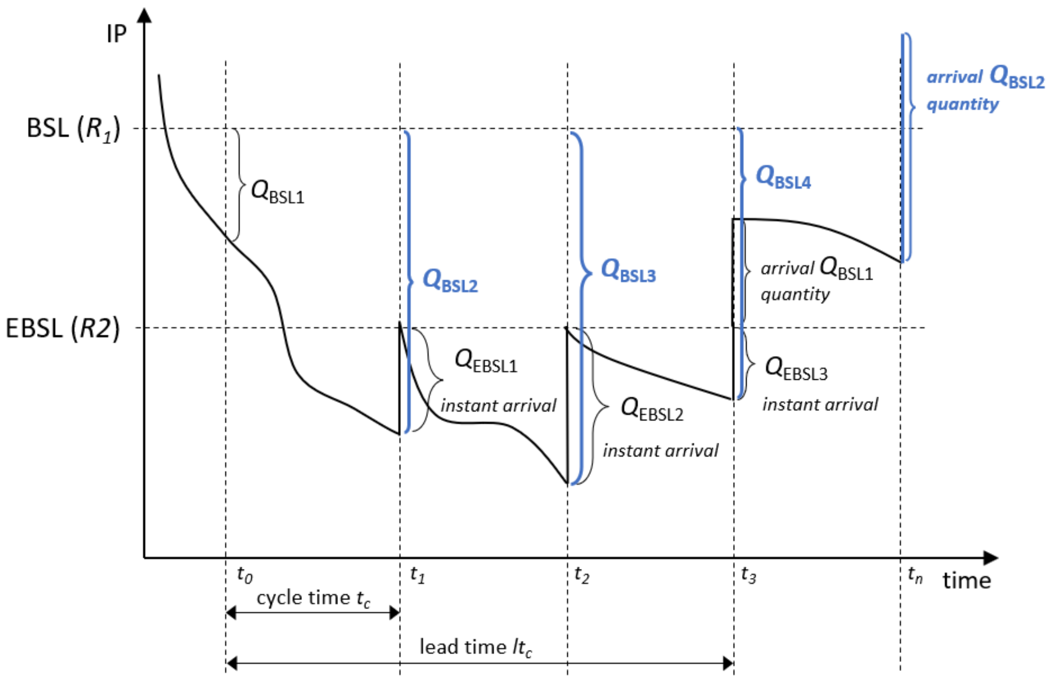

Figure 4.2: Policy 2: The exemplified cycle of the replenishment policy.

There are four decision-making strands for policy 2:

(1) If the IP is above the BSL at the beginning of the period, no action will be taken in this period.

(2) If the IP is below the BSL but above the E-BSL at the beginning of the period, a regular order is triggered. The volume of the regular order depends on the difference between the IP at the beginning of the period and the BSL.
(3) If the IP is below the E-BSL at the beginning of the period, an expediting order is triggered, which is delivered instantaneously in the same period. The volume of the expediting order depends on the difference between the IP at the beginning of that period and the E-BSL.
(4) If the IP is below the E-BSL, a regular order is placed in addition to the already placed expediting order. The quantity of the regular placed order is the difference between the IP at the end of the period and the BSL.

Figure 4.3 illustrates the decision-making process and the corresponding action to be taken at the beginning of each period for ***Policy 3***.

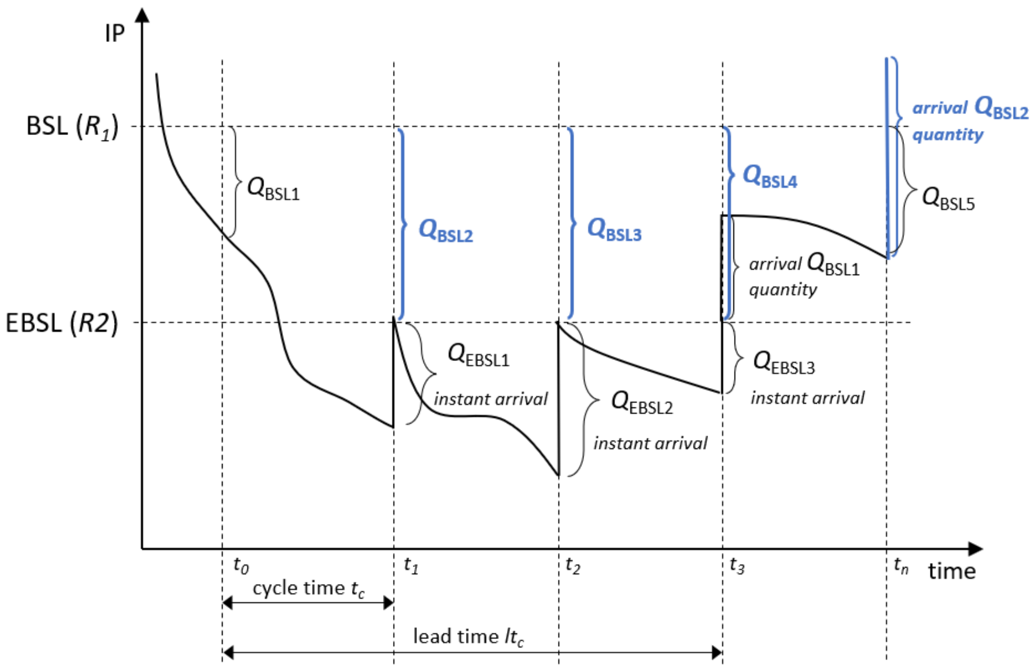

Figure 4.3: Policy 3: The exemplified cycle of the replenishment policy.

There are four decision-making strands for policy 3:

(1) If the IP is above the BSL at the beginning of the period, no action will be taken in this period.

(2) If the IP is below the BSL but above the E-BSL at the beginning of the period, a regular order is triggered. The volume of the regular order depends on the difference between the IP at the beginning of the period and the BSL.
(3) If the IP is below the E-BSL at the beginning of the period, an expediting order is triggered, which is delivered instantaneously in the same period. The volume of the expediting order depends on the difference between the IP at the beginning of that period and the E-BSL.
(4) If the IP falls below the E-BSL, a regular order is placed in addition to the already placed expediting order. The quantity of the regular placed order is the difference between the BSL and the E-BSL.

Figure 4.4 finally illustrates ***Policy 4***, the decision-making process, and the corresponding action to be taken at the beginning of each period.

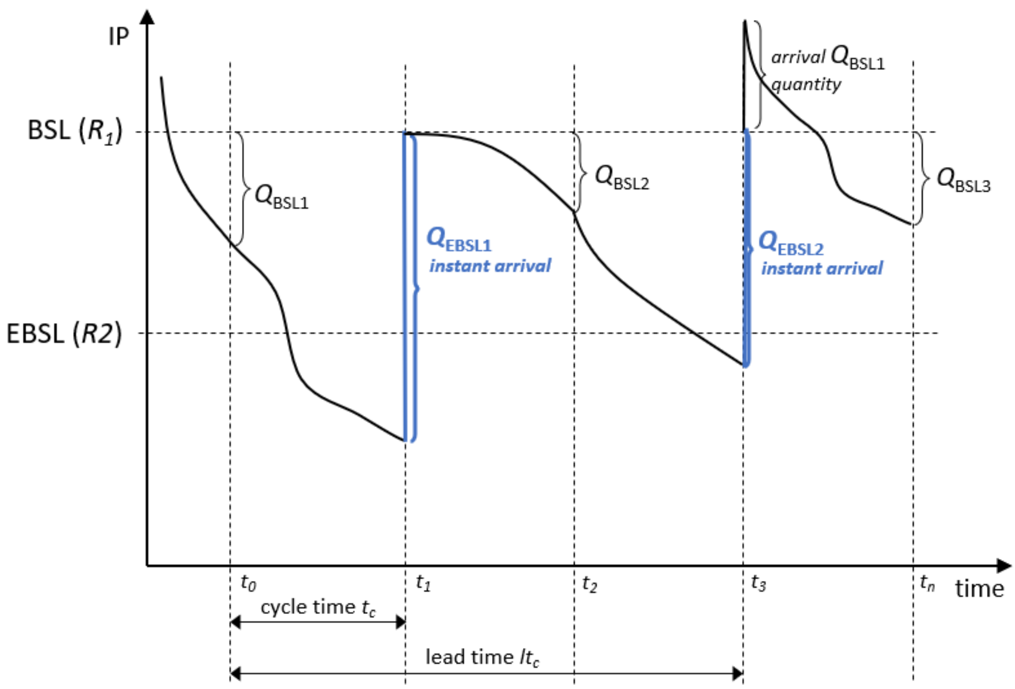

Figure 4.4: Policy 4: The exemplified cycle of the replenishment policy.

For policy four there are three decision-making strands:

(1) If the IP is above the BSL at the beginning of the period, no action will

be taken in this period.

(2) If the IP is below the BSL but above the E-BSL at the beginning of the period, a regular order is triggered. The volume of the regular order depends on the difference between the IP at the beginning of the period and the BSL.

(3) If the IP falls below the E-BSL, an expediting order is triggered, which is delivered instantaneously in the same period. The volume of the expediting order depends on the difference between the IP at the beginning of that period and the BSL.

In the following, we summarise the four different inventory policies in a simplified notation:

Policy 1:

- (1) If IP > BSL we do not order.
- (2) If E-BSL < IP < BSL we place regular orders for the amount BSL - IP.
- (3) If IP < E-BSL we place expediting orders for the amount E-BSL - IP.

Policy 2:

- (1) If IP > BSL we do not order.
- (2) If E-BSL < IP < BSL we place regular orders for the amount BSL - IP.
- (3) If IP < E-BSL we place expediting orders for the amount E-BSL - IP.
- (4) If IP < E-BSL we place regular orders for the amount BSL - IP.

Policy 3:

- (1) If IP > BSL we do not order.
- (2) If E-BSL < IP < BSL we place regular orders for the amount BSL - IP.
- (3) If IP < E-BSL we place expediting orders for the amount E-BSL - IP.
- (4) If IP < E-BSL we place regular orders for the amount BSL - E-BSL.

Policy 4:

- (1) If IP > BSL we do not order.
- (2) If E-BSL < IP < BSL we place regular orders for the amount BSL - IP.
- (3) If IP < E-BSL we place expediting orders for the amount BSL - IP.

It is worth noting that each of these four inventory policies is applied to case one with deterministic lead time and case two with stochastic lead time, respectively.

4.4 Case 1: Optimal Inventory Policies for Stochastic Demand and Deterministic Lead Time with Expediting

This chapter looks at the four inventory policies for stochastic demand, a deterministic lead time, and the possibility of expediting orders. The simulation model we use is based on the research of Kostic (2019) and was created in the Rockwell Arena Simulation simulation software. We will take Kostic's simulation model, adapt the model to specific parameters, and use it for our own optimisation and identification of optimal inventory policies. The following chapters describe the simulation model and examine the individual building blocks and variables. We then detail our simulation design, optimisation, and results.

4.4.1 Model Description and Simulation Design

The presented stochastic demand and deterministic lead time model with expediting is originally based on the research and studies of Lawson and Porteus (2000). The researchers extended the classical multistage inventory by Clark and Scarf (1960) with the possibility to expedite orders. Lawson and Porteus (2000) assume for their model that the expediting delivery time is zero and occurs instantaneously.

Normal orders are delivered within a fixed review period of one week. Our model is a simplified simulation model with a single-stage inventory system. We have adjusted the model only to the point that we also allow delivery times that correspond to greater than one period. In our model, the customer is willing to wait for his delivery if insufficient stock is available and the system allows for a negative inventory value.

A supply chain manager must make a sequence of inventory replenishment decisions at the beginning of a number of regularly spaced intervals. Purchasing, holding, and shortage costs are charged during inventory replenishment decisions. The objective is to minimise the value of all costs charged during replenishment decisions and to determine the optimal inventory policy for each of the four distinct inventory policies. Next, we discuss the attributes and variables of the model.

Our model has a finite replication length of 1000 system days to ensure a steady-state condition. A customer demand with a Poisson (10) distribution is generated every regular interval, each system day. The simulation is set up in such a way that a customer is willing to wait for his delivery and, therefore, the system allows a negative inventory value to calculate the backlog costs.

We use the following cost elements for our analysis and optimisation:

- Holding costs: 1 unit
- Regular order costs: 3 units
- Expediting order costs: 5 units
- Backlog costs (penalty) for unserved customer orders: 5 units

These costs are added up for each period. The cost structure is realistic in our view, especially since the expediting costs in our example are set 66.67% higher than the regular ordering costs, reflecting the additional acceleration effort in the delivery company and our fictitious company. We calculate the backlog costs at the same level as the expediting costs, as we explicitly want to show the trade-off between regular ordering costs, expediting ordering costs, and backlog costs. Unit holding costs are set at 1, which is comparatively high, as companies usually calculate a theoretical interest rate of 10% of the inventory value. In our analysis, we explicitly want to show that in a time with high volatility, cash flow is very important, and tight-up capital in inventory should be minimised.

Since we used deterministic variables, stochastic data, and probability functions for our investigation, we have to consider a high confidence interval. For our model, we assume a confidence interval of 95%. With an increase in the number of replications per simulation, we can obtain a high confidence interval precision. We aim to achieve an interval precision of $\leq 1\%$. Since in our first study, the demand follows a Poisson independent and identically distributed function, we check that we have a high interval precision for the total costs. To do this, we first simulated 10 replications. Already after 10 replications, we reached high robustness in relation to the half-width to the average. The confidence interval precision was at 2.27% for the total cost variable. Since we know all the necessary values, we use the following formula to calculate the required number of replications to meet our confidence interval precision requirement of $\leq 1\%$.

$$n = t^2_{(n-1,1-\frac{\alpha}{2})} \frac{S^2}{h^2}$$

We need to solve the equation for n (number of replications). The equation cannot be solved because t (t values for confidence intervals) and s (sample standard deviation) depend directly on n. Instead, we use the following formula for an approximation.

$$n = n_0 \frac{h_0^2}{h^2}$$

For n_0 we have our 10 replications, and for h_0^2 the half-width of the 10 replications is 1,313.77, resulting in a confidence interval precision at 2.27%. For h^2 we want our half-width value to be $\leq 1\%$, resulting in an expected half-width value of 577.61. The result is 51.73 replications needed, rounded up to 52 replications for our model.

Before determining optimal inventory policies using simulation, we check when a steady-state condition is reached and if a warm-up period is required. For this purpose, we plot the inventory development over the entire simulation span in a graph. Figure 4.5 shows that the system fluctuates too much in the front section and is unstable. This transient phase lasts about 20 system days. We set the warm-up period to 50 system days for further simulation and optimisation. Next, we start optimisation and search for the optimal inventory policy based on the system parameters presented.

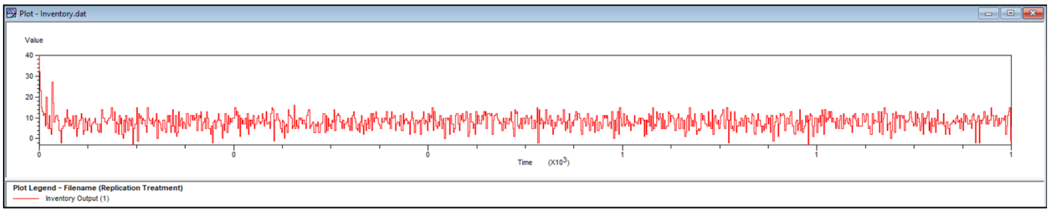

Figure 4.5: Inventory Time Plot Output Analyzer

We aim to minimise total costs under the system conditions mentioned. We consider three optimisation models. First, we will look at the standard model where the customer accepts waiting times and backlog costs are generated as a result. In the second model, we set the service level to 95%, and at least 95% of the customers should be served on time. Since this value represents a single number, but we optimise our simulation under a stochastic condition, it would hardly be possible for the simulation optimisation to reach exactly this value. We have set the system conditions in such a way that the simulation optimises against the 95% service level to the closest value of $\geq$ 95%. We want to compare the cost difference between 95%, the 100% service level, and the customer's acceptance of a delivery delay.

For optimisation, we use the OptQuest module of Arena. The module has a built-in optimisation routine, so not all possible permutations must be carried out. Once the first optimal point is found, further optimisation is performed around this point. This ensures that the optimisation cycle time is significantly reduced. For optimisation to be performed correctly, we must specify the constraints, controls, and responses in OptQuest. In the following, we graphically illustrate the optimisation as it is carried out in OptQuest.

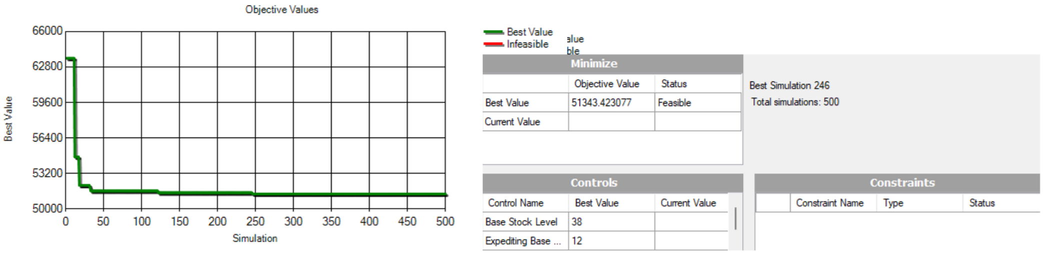

Figure 4.6: Example of Arena OptQuest optimisation run without constraints

Figure 4.6 shows on the left-hand side how OptQuest systematically optimises the cost minimisation target, taking into account the cost functions and the BSL and E-BSL values. The right-hand side shows at which iteration and under which BSL and E-BSL value a cost minimum was reached.

4.4.2 Results Case 1: Optimal Inventory Policies for Stochastic Demand and Deterministic Lead Time with Expediting

The results for Case 1 and each of the four policies and the 3 different models, (1) without service level constraint, (2) with 95% service level constraint (3) and 100% service level constraint are summarised in Table 4.1 below.

Type	**Policy 1**			**Policy 2**		
Model	(1)	(2)	(3)	(1)	(2)	(3)
Base Stock Level	38	36	52	12	9	27
Expediting Base Stock Level	12	11	25	12	13	29
Total Regular Order Costs	18,053.37	13,988.31	20,335.62	16,904.02	11,639.88	14,704.21
Total Expediting Order Costs	19,972.88	26,641.83	16,229.13	21,857.69	30,563.27	25,581.44
Total Backlog Costs	1,307.69	2,562.88	0.00	1,745.00	2,322.60	0.00
Total Holding Costs	12,009.54	8,354.63	27,029.17	6,116.33	3,362.29	19,976.58
Total Costs	51,343.42	51,547.65	63,593.92	45,623.04	47,888.04	60,262.23
Service Level	97.45%	*95.03%	100%	96.18%	*95.15%	100%

Type	**Policy 3**			**Policy 4**		
Model	(1)	(2)	(3)	(1)	(2)	(3)
Base Stock Level	21	21	38	21	23	36
Expediting Base Stock Level	12	12	29	6	6	22
Total Regular Order Costs	23,115.17	23,115.17	23,155.15	15,182.13	16,879.56	14,216.31
Total Expediting Order Costs	11,559.04	11,559.04	11,577.40	24,708.85	22,001.84	26,381.63
Total Backlog Costs	1,911.25	1,911.25	0.00	3,023.65	2,493.37	0.00
Total Holding Costs	3,756.54	3,756.54	20,082.27	7,131.33	8,830.10	21,711.83
Total Costs	40,342.00	40,342.00	55,082.27	50,045.96	50,204.85	62,309.77
Service Level	95.26%	*95.26%	100%	93.96%	*95.04%	100%

Table 4.1: Results Case 1: 4 optimal inventory policies for an inventory system with stochastic demand and deterministic lead time with expediting

The results show that a service level requirement has a significant effect on a company's cost structure. Therefore, when planning the costs and design of the necessary storage and warehouse space, one must look very carefully at which service level a product portfolio can and should be offered.

4.4.3 Chapter Summary and Results

The results of our simulation optimisation clearly show that each inventory policy is different and leads to significantly different total costs. Each policy has been defined differently and accordingly yields different BSL and E-BSL values although the demand and lead time distribution and cost assumptions are the same. The different values of BSL and E-BSL are of correspondingly high significance for companies, as these values also require a different underlying supply chain management strategy and inventory policy, as we will see below.

It is interesting to note that for policies 1 and 2 the system optimises itself without a predefined service level above the 95% service level model and is not only optimal in terms of total cost but also has lower backlog costs, leading to a higher overall service level. However, the holding costs are correspondingly higher. This implies the need for a higher inventory level and storage space; this also ensures that customer demand can be met and the backlog is correspondingly lower. Interestingly, in policy 3 we see the condition that the cost optimum is at a service level of about 95% for the model without a predefined service level. Therefore, the values for the two models in our study are identical. For all other policies, the service level in the model without a predefined service level deviates significantly more from the value of 95%. For policy 4, we can summarise that in the model without a service level requirement, the service level is only 93.96%, which is below all other service levels for this model. Furthermore, costs are higher than in policies 2 and 3 and only marginally lower by 2.53% than in policy 1. In addition, the total costs for the 95% and the model of 100% service level are higher than in policies 2 and 3 and also only marginally lower than in policy 1 by 2.60% for the 95% and 2.02% for the 100% service level.

Policy 2 has a lower total cost compared to policy 1 by 11.14% for the model without a predefined service level, by 7.10% for the model of 95% service level, and by 5.24% for the model of 100%. In comparison to policy 4, the percentage cost reduction values are as follows 8.84%, 4.61% and 3.29% for the corresponding service level models. The results of policy 3 are even better. Compared to policy 1, which corresponds to a cost reduction of 21.43%, 21.74% and 13.38%, compared to policy 2 by 11.58%, 15.76% and 8.60%, compared to policy 4 19.39%, 19.65% and 11.60% for the respective models without a predefined service level, for the 95% and 100% service level. We also see that the achievement of a 100% service level has a significant influence on inventory holding costs, as expected.

One notable finding in the results is worth mentioning. In policy 2, the E-BSL value is equal to or greater than the BSL value. In the model of no predefined service level, our inventory manager places a material replenishment order of the difference between the IP and the BSL respectively the E-BSL for IP<BSL and IP<E-BSL, which has the same volume for expedited orders and orders with a deterministic lead time in that case. Interestingly, the system has been optimised in terms of cost by setting the BSL below the E-BSL. The reason for this is that our inventory manager follows a fixed sequence. First, he checks that the IP is below the BSL. Only then he places a regular order according to the convention "if E-BSL < IP < BSL, we place regular orders for the amount BSL - IP". At this point, it does not matter if the E-BSL is already below the IP. Only when the IP is below the BSL that the following two processes occur in sequence: first "if IP < E-BSL we place expediting orders for the amount E-BSL - IP" and at the end of the system we carry out the process "if IP < E-BSL we place regular orders for the amount BSL - IP". As a result, the system achieves lower inventory holding costs and lower total costs compared to inventory policies 1 and 4 without the option to place regular orders below the E-BSL.

Finally, the analysis provides interesting insights into dual replenishment strategies in which a system places, in addition to expediting orders, regular orders with a deterministic lead time below the E-BSL value. We implemented this systematic in policies 2 and 3. For policies 1 and 4 the system triggers only expediting orders if the IP is below the E-BSL value. With our investigation and research for the case described here, we can prove with the help of simulation optimisation that a dual replenishment strategy as implemented in policy 2 and 3 is significantly better in terms of total costs than a replenishment strategy where only expediting orders are placed below the E-BSL trigger point as in policy 1 and 4. Our results are therefore consistent with previous research and also show that in our modified simulation model and inventory policy, expediting is cost effective.

4.5 Case 2: Optimal Inventory Policies for Stochastic Demand and Lead Time with Expediting

Our next case looks at a special simulation model where the demand and delivery time are stochastic. In this simulation, we also use the basic model from Kostic (2019), which we have adapted with regard to the probability distribution. Kostic's model assumes a percentage probability of delivery for each regular order. We have adapted our model to use a triangular distribution function with a minimum, median, and maximum value for the probability of delivery. In the following, we will describe this model and the simulation design.

4.5.1 Model Description and Simulation Design

The model is based on the research of Kaplan (1970), who studied a dynamic inventory model with stochastic lead times. In the Kaplan (1970)) model, there is no order crossing and the complexity has been reduced to the point where there is no multidimensionality that cannot be computed easily. Furthermore, it is assumed that the probability of an outstanding order arriving in the actual period increases with the age of the order.

Our model is based on the Kaplan (1970) model with the extension allowing us to expedite orders. A regularly placed order has an independent and identically distributed triangular distribution function to arrive between 2 and 7 system days with the median at 5 system days. New triggered regular orders are placed in a delivery queue. At the beginning of the next period, before a new customer demand is triggered, it is checked again whether the probability of delivery for the outstanding order in the queue occurs. If probability occurs, the replenishment order from a previous period is added to the stock. If the probability does not occur, the order is again delayed for one period. Further replenishment orders, which were triggered in this period or earlier, line up one after the other in the queue until the probability for the first order in the queue applies. For this reason, we exclude order crossing. The second case under investigation is more complex, but the same decision-making strands and the same four Policies are applicable.

We use the same starting conditions for the initial model with a finite replication length of 1000 system days to ensure a steady state condition. A customer demand with a Poisson (10) distribution is generated every regular interval, each system day. The simulation is set up so that a customer is willing to wait for his delivery, and the system, therefore, allows a negative inventory value to calculate the backlog costs.

We use the same cost elements for the analysis and optimisation per period:

- Holding costs: 1 unit
- Regular order costs: 3 units
- Expediting order costs: 5 units
- Backlog costs (penalty) for unserved customer order: 5 units

These costs are added up for each period.

Since we use one additional stochastic variable in the stochastic demand and lead time model, we need to recalculate the required replications to a confidence interval of 95% and an interval precision of $\leq 1\%$. First, we run the simulation with ten replications. The precision of the confidence interval for the total cost factor was 1.92% for the total cost variable. We use the formula from Chapter 3.2 to calculate the number of replications to meet our confidence interval precision requirement of $\leq 1\%$. The result shows that we might use rounded seven replications to achieve our desired confidence interval and interval precision. We decided to keep the 52 replication length as a standard for our simulation optimisation. For case 2, we also use the same simulation and optimisation environment in Arena. The parameters have also been adopted for the steady-state condition and the softened 95% service level model.

4.5.2 Results Case 2: Optimal Inventory Policies for Stochastic Demand and Lead Time with Expediting

The results for Case 2 and each of the four policies and the three different models, (1) without service level constraint, (2) with 95% service level constraint, (3) and 100% service level constraint, are summarised in Table 4.2 below.

Type	**Policy 1**			**Policy 2**		
Model	(1)	(2)	(3)	(1)	(2)	(3)
Base Stock Level	38	36	50	11	13	25
Expediting Base Stock Level	12	11	27	12	11	26
Total Regular Order Costs	17,166.75	14,071.33	7,623.06	15,629.25	17,918.77	15,655.96
Total Expediting Order Costs	21,378.08	26,477.31	37,251.83	23,942.12	20,169.33	23,968.85
Total Backlog Costs	1,367.40	2,573.08	0.00	1,870.77	2,343.85	0.00
Total Holding Costs	11,309.00	8,249.38	19,807.75	5,374.06	7,586.06	18,968.02
Total Costs	51,221.23	51,371.10	64,682.63	46,816.19	48,018.00	58,592.83
Service Level	97.33%	*95.00%	100%	96.00%	*95.12%	100%
Type	**Policy 3**			**Policy 4**		
Model	(1)	(2)	(3)	(1)	(2)	(3)
Base Stock Level	20	18	34	21	27	35
Expediting Base Stock Level	12	12	24	7	4	21
Total Regular Order Costs	18,360.29	15,500.08	20,185.85	13,228.33	18,885.63	13,298.19
Total Expediting Order Costs	19,365.96	24,170.48	16,502.98	27,898.17	18,616.44	27,919.90
Total Backlog Costs	1,792.98	2,170.67	0.00	2,258.75	2,547.02	0.00
Total Holding Costs	4,750.06	3,474.73	18,362.77	7,935.19	15,085.71	21,432.69
Total Costs	44,269.29	45,315.96	55,053.60	51,320.44	55,134.81	62,650.79
Service Level	95.95%	*95.21%	100.00%	95.60%	*95.38%	100.00%

Table 4.2: Results Case 2: 4 optimal inventory policies for an inventory system with stochastic demand and lead time with expediting

Service levels also play an important role in our investigation of optimal inventory policies for stochastic demand and lead times with expediting.

4.5.3 Chapter Summary and Results

Our second case shows partly significantly different results from our first case. In Table 4.3, in the row **% Cost Comparison Model (1) vs. (2)**, we show the percentage of cost increase or reduction of the second case with stochastic lead times compared to our first case with deterministic lead times. Considering only the total costs and the respective percentage deviation between case (1) and case

(2), we can derive that stochastic lead times in specific inventory policies have a significant negative impact on the overall cost structure.

Type	**Case (1) - Policy 1**			**Case (2) - Policy 1**		
Model	(1)	(2)	(3)	(1)	(2)	(3)
Base Stock Level	38	36	52	38	36	50
Expediting Base Stock Level	12	11	25	12	11	27
Total Regular Order Costs	18,053.37	13,988.31	20,335.62	17,166.75	14,071.33	7,623.06
Total Expediting Order Costs	19,972.88	26,641.83	16,229.13	21,378.08	26,477.31	37,251.83
Total Backlog Costs	1,307.69	2,562.88	0.00	1,367.40	2,573.08	0.00
Total Holding Costs	12,009.54	8,354.63	27,029.17	11,309.00	8,249.38	19,807.75
Total Costs	51,343.42	51,547.65	63,593.92	51,221.23	51,371.10	64,682.63
Service Level	97.45%	*95.03%	100%	97.33%	*95.00%	100%
% Cost Comparison Case (1) vs. (2)	-0.24%	-0.34%	1.71%			

Type	**Case (1) - Policy 2**			**Case (2) - Policy 2**		
Model	(1)	(2)	(3)	(1)	(2)	(3)
Base Stock Level	12	9	27	11	13	25
Expediting Base Stock Level	12	13	29	12	11	26
Total Regular Order Costs	16,904.02	11,639.88	14,704.21	15,629.25	17,918.77	15,655.96
Total Expediting Order Costs	19,972.88	26,641.83	16,229.13	23,942.12	20,169.33	23,968.85
Total Backlog Costs	1,307.69	2,562.88	0.00	1,870.77	2,343.85	0.00
Total Holding Costs	12,009.54	8,354.63	27,029.17	5,374.06	7,586.06	18,968.02
Total Costs	51,343.42	51,547.65	63,593.92	46,816.19	48,018.00	58,592.83
Service Level	97.45%	*95.03%	100%	96.00%	*95.12%	100%
% Cost Comparison Case (1) vs. (2)	2.62%	0.27%	-2.77%			

Type	**Case (1) - Policy 3**			**Case (2) - Policy 3**		
Model	(1)	(2)	(3)	(1)	(2)	(3)
Base Stock Level	21	21	38	20	18	34
Expediting Base Stock Level	12	12	29	12	12	24
Total Regular Order Costs	23,115.17	23,115.17	23,155.15	18,360.29	15,500.08	20,185.85
Total Expediting Order Costs	11,559.04	11,559.04	11,577.40	19,365.96	24,170.48	16,502.98
Total Backlog Costs	1,911.25	1,911.25	0.00	1,792.98	2,170.67	0.00
Total Holding Costs	3,756.54	3,756.54	20,082.27	4,750.06	3,474.73	18,362.77
Total Costs	40,342.00	40,342.00	55,082.27	44,269.29	45,315.96	55,053.60
Service Level	95.26%	*95.26%	100%	95.95%	*95.21%	100%
% Cost Comparison Case (1) vs. (2)	9.73%	12.33%	-0.05%			

Type	**Case (1) - Policy 4**			**Case (2) - Policy 4**		
Model	(1)	(2)	(3)	(1)	(2)	(3)
Base Stock Level	21	23	36	21	27	35
Expediting Base Stock Level	6	6	22	7	4	21
Total Regular Order Costs	15,182.13	16,879.56	14,216.31	13,228.33	18,885.63	13,298.19
Total Expediting Order Costs	24,708.85	22,001.84	26,381.63	27,898.17	18,616.44	27,919.90
Total Backlog Costs	3,023.65	2,493.37	0.00	2,258.75	2,547.02	0.00
Total Holding Costs	7,131.33	8,830.10	21,711.83	7,935.19	15,085.71	21,432.69
Total Costs	50,045.96	50,204.85	62,309.77	51,320.44	55,134.81	62,650.79
Service Level	93.96%	*95.04%	100%	95.60%	*95.38%	100%
% Cost Comparison Case (1) vs. (2)	2.55%	9.82%	0.55%			

Table 4.3: Comparison of the four different inventory policies and the two **cases**

Our in-depth analysis of the results, in particular of the BSL, the E-BSL and the different inventory policies, shows that a stochastic lead time can have a significant impact on total costs. However, the degree of influence is strongly linked to the underlying inventory policy. For example, we see a comparatively small influence of stochastic lead times for policies 1 and 2 and a considerably larger influence for policies 3 and 4. Especially in policy 3, the influence is strongly evident. The total costs of the model without a predefined service level increased by 9.73% and by as much as 12.33% with a predefined service level of 95%. Stochastic lead times apply only to regular orders. Expedited orders are added to stock immediately after the order is placed. We see evidence in our simulation optimisation that the system "bypasses" a stochastic, unpredictable lead time and triggers more expensive reliable expediting orders. That effect leads to a change in the cost structure. Costs for regular orders are significantly lower in case (2) policy 3 and the expediting costs are higher, which implies that the total cost increase is related to the stochastic lead time paradigm shift to predictable expensive immediate available inventory. Regular ordering costs are 20.57% lower in the model with no predefined service level and even 32.94% lower in the model with 95% service level in case (2). On the other hand, the expediting costs increased by 67.54% in the model of no predefined service level and by 109.10% in the 95% model. These results strengthened a negative cost correlation between stochastic lead time and costs for our two cases in most of the analysed policies. However, we also derive from our analysis and investigation that the results indicate a strong sensitivity between stochastic lead times for specific inventory policies. Furthermore, we would like to mention at this point that a stochastic lead time in our analysis follows a distribution function in which orders can be delivered earlier or later compared to a deterministic lead time case. Late deliveries can therefore lead to a higher backlog, which is penalised with 5 cost units. Earlier deliveries, on the other hand, have only slightly negative consequences in our model, as the holding cost is set at 1 cost unit, which is comparatively low compared to the backlog costs. Therefore, it is advisable for future research to study and also impose an additional penalty on earlier deliveries in addition to the holding costs.

Based on these key findings, we can conclude that a stochastic delivery time generally has a rather negative impact on the total cost of ownership for our inventory policies.

4.6 Sensitivity Analysis

In the previous two chapters, we have used intensive simulation optimisation to analyse and derive optimal inventory policies for the case with stochastic demand and deterministic lead time with expediting and the case with stochastic demand and lead time with expediting. We analysed the influence of the three models without service level, 95% service level and 100% service level of the total cost structure and the cost groups. The objective of our optimisation was to find the optimal inventory policies for these corresponding cases under specified cost conditions.

In the following, we would like to analyse which of the cost factors have the greatest influence on inventory policies and how the total costs are affected. For this purpose, we examine the sensitivity of the total costs and the influence on the BSL and E-BSL values. Therefore, we conducted a fully factorial experiment. For our experiments, we only consider the two models without a predefined service level and with a 100% service level. This is because our previous research and optimisation simulations have shown that in most models having a predefined service level of 95% is counterproductive when optimising costs. In total, we will run 128 experiments made up of the following cost factors:

- Regular order costs: 1 unit and 2 units
- Expediting order costs: 7 units and 9 units
- Backlog costs (penalty) for unserved customer orders: 7 units and 9 units
- Holding costs: 3 units and 5 units

We have only ever changed one cost factor. The other cost factors stayed at the initial "base case" cost factor levels. In each of the following tables, a cost factor is adjusted, and the results are presented.

First, we consider the case where the regular order cost is reduced from 3 costs per unit in the base case to 1 and 2 costs per unit.

Stochastic demand and deterministic lead time case with expediting

Type	**Policy 1**					
Ordering Cost	1		2		Base Case - 3	
BSL	35	54	35	54	38	52
EBSL	8	26	8	26	12	25
Regular Order Costs	7,344.27	7,661.02	14,688.54	15,322.04	18,053.37	20,335.62
Expediting Order Cost	13,330.48	11,950.48	13,330.48	11,900.96	19,972.88	16,229.13
Backlog Costs	4,781.63	0.00	4,781.63	0.00	1,307.69	0.00
Holding Costs	12,064.04	30,844.44	12,064.04	30,844.44	12,009.54	27,029.18
Total Costs	37,520.42	50,406.42	44,864.69	58,067.44	51,343.42	63,593.92
Service Level	87.26%	100%	89.34%	100%	97.45%	100%

Type	**Policy 2**					
Ordering Cost	1		2		Base Case - 3	
BSL	12	29	12	29	12	27
E-BSL	12	29	12	29	12	29
Regular Order Costs	5,634.67	5,643.06	11,269.35	11,286.12	16,904.02	14,704.21
Expediting Order Cost	21,857.69	21,900.77	21,857.69	21,900.77	21,857.69	25,581.44
Backlog Costs	1,745.00	0.00	1,745.00	0.00	1,745.00	0.00
Holding Costs	5,116.33	21,747.15	5,116.33	21,747.15	5,116.33	19,976.58
Total Costs	34,353.69	49,290.98	39,988.37	54,934.04	45,623.04	60,262.23
Service Level	94.92%	100%	95.64%	100%	96.18%	100%

Type	**Policy 3**					
Ordering Cost	1		2		Base Case - 3	
BSL	21	38	21	38	21	38
E-BSL	12	29	12	29	12	29
Regular Order Costs	7,705.06	7,718.38	15,410.12	15,436.77	23,115.17	23,155.17
Expediting Order Cost	11,559.04	11,577.40	11,559.04	11,577.40	11,559.04	11,577.40
Backlog Costs	1,911.25	0.00	1,911.25	0.00	1,911.25	0.00
Holding Costs	3,756.54	20,349.71	3,756.54	20,349.71	3,756.54	20,082.27
Total Costs	24,931.66	39,645.50	32,636.94	47,363.88	40,342.00	55,082.27
Service Level	92.33%	100%	94.14%	100%	95.26%	100%

Type	**Policy 4**					
Ordering Cost	1		2		Base Case - 3	
BSL	23	40	23	40	21	36
E-BSL	4	22	6	22	6	22
Regular Order Costs	6,041.29	5,853.46	11,161.19	11,706.92	15,182.13	14,216.31
Expediting Order Cost	19,929.90	20,885.00	22,123.27	20,885.00	24,708.85	26,381.63
Backlog Costs	3,659.04	0.00	2,507.11	0.00	3,023.65	0.00
Holding Costs	9,170.06	25,383.23	8,876.60	25,383.23	7,131.33	21,711.83
Total Costs	38,800.29	52,121.79	44,578.33	57,975.25	50,045.96	62,309.77
Service Level	90.57%	100%	94.38%	100%	93.96%	100%

Table 4.4: Regular ordering costs sensitivity analysis for stochastic demand and deterministic lead time case with expediting for the four different inventory policies

The first interesting finding in the sensitivity analysis in Table 4.4 is that the service level drops when the regular order costs are significantly lower than in the base case. This can be derived from the fact that for our defined cost structure, it is cheaper to accept partially higher backlog costs than to place more and higher regular orders. Higher regular orders lead to an immediate negative effect on holding costs. Therefore, the system optimises itself in terms of total costs with a negative effect on backlog costs which has an adverse effect on the service level.

Second, conversely, in a situation where we would have increased the costs from 1 ordering cost per unit to 3 which is an increase of a factor of 200%, the total cost for policy 1 without service level constraint would increase by 36.84% and with a 100% service level by just 26.16%, for policy 2 by 32.80% and by 22.26%, for policy 3 by 61.81% and 38.94% and policy 4 by 28.98% and 19.56%. The increase for the 2 ordering costs per unit case is correspondingly lower.

Third, the influence on the inventory policy for the BSL and E-BSL is vanishingly small. A slight change can only be seen in policy 1 base case and policy 4. For the other two policies, a change in regular order costs does not lead to any meaningful change. We conclude for the stochastic demand and deterministic lead time case a low sensitivity to reduction in regular ordering costs.

Next, we analyse the case for stochastic demand and lead time model with expediting in terms of the regular ordering costs. The sensitivity results also in the case with stochastic demand and lead times are similar to the previous case shown in Table 4.4. The total costs show an even lower sensitivity compared to the reduction in regular order costs. The total cost for policy 1 without service level constraint would increase by 35.87% (-0.97% vs. previous model) and with a 100% service level by just 26.25% (+0.08% vs. previous model), for policy 2 by 31.17% (-1.64% vs. previous model) and by 22.40% (+0.14% vs. previous model), for policy 3 by 41.17% (-20.64% vs. previous model) and 32.35% (-6.59% vs. previous model) and for policy 4 by 24.83% (-4.16% vs. previous model) and 16.48% (-3.08% vs. previous model). The increase for the 2 ordering costs per unit case is, as in the previous case, lower. Although the cost structure and total costs are comparable to the previous case, it is noticeable that the service levels in all four policies are significantly better than in the first case analysed. In fact, they are very close to the level of the base case, even though the total costs are significantly lower. It is interesting to note that the sensitivity to a change in ordering costs in both cases is low in terms of total costs but that the sensitivity of the service levels is significantly higher, and the service level in the case of stochastic demand and deterministic lead time with expediting is substantially lower in comparison to the case with stochastic demand and lead time with expediting. Based on the results of the cost factors, we can conclude that the entire system has optimised itself in terms of total cost, taking into account the various cost factors. Based on the optimisation criteria (minimising total costs), it is more cost-optimal to accept higher backlog costs than significantly higher expediting costs. However, the increased backlog costs lead to a corresponding reduction in service levels.

Stochastic demand and lead time case with expediting

Type	Policy 1					
Ordering Cost	1		2		Base Case - 3	
BSL	40	55	38	54	38	50
EBSL	12	26	11	27	12	27
Regular Order Costs	7,422.92	7,749.56	13,479.88	12,411.54	17,166.75	7,623.06
Expediting Order Cost	12,937.21	11,389,04	16,348.75	19,054.71	21,378.08	37,251.83
Backlog Costs	942,79	0.00	1,802.02	0.00	1,367.4	0.00
Holding Costs	16,396.65	32,096.62	13,121.19	27,766.54	11,309.00	19,807.75
Total Costs	37,699.58	51,235.21	44,751.85	59,232.79	51,221.23	64,682.63
Service Level	97.50%	100%	95.97%	100%	97.33%	100%

Type	Policy 2					
Ordering Cost	1		2		Base Case - 3	
BSL	12	27	12	25	11	25
E-BSL	12	26	12	26	12	26
Regular Order Costs	5,584.12	5,777.23	11,168.23	10,437.31	15,629.25	15,655.96
Expediting Order Cost	22,084.81	21,157.12	22,084.81	23,968.85	23,942.12	23,968.85
Backlog Costs	1,667.31	0.00	1,667.31	0.00	1,870.77	0.00
Holding Costs	6,355.60	20,935.87	6,355.60	18,968.02	5,374.06	18,968.02
Total Costs	35,691.83	47,870.21	41,275.94	53,374.17	46,816.19	58,592.83
Service Level	95.33%	100%	95.96%	100%	96.00%	100%

Type	Policy 3					
Ordering Cost	1		2		Base Case - 3	
BSL	22	34	21	34	20	34
E-BSL	12	24	12	24	12	24
Regular Order Costs	6,721.80	6,728.62	12,918.31	13,457.23	18,360.29	20,185.85
Expediting Order Cost	16,486.06	16,502.98	17,732.79	16,502.98	19,365.96	16,502.98
Backlog Costs	1,483.75	0.00	1,636.83	0.00	1,792.98	0.00
Holding Costs	6,667.78	18,364.77	5,616.67	18,364.77	4,750.06	18,362.77
Total Costs	31,359.40	41,596.37	37,904.60	48,324.98	44,269.29	55,053.60
Service Level	95.27%	100%	95.68%	100%	95.95%	100%

Type	Policy 4					
Ordering Cost	1		2		Base Case - 3	
BSL	23	35	23	35	21	35
E-BSL	5	21	5	21	7	21
Regular Order Costs	5,438.46	4,432.73	10,876.92	8,865.46	13,228.33	13,298.19
Expediting Order Cost	22,763.85	27,919.90	22,763.85	27,919.90	27,898.17	27,919.90
Backlog Costs	2,893.65	0.00	2,893.65	0.00	2,258.75	0.00
Holding Costs	10,017.58	21,432.69	10,017.58	21,432.69	7,935.19	21,432.69
Total Costs	41,113.54	53,785.33	46,552.00	58,218.06	51,320.44	62,650.79
Service Level	92.96%	100%	93.78%	100%	95.38%	100%

Table 4.5: Regular ordering costs sensitivity analysis for stochastic demand and lead time case with expediting for the four different inventory policies

The BSL and E-BSL values are also close to each other in this case. However, they show a slightly higher variance than in the previously shown model. Again, we can conclude that there is very little sensitivity to a change in regular order costs.

The next two tables show the effects of increasing the expediting costs on the corresponding parameters.

Stochastic demand and deterministic lead time case with expediting

Type	**Policy 1**					
Expediting Cost	7		9		Base Case - 5	
BSL	35	53	37	53	38	52
EBSL	8	24	8	24	12	25
Regular Order Costs	22,032.81	22,717.33	23,636.42	22,717.33	18,053.37	20,335.62
Expediting Order Cost	18,662.67	17,246.25	19,325.94	22,173.75	19,972.88	16,229.13
Backlog Costs	4,781.63	0.00	4,038.94	0.00	1,307.69	0.00
Holding Costs	12,064.04	29,771.29	15,467.67	29,771.29	12,009.54	27,029.18
Total Costs	57,541.15	69,734.87	62,469.98	74,662.37	51,343.42	63,593.92
Service Level	91.69%	100%	93.53%	100%	97.45%	100%

Type	**Policy 2**					
Expediting Cost	7		9		Base Case - 5	
BSL	12	29	13	29	12	27
E-BSL	12	29	12	29	12	29
Regular Order Costs	16,904.02	16,929.17	17,335.10	16,929.17	16,904.02	14,704.21
Expediting Order Cost	30,600.77	30,661.08	38,082.12	39,421.38	21,857.69	25,581.44
Backlog Costs	1,745.00	0.00	1,592.12	0.00	1,745.00	0.00
Holding Costs	5,116.33	21,747.15	6,099.87	21,747.15	5,116.33	19,976.58
Total Costs	54,366.12	69,377.40	63,109.19	78,097.71	45,623.04	60,262.23
Service Level	96.79%	100%	97.48%	100%	96.18%	100%

Type	**Policy 3**					
Expediting Cost	7		9		Base Case - 5	
BSL	21	38	21	38	21	38
E-BSL	12	29	12	29	12	29
Regular Order Costs	23,115.17	23,155.15	23,115.17	23,155.15	23,115.17	23,155.17
Expediting Order Cost	16,182.65	16,208.37	20,806.27	20,839.33	11,559.04	11,577.40
Backlog Costs	1,911.25	0.00	1,911.25	0.00	1,911.25	0.00
Holding Costs	3,756.54	20,349.71	3,756.54	20,349.71	3,756.54	20,082.27
Total Costs	44,965.62	59,713.23	49,589.23	64,344.19	40,342.00	55,082.27
Service Level	95.75%	100.00%	96.15%	100.00%	95.26%	100.00%

Type	**Policy 4**					
Expediting Cost	7		9		Base Case - 5	
BSL	23	35	25	41	21	36
E-BSL	5	21	2	21	6	22
Regular Order Costs	17,414.13	14202,17	19,501.27	18,483.46	15,182.13	14,216.31
Expediting Order Cost	29,454.12	36,961.62	31,639.33	34,821.52	24,708.85	26,381.63
Backlog Costs	3,065.48	0.00	4,250.10	0.00	3,023.65	0.00
Holding Costs	9,033.23	20,700.83	12,637.83	26,685.87	7,131.33	21,711.83
Total Costs	58,966.96	71,865.10	68,028.52	79,991.04	50,045.96	62,309.77
Service Level	94.80%	100.00%	93.75%	100.00%	93.96%	100.00%

Table 4.6: Expediting costs sensitivity analysis for stochastic demand and deterministic lead time case with expediting for the four different inventory policies

An interesting residual result in terms of service level is policy 1. In the other policies, the service level without constraint, is comparable or even slightly higher than in the base case. This is not the case for policy 1. The reason lies in the definition of the inventory policy. In an optimal inventory policy the optimisation tends to place more regular orders with a corresponding lead time. In addition, significantly fewer expediting orders are placed, which is evident in the cost result for expediting order costs. Factoring in the price increase, even fewer expediting orders are placed. The lack of an immediate increase in IP due to the reduced placement of expediting orders, we see an increase in the backlog costs and ultimately a corresponding reduction in service level.

The percentage of cost increase for expediting costs is 40% for the 7 cost units and 80% for the 9 cost units. For sensitivity analysis, we look at the cost increase on the 9 cost units. The total cost for policy 1 without service level constraint increased by 21.67% and with a 100% service level by 17.40%, for policy 2 by 38.33% and by 29.60%, for policy 3 by 22.92% and 16.81% and for policy 4 by 35.93% and 32.83%. The increase for the 7 expediting order costs per unit is correspondingly by approximately 50% lower. The influence on the inventory policy for the BSL and E-BSL is small. A slight change can only be seen in policy 1 and policy 4. For the other two policies, there is only a minor change in the 100% service level base case in policy 2.

In summary, we can also say in this sensitivity analysis that the expediting costs have a higher sensitivity than the regular order costs, but the sensitivity overall is still comparatively low.

Interestingly, in the results with the stochastic demand and lead time case for expediting cost sensitivity in Table 4.7, we see comparable service levels or even higher service levels in many results in comparison to the base case.

The influence on total costs in the stochastic lead time case shows for most results a slightly lower sensitivity compared to the deterministic lead time for expediting order costs. We also compare the base case vs. the 9 expediting order costs case. The total cost for policy 1 without service level constraint increase by 19.99% (-1.68% vs. previous model) and with a 100% service level by just 15.06% (-2.34% vs. previous model), for policy 2 by 36.38% (-1.95% vs. previous model) and by 30.45%

(+0.86% vs. previous model), for policy 3 by 30.20% (+7.28% vs. previous model) and 23.98% (+7.17% vs. previous model) and for policy 4 by 35.33% (-0.60% vs. previous model) and 32.29% (-0.54% vs. previous model).

Stochastic demand and lead time case with expediting

Type	**Policy 1**					
Expediting Cost	7		9		Base Case - 5	
BSL	40	55	38	54	38	50
EBSL	12	25	8	25	12	27
Regular Order Costs	22,268.77	23,769.92	24,707.13	23,455.85	17,166.75	7,623.06
Expediting Order Cost	18,112.10	14,739.31	16,112.60	19,795.85	21,378.08	37,251.83
Backlog Costs	942.79	0.00	3,586.25	0.00	1,367.40	0.00
Holding Costs	16,396.65	32,761.56	17,053.13	31,175.077	11,309.00	19,807.75
Total Costs	57,720.31	71,270.79	61,459.12	74,426.77	51,221.23	64,682.63
Service Level	98.37%	100%	94.16%	100%	97.33%	100%

Type	**Policy 2**					
Expediting Cost	7		9		Base Case - 5	
BSL	12	25	14	30	11	25
E-BSL	12	26	11	25	12	26
Regular Order Costs	16,752.35	15,655.96	18,495.00	19,552.85	15,629.25	15,655.96
Expediting Order Cost	30,918.73	33,556.38	34,493.02	31,632.06	23,942.12	23,968.85
Backlog Costs	1,667.31	0.00	2,167.60	0.00	1,870.77	0.00
Holding Costs	6,355,60	18,968.02	8,690.75	25,250.98	5,374.06	18,968.02
Total Costs	55,693.98	68,180.37	63,846.37	76,435.88	46,816.19	58,592.83
Service Level	97.01%	100%	96.60%	100%	96.00%	100%

Type	**Policy 3**					
Expediting Cost	7		9		Base Case - 5	
BSL	22	34	22	34	20	34
E-BSL	12	24	11	24	12	24
Regular Order Costs	20,165.42	20,185.85	20,784.12	20,185.85	18,360.29	20,185.85
Expediting Order Cost	23,080.48	23,104.17	27,700.44	29,705.37	19,365.96	16,502.98
Backlog Costs	1,483.75	0.00	2,136.44	0.00	1,792.98	0.00
Holding Costs	6,667.79	18,364.77	7,016.35	18,364.77	4,750.06	18,362.77
Total Costs	51,397.44	61,654.79	57,637.35	68,255.98	44,269.29	55,053.60
Service Level	97.11%	100%	96.29%	100%	95.95%	100%

Type	**Policy 4**					
Expediting Cost	7		9		Base Case - 5	
BSL	23	35	25	41	21	35
E-BSL	5	21	2	21	7	21
Regular Order Costs	16,315.38	13,298.19	19,032.23	17,568.58	13,228.33	13,298.19
Expediting Order Cost	31,869.38	39,087.87	32,970.12	37,608.75	27,898.17	27,919.90
Backlog Costs	2,893.65	0.00	4,145.48	0.00	2,258.75	0.00
Holding Costs	10,017.58	21,432.69	13,305.58	27,702.29	7,935.19	21,432.69
Total Costs	61,096.00	73,818.75	69,453.40	82,879.62	51,320.44	62,650.79
Service Level	95.26%	100%	94.03%	100%	95.38%	100%

Table 4.7: Expediting costs sensitivity analysis for stochastic demand and lead time case with expediting for the four different inventory policies

Also, for our stochastic demand and lead time case with expediting, we see a comparatively low sensitivity in regard to the increased expediting costs.

Next, we examine the sensitivity of an increase in backlog costs in our key performance indicators.

Stochastic demand and deterministic lead time casw with expediting

Type	Poliy 1					
Backlog Cost	7		9		Base Case - 5	
BSL	38	52	38	52	38	52
EBSL	12	25	12	25	12	25
Regular Order Costs	18,053.31	20,335.62	18,053.31	20,335.62	18,053.31	20,335.62
Expediting Order Cost	19,972.88	16,229.13	19,972.88	16,229.13	19,972.88	16,229.13
Backlog Costs	1,830.77	0.00	2,353.85	0.00	1,307.69	0.00
Holding Costs	12,009.54	27,029.17	12,009.54	27,029.17	12,009.54	27,029.18
Total Costs	51,866.50	63,593.92	52,389.58	63,593.92	51,343.42	63,593.93
Service Level	96.47%	100%	95.51%	100%	97.45%	100%

Type	Policy 2					
Backlog Cost	7		9		Base Case - 5	
BSL	12	27	13	27	12	27
E-BSL	13	29	13	29	12	29
Regular Order Costs	15,873.63	14,704.21	16,905.23	14,704.21	16,904.02	14,704.21
Expediting Order Cost	23,575.87	25,581.44	21,860.67	25,581.44	21,857.69	25,581.44
Backlog Costs	1,721.19	0.00	1,890.17	0.00	1,745.00	0.00
Holding Costs	5,026.27	19,976.58	5,977.77	19,976.58	5,116.33	19,976.58
Total Costs	46,196.96	60,262.23	46,633.85	60,262.23	45,623.04	60,262.23
Service Level	96.27%	100%	95.95%	100%	96.18%	100%

Type	Policy 3					
Backlog Cost	7		9		Base Case - 5	
BSL	22	38	22	38	21	38
E-BSL	13	29	13	29	12	29
Regular Order Costs	23,395.56	23,155.15	23,117.42	23,155.15	23,115.17	23,155.17
Expediting Order Cost	11,101.44	11,577.40	11,560.29	11,577.40	11,559.04	11,577.40
Backlog Costs	2,258.03	0.00	2,067.58	0.00	1,911.25	0.00
Holding Costs	4,694.65	20,349.71	4,601.85	20,349.71	3,756.54	20,082.27
Total Costs	41,449.69	55,082.27	41,347.13	55,082.27	40,342.00	55,082.27
Service Level	94.55%	100%	95.00%	100%	95.26%	100%

Type	Policy 4					
Backlog Cost	7		9		Base Case - 5	
BSL	23	35	23	35	21	36
E-BSL	8	22	8	22	6	22
Regular Order Costs	15,185.77	13,132.27	15,185.77	13,132.27	15,182.13	14,216.31
Expediting Order Cost	24,713.46	28,169.52	24,713.46	28,169.52	24,708.85	26,381.63
Backlog Costs	2,146.17	0.00	2,759.37	0.00	3,023.65	0.00
Holding Costs	8,828.02	20,963.92	8,828.02	20,963.92	7,131.33	21,711.83
Total Costs	50,873.42	62,394.37	51,486.62	62,394.37	50,045.96	62,309.77
Service Level	95.78%	100%	94.64%	100%	93.96%	100%

Table 4.8: Backlog costs sensitivity analysis for stochastic demand and deterministic lead time case with expediting for the four different inventory policies

In Table 4.8 the first interesting finding is that the BSL and E-BSL values are for many cases the same or just with minor deviations from the base case.

Second, for the cases where the BSL and E-BSL follows the same optimal inventory policy, there is no change in the cost structure for the different cost factors. Only a change in the inventory policy will lead to a slight change in total costs and cost structure.

Third, the results below show that backlog costs have a negligible impact on total costs, although there is an increase in backlog costs from 5 cost units to 7 cost units (+40%) and from 5 cost units to 9 cost units (+80%). We compare the following the base case with the backlog cost increase to 9 cost units. The total cost for policy 1 without service level constraint increased by 2.04% and with a 100% service level by 0.00%, for policy 2 by 2.22% and by 0.00%, for policy 3 by 2.49% and 0.00% and for policy 4 by 2.88% and 0.00%. The increase for the 7 backlog costs per unit is approximately 50% lower. We see only a marginal change in the cost structure, and thus a barely measurable sensitivity of the cost structure to an increase in backlog costs.

The results of the sensitivity analysis for the backlog costs for the case with stochastic lead times in Table 4.9 are comparable to those for deterministic lead times. Although the inventory policies are slightly different and there are fewer equal BSL and E-BSL values than in the base case, deviations are marginal even in this analysis.

The total costs deviate marginally from the deterministic lead time case. For policy 1 without service level constraint increase by 1.57% (-0.46% vs. previous model) and with a 100% service level by just 2.72% (-2.72% vs. previous model), for policy 2 by 2.15% (-0.07% vs. previous model) and by 0.00% (0.00% vs. previous model), for policy 3 by 2.28% (-0.21% vs. previous model) and 0.00% (0.00% vs. previous model) and for policy 4 by 2.61% (-0.27% vs. previous model) and 0.00% (0.00% vs. previous model).

Stochastic demand and lead time case with expediting

Type	**Policy 1**					
Backlog Cost	7		9		Base Case - 5	
BSL	38	53	38	53	38	50
EBSL	13	29	13	29	12	27
Regular Order Costs	14,424.75	10,148.13	14,424.75	10,148.13	17,166.75	7,623.06
Expediting Order Cost	25,894.03	33,008.27	25,894.03	33,008.27	21,378.08	37,251.83
Backlog Costs	1,330.94	0.00	1,711.21	0.00	1,367.40	0.00
Holding Costs	9,997.06	23,282.92	9,997.06	23,282.92	11,309.00	19,807.75
Total Costs	51,646.79	66,439.33	52,027.06	66,439.33	51,221.23	64,682.63
Service Level	97.42%	100%	96.71%	100%	97.33%	100%

Type	**Policy 2**					
Backlog Cost	7		9		Base Case - 5	
BSL	12	25	12	25	11	25
E-BSL	13	26	13	26	12	26
Regular Order Costs	15,629.13	15,655.96	15,629.13	15,655.96	15,629.25	15,655.96
Expediting Order Cost	23,941.83	23,968.85	23,941.83	23,968.85	23,942.12	23,968.85
Backlog Costs	1,579.85	0.00	2,031.23	0.00	1,870.77	0.00
Holding Costs	6,218.92	18,968.02	6,218.92	18,968.02	5,374.06	18,968.02
Total Costs	47,369.73	58,592.83	47,821.12	58,592.83	46,816.19	58,592.83
Service Level	96.66%	100%	95.75%	100%	96.00%	100%

Type	**Policy 3**					
Backlog Cost	7		9		Base Case - 5	
BSL	21	34	21	34	20	34
E-BSL	13	24	13	24	12	24
Regular Order Costs	18,360.75	20,185.85	18,360.75	20,185.85	18,360.29	20,185.85
Expediting Order Cost	19,371.25	16,502.98	19,371.25	16,502.98	19,365.96	16,502.98
Backlog Costs	1,509.44	0.00	1,940.71	0.00	1,792.98	0.00
Holding Costs	5,606.96	18,364.77	5,606.96	18,364.77	4,750.06	18,362.77
Total Costs	44,848.40	55,053.60	45,279.67	55,053.60	44,269.29	55,053.60
Service Level	96.63%	100%	95.71%	100%	95.95%	100%

Type	**Policy 4**					
Backlog Cost	7		9		Base Case - 5	
BSL	22	35	22	35	21	35
E-BSL	8	21	9	21	7	21
Regular Order Costs	13,238.37	13,298.19	12,402.46	13,298.19	13,228.33	13,298.19
Expediting Order Cost	27,906.15	27,919.90	29,268.56	27,919.90	27,898.17	27,919.90
Backlog Costs	2,177.67	0.00	2,157.92	0.00	2,258.7	0.00
Holding Costs	8,770.73	21,432.69	8,831.02	21,432.69	7,935.19	21,432.69
Total Costs	52,092.92	62,650.79	52,659.96	62,650.79	51,320.44	62,650.79
Service Level	95.82%	100%	95.90%	100%	95.60%	100%

Table 4.9: Backlog costs sensitivity analysis for stochastic demand and lead time case with expediting for the four different inventory policies

In summary, for the deterministic and stochastic lead time cases, we see barely measurable sensitivity of the cost structure to an increase in backlog costs.

Table 4.10 shows the sensitivity of holding costs to optimal inventory policies, total costs, and service levels for the stochastic demand and the deterministic lead time case with expediting.

Stochastic demand and deterministic lead time case with expediting

Type	**Policy 1**					
Holding Cost	3		5		Base Case - 1	
BSL	30	24	27	44	38	52
EBSL	11	29	10	29	12	25
Regular Order Costs	1,151.71	0.00	403.38	168.81	18,053.37	20,335.62
Expediting Order Cost	47,919.71	49,928.37	49,161.92	49,647.88	19,972.88	16,229.13
Backlog Costs	4,025.38	0.00	6,151.44	0.00	1,307.69	0.00
Holding Costs	6,255.58	56,296.73	6,735.87	95,241.06	12,009.54	27,029.18
Total Costs	59,352.38	106,225.10	62,452.62	145,057.75	51,343.42	63,593.92
Service Level	93.22%	100%	90.15%	100%	97.45%	100%

Type	**Policy 2**					
Holding Cost	3		5		Base Case - 1	
BSL	8	24	7	23	12	27
E-BSL	10	29	10	29	12	29
Regular Order Costs	14,676.52	9,841.04	13,250.83	7,926.23	16,904.02	14,704.21
Expediting Order Cost	25,532.60	33,625.96	27,886.63	36,795.96	21,857.69	25,581.44
Backlog Costs	5,562.40	0.00	6,490.77	0.00	1,745.00	0.00
Holding Costs	6,356,83	55,294.96	8,437.98	90,129.52	5,116.33	19,976.58
Total Costs	52,128.35	98,761.96	56,066.21	134,851.71	45,623.04	60,262.23
Service Level	89.33%	100%	88.42%	100%	96.18%	100%

Type	**Policy 3**					
Holding Cost	3		5		Base Case - 1	
BSL	18	37	17	36	21	38
E-BSL	10	29	9	29	12	29
Regular Order Costs	21,960.52	22,003.10	21,958.21	20,084.48	23,115.17	23,155.17
Expediting Order Cost	13,457.40	13,480.67	13,455.58	16,658.08	11,559.04	11,577.40
Backlog Costs	5,261.63	0.00	7,628.08	0.00	1,911.25	0.00
Holding Costs	5,365.96	59,117.02	6,322.98	96,697.02	3,756.54	20,082.27
Total Costs	46,045.52	94,600.79	49,364.85	133,439.58	40,342.00	55,082.27
Service Level	88.57%	100%	84.55%	100%	95.26%	100%

Type	**Policy 4**					
Holding Cost	3		5		Base Case - 1	
BSL	11	30	10	30	21	36
E-BSL	7	22	7	22	6	22
Regular Order Costs	362.13	5,731.96	88.90	5,731.96	15,182.13	14,216.31
Expediting Order Cost	49,238.17	40,430.87	49,686.63	5,731.96	24,708.85	26,381.63
Backlog Costs	4,472.12	0.00	6,300.19	0.00	3,023.65	0.00
Holding Costs	5,517.63	54,498.06	6,490.67	90,830.10	7,131.33	21,711.83
Total Costs	59,590.06	100,660.88	62,566.40	136,992.92	50,045.96	62,309.77
Service Level	92.50%	100%	89.93%	100%	93.96%	100%

Table 4.10: Holding costs sensitivity analysis for stochastic demand and deterministic lead time case with expediting for the four different inventory policies

The table above shows the results of the optimisation simulation under the new conditions and a significantly increased unit holding cost value from 1 to 3 unit holding costs which is a percentage increase of 200% and to 5 unit holding costs which is a percentage increase of 400%.

One of the first indicators to show significant deviations, compared to the sensitivity analyses discussed previously, is the service level, which is significantly lower than the base case. The result also confirms a basic assumption that if the holding costs in particular, are as high as or equal to the backlog costs or expediting costs, the service level will probably be lower. Our investigation confirms this assumption.

Furthermore, in the sensitivity analysis of the holding costs, we see a clear deviation for most of the BSL and E-BSL values from the base case. The deviations are also higher than in the previous sensitivity analyses. The cost sensitivity analysis shows interesting results.

In the following, we compare the base case with the holding cost increase from 1 cost unit to 5 cost units. The total cost for policy 1 without service level constraint increased by 21.64% and with a 100% service level by 128.10%, for policy 2 by 22.89% and by 123.77%, for policy 3 by 22.37% and 142.26% and policy 4 by 25.02% and 119.54%. The increase for the 3 holding costs per unit is correspondingly lower. We conclude that the holding costs have the highest influence on the cost structure and thus show the highest sensitivity in our study.

The following table shows the sensitivity of holding costs on optimal inventory policies, total costs, and service levels for the stochastic demand and lead time case with expediting. The results of the optimisation simulation for the case with stochastic demand and lead time are comparable to the analysis results in Table 4.10.

Stochastic demand and lead time case with expediting

Type	Policy 1					
Holding Cost	3		5		Base Case - 1	
BSL	30	48	25	48	38	50
EBSL	11	25	10	25	12	27
Regular Order Costs	780.81	7,427.77	158.48	7,485.46	17,166.75	7,623.06
Expediting Order Cost	48,526.83	37,941.06	49,567.88	37,400.00	21,378.08	37,251.83
Backlog Costs	4,046.44	0.00	6,182.31	0.00	1,367.40	0.00
Holding Costs	6,067.96	53,364.40	6,589.04	88,940.67	11,309.00	19,807.75
Total Costs	59,422.04	98,733.23	62,297.71	133,826.13	51,221.23	64,682.63
Service Level	93.19%	100%	90.11%	100%	97.33%	100%

Type	Policy 2					
Holding Cost	3		5		Base Case - 1	
BSL	8	23	6	23	11	25
E-BSL	11	26	10	26	12	26
Regular Order Costs	12,973.38	12,997.79	11,413.21	12,997.79	15,629.25	15,655.96
Expediting Order Cost	28,388.46	28,437.21	30,974.04	28,437.21	23,942.12	23,968.85
Backlog Costs	4,044.42	0.00	6,963.56	0.00	1,870.77	0.00
Holding Costs	9,098.65	51,588.75	9,485.96	85,981.25	5,374.06	18,968.02
Total Costs	54,504.92	93,023.75	58,836.77	127,416.25	46,816.19	58,592.83
Service Level	92.58%	100%	88.16%	100%	96.00%	100%

Type	Policy 3					
Holding Cost	3		5		Base Case - 1	
BSL	17	34	15	29	20	34
E-BSL	10	24	9	26	12	24
Regular Order Costs	17,062.85	20,185.85	25,233.81	x,806.79	18,360.29	20,185.85
Expediting Order Cost	21,472.98	16,502.98	8,274,52	35,284.90	19,365.96	16,502.98
Backlog Costs	4,708.07	0.00	7,470.96	0.00	1,792.98	0.00
Holding Costs	7,824.00	55,094.31	13,869.31	80,563.94	4,750.06	18,362.77
Total Costs	51,067.90	91,783.13	54,848.60	124,655.63	44,269.29	55,053.50
Service Level	90.78%	100%	86.38%	100%	95.95%	100%

Type	Policy 4					
Holding Cost	3		5		Base Case - 1	
BSL	11	31	10	35	21	35
E-BSL	7	22	6	21	7	21
Regular Order Costs	359.65	7,247.31	359.65	13,298.19	13,228.33	13,298.19
Expediting Order Cost	49,232.69	37,904.71	49,225.48	27,919.90	27,898.17	27,919.90
Backlog Costs	4,464.81	0.00	6,610.58	0.00	2,258.75	0.00
Holding Costs	5,523.46	56,328.40	6,365.58	107.163,46	7,935.19	21,432.69
Total Costs	59,580.62	101,480.42	62,561.29	148.381,56	51,320.44	62,650.79
Service Level	92.51%	100%	89.43%	100%	95.60%	100%

Table 4.11: Holding costs sensitivity analysis for stochastic demand and lead time case with expediting for the four different inventory policies

The results in Table 4.11 differs in the BSL and E-BSL values from the base case, as in the previous analysis. The cost sensitivity analysis is comparable but shows some significant deviations from the deterministic lead time case. For policy 1 without a service level constraint, an increase by 21.62% (-32.38% vs. previous model) and with a 100% service level by 106.90% (-21.20% vs. previous model) vs. the base case, for policy 2 by 25.68% (+2.79% vs. previous model) and by 117.56%

(-6.31% vs. previous model), for policy 3 by 23.90% (+1.53% vs. previous model) and 126.43% (-15.83% vs. previous model) and for policy 4 by 21.90% (-3.11% vs. previous model) and 136.84% (+17.30% vs. previous model). Interestingly, in some inventory policies, we see a significant reduction in the total costs in the case of stochastic lead times compared to deterministic lead times. We conclude that due to the stochastic lead time distribution of 3, 5, and 7 days, the impact of certain inventory policies of the 3-day lead time leads to a significant reduction in costs compared to a 5-day deterministic lead time, especially with increased holding costs.

4.6.1 Chapter Summary and Results

The results of 128 conducted analyses during the fully factorial experiments show numerous and profound results. We systematically demonstrated that certain cost factors play a negligible role in sensitivity, despite a significant influence on the total cost of the base case. So it is very interesting to see that a simulation optimisation yields counterintuitive results. For example, an increase in backlog costs does not have a meaningful impact on the total cost structure, as the simulation optimisation adjusts all variables to minimise costs. This is an important finding of our study and shows that a simulation optimisation over several variables systematically reduces and even eliminates a MyOpic bias. To increase the depth of our analysis and investigate the impact of a potential bias for other inventory policies, we defined and analysed in total four different inventory policies, where the reorder point quantity for regular and expedited orders changes depending on the policy. The analysis shows that even if the inventory policy is similar for certain material groups, we can explicitly recommend an adjustment of the inventory policy based on the reorder point level, cost factors and deterministic or stochastic lead times. This depth of analysis has enabled us to extend our findings for use in practical applications and research. If an inventory manager applies the same inventory policy with the same BSL and E-BSL values to an increase in backlog cost, the costs naturally increase. Through simulation optimisation, we were able to detect and investigate this fact. Our research results show that the optimal inventory policy can be derived using sensitivity analysis in combination with simulation optimisation over several variables. This result has far-reaching implications for the industry, as MyOpic decisions and optimisations are made not only at the supply chain level but also at the site level. It is not uncommon to focus on one key performance indicator, such as inventory carrying costs, and try to reduce these through inventory reduction measures. However, the total cost of the supply chain may increase because, for example, the cost of expediting orders rises sharply. The sensitivity analysis that has been carried out not only clearly shows this correlation but also provides additional insight into how the cost values and service levels change with different inventory policies. As a result, our analysis not only provides far-reaching insights for an inventory manager but also provides fundamental decision support for different inventory policies and circumstances where delivery times evolve stochastically or deterministically.

Moreover, we present a wide-ranging sensitivity analysis of different cost factors and use of simulation optimisation to optimise multidimensional cost functions using simulation to find the optimal inventory policies for every of the 128 cases. Our results not only show the deviation of each cost factor, order cost, backlog cost, expediting cost and holding cost, with a change in the respective individual values in the sensitivity analysis but also provide an important and interesting insight into how not only the other cost factors change at the same time but also how the BSL, E-BSL and also the service level change. The depth of the analysis allows us to look at these values not just for one scenario but for the four different policies, for the two cases with stochastic demand and deterministic lead time with expediting and with stochastic demand and lead time with expediting. With the help of the sensitivity analysis, we confirmed our results from the previous chapter that, in most cases, a stochastic lead time leads to higher total costs in absolute terms than a predictable, deterministic lead time.

In summary, we would like to highlight three aspects identified and elaborated through sensitivity analysis. First, without assessing the sensitivity of the cost drivers, it could be assumed that an increase in a single cost factor would directly increase total costs. Through the sensitivity analysis, we demonstrated that an increase in a cost factor does not necessarily lead to an increase in total costs or only to a marginal increase and that the overall system, therefore, has a low sensitivity. Second, the sensitivity analysis, in which we conducted an additional 128 simulations, confirmed our basic result that inventory policies are generally more sensitive to stochastic than to deterministic lead times. The third insight is that only the simultaneous optimisation of the four cost factors to minimise total costs during the base-case calculations and the sensitivity analysis made it possible to avoid a myopic bias and not fall into the trap of minimising only one cost factor, e.g. holding costs.

4.7 Conclusion and Future Research

With a simulation optimisation of 152 optimisation runs to determine optimal inventory policies and a detailed sensitivity analysis, we were able to present one of the most comprehensive studies in the field of simulation optimisation and contribute to research in the field of optimal warehousing strategies with stochastic demand and deterministic lead times with expediting and stochastic demand and lead times with expediting.

Our results are not only interesting for theoretical research, but they also provide a high added value for practitioners in industry who have to adapt to the realities of a volatile post-pandemic world and unpredictable demand and lead times. The results of the sensitivity analysis are particularly noteworthy. The optimal inventory policy should be derived using sensitivity analysis combined with multi-variable simulation optimisation to eliminate a MyOpic bias, especially in the case of increased cost pressure and cost increases.

Moreover, we show a consideration of the total cost of ownership and not only the optimisation of one variable at a time during an optimisation run. The simultaneous optimisation of different cost variables makes our simulation optimisation interesting. In addition, simulation optimisation and sensitivity analysis can be used to examine different material replenishment strategies. Scenarios can be created and tested to determine which dual replenishment strategies are cost-optimal and impact the required inventory storage space. Therefore, the replenishment and stocking strategy greatly impacts many factors of an industrial operation.

In the introduction to chapter 4.1 of our third essay, we have adequately explained why the simulation approach suits the above inventory control problem well. Next, we discuss the advantages and disadvantages of simulation optimisation and explain why we chose the approach over analytical optimisation. Throughout the learning curve of the application, simulation design, debugging, analysis and final evaluation, we found the realism and flexibility of the simulation method to be a great strength. The simulation methodology allowed us to model complex and dynamic systems with a high degree of realism. It could handle complicated scenarios, including variable demand, lead times and stochastic elements, providing a more flexible representation of real-world complexities. Another important strength for us was the ability to analyse a wide range of scenarios in a very short time. Simulation excels at scenario analysis, allowing the exploration of multiple what-if scenarios. This is valuable for understanding how different factors and variables in the environment have an impact on the performance of the inventory control problem. Another strength is the easy and rapid adaptability of the simulation models in responding to changes. Simulation is well suited to dynamic environments where conditions change over time. It can adapt to evolving scenarios and capture the impact of parameter changes on the inventory system. Finally, we see a fundamental strength in dealing with complex policies and multi-variable decision spaces. Simulation can handle complex inventory control policies that may not have closed-form analytical solutions. It allows policies to be tested and optimised in a simulated environment, providing insight into their effectiveness. There are, however, some disadvantages that we would like to point out. Although our simulation model is not extremely complex, programming the model was time-consuming and resource-intensive. Running the 152 simulations took several days and required significant computational resources. Here, for example, lies the strength of analytical optimisation, as analytical methods can be more computationally efficient than simulation for certain classes of inventory control problems with well-defined structures. The biggest fundamental weakness is the lack of an optimality guarantee. Simulation provides insights into system behaviour but does not guarantee identifying an optimal solution. It focuses more on observing and understanding system dynamics than finding the globally optimal policy. Despite these weaknesses, especially the latter one, simulation optimisation is the optimal method for our inventory control problem, especially because we are optimising over several variables. Analytical methods can become challenged when dealing with nonlinear relationships or complex cost structures, as in our inventory control problem.

There are also limitations in our optimisation model that we will briefly discuss next. Our cost model is based on assumptions that we know from theoretical and practical applications of cooperation partners. These costs vary from company to company and from sector to sector. Some limitations must be considered when interpreting the results.

Another limitation is the case of lost sales. As Bijvank and Vis (2011) pointed out in their research, unmet demand in most practical applications can be claimed as lost sales and not as backlog penalty costs. Additionally, lost sales are far more economically negative for a company than calculating backlog costs. We did not take this limitation into account in our study. Moreover, our only focus was on minimising total costs and not on the revenue function and an optimum in terms of costs and revenue.

There are also some limitations to our probability functions: First, we only looked at the Poisson (10) distribution in our analysis of demand generation. Second, we chose a triangular distribution for the stochastic lead time case.

Finally, in our simulation optimisation, we do not allow for order crossing, although we are aware that, in practice, order crossing occurs in the case of stochastic lead times.

Stochastic lead times, in the sense of actual randomness in the time it takes for the ordered materials to be delivered, are very difficult to calculate and pose a real problem. If a company did not know when the ordered materials arrive, it would be impossible for the company to operate. Many of the theoretical and practical research approaches reduce the complexity of such an analysis to simulate only a single part and customer demand. Due to the dimensional complexity, replicating daily reality would bring any simulation to a standstill. Although our simulations and analyses are not as complex as reality, it was complex enough for our simulation and optimisation that each simulation took a corresponding amount of time to generate a valid result. To the best of our knowledge, we were the first to perform this depth of different simulations and compare the optimal inventory policies for the four simulation levels, inventory scheduling policies and service levels.

After resolving the research questions, one of the primary questions was whether it is worth and necessary to simulate and optimise stochastic lead time as there are way more complex to handle versus a deterministic lead time. Our results suggest that deterministic lead-time data is a good approximation as long as the stochastic data are not too spread out and completely random. We conclude that choosing a stochastic or deterministic lead time model depends on the application and the business environment. If the company operates in a sector that produces a commodity with comparatively predictable demand, a more straightforward simulation optimisation will be sufficient to answer business-related questions. Suppose the company operates in a sector with high raw material costs, high market volatility, and high service level expectations. In that case, we highly recommend investing the time to increase the complexity of the simulation. Therefore, our results, especially for market participants in the latter field, provide meaningful and interesting research results, even if they do not reflect the reality 100%.

We already presented some limitations of our study in previous chapters. Finding solutions for these limitations is the first step for future research. First, it would be essential to look at the lost sales case. We know by now that an undelivered customer is usually a lost customer. What influence does this case have on the optimal inventory policy, total costs, and revenue? Second, it would be exciting to see how costs and revenue develop with higher variability and a lower probability of lead times. The results would be a continuation of the study. The simulation and parameters must also be adjusted with new ideas and implications to provide valid results. Finally, it would be essential to win an organisation as a partner that is available with complexity-reduced but realistic data for the simulation and implementation of the results in the live system. These adjustments would be an added value for the partner organisation and bring considerable value to research and practice.

Chapter **5**

Conclusion and Outlook

The central research topic throughout this work is to improve customer service, reduce total costs, and enable more efficient resource allocation. To answer the broader research topic, we need to bring together the three answers of RQ 1 to RQ 3. These three questions have been addressed throughout the previous chapters in an essay format and will be recapped in the following, together with our contributions. We will critically review our approach and its limitations and give an outlook on possible future work in the broader field of supply network research.

5.1 Contribution to the research area

Our contribution to the literature and research on the wider field of supply chain management is threefold. In all three essays, we found new results and contributed to the literature in each of the RQ main realms. Especially in the first two RQs, we were able to work on the topic from a theoretical and practical point of view and contribute to new results. We could also test the results in a real environment and confirm them accordingly.

In order to answer the first RQ (*What strategies can be implemented to reduce supply network complexity in regulated markets while ensuring compliance with regulatory requirements?*), we have defined and developed a sophisticated simulation model that acts as a digital twin, representing a supply chain of antibody manufacturing. We used the model to investigate the impact of a strategy to reduce complexity in a company operating in a regulated environment and the improvements that can be achieved. Based on our review and evaluation of the literature, the results of our analysis, the detailed presentation of antibody manufacturing and the shortening of the supply chain is the first publication in the field of supply chain management with a focus on regulated products. We have been able to make a further contribution to practice and research by showing that the costs of the supply chain in the field of regulated products, in our case antibody production, are very high and lag behind already optimised concepts, such as in the automotive industry. Our findings also confirm the prevailing view in the literature that the supply chain in regulated markets has been underestimated and has not been the focus of attention in the past. Therefore, companies and future research should focus on optimising supply chains in regulated environments. Finally, we contributed not only with the results of shortening the supply chain and the sensitivity analysis performed but also with the scenario analysis on the potential return on investment when implementing a restructuring project in the regulated market sector. Our results, which have a high degree of validity and reliability, indicate that a reduction in complexity can have a high potential for improvements in the company under study. Furthermore, we were able to present in a sensitivity analysis that companies operating under such supply and production conditions should focus their attention on improving processing time and inventory holding costs. We were also able to contribute to the research field by exploring knowledge about supply chain-driven change processes, such as the reduction of complexity in regulated market environments.

Using SNA and graph theory is not new in the supply chain world. However, the number of studies and publications based on real data sets is very limited because of the difficulty in obtaining the data to conduct such studies and analyses. Working with a partner organisation, we obtained the relevant data, studied, investigated, and analysed this data in theory, and tested and verified the theoretical research results in a practical example, making a further contribution to this research area and increasing the knowledge in research and practice. This allowed us to be the first to publish a comprehensive set of research results and network metrics for the SARS-CoV-2 PCR test kit supply network in the regulated market. The depth and characteristics of the structural attributes of the supply network and the social network analysis metrics for the test kits are, to the best of our knowledge, the highest we have found for the research of supply networks for regulated products based on our literature review. We have not only analysed, calculated and interpreted the classic social network analysis metrics at the node level but also carried out in-depth analyses at the global network level for subgroups and cutpoints. Particularly in recent years, during the COVID-19 pandemic, our research focus has received much attention. As a result of this significant supply chain disruption, many researchers and companies have begun to work on the early identification of supply risks and the development of measures to mitigate risks to organisations, ensure product availability to customers and maintain business operations. Based on these circumstances, we have defined the second RQ (*What impacts the supply network of organisations in the regulated market environment and what strategies can organisations adopt to mitigate these risks?*), which we were able to answer in depth. Our empirical research demonstrates that the combination of SNA, network graph visualisation and MCS in conjunction with our developed SNRS is novel to theory and practice and represents a systematic approach that can improve decision-makers ability to identify and manage risks in supply networks. We were able to demonstrate that the structural resilience of a network for regulated products can be systematically increased by applying our SNRS methodology, providing new insights for practice and research. In addition, we were able to confirm and reinforce previous research in other industries that the application of the SNA methodology adds significant value to the analysis of supply networks. We applied our approach to an essential real-world example of a supply network of SARS-CoV-2 PCR test kits in the regulated market. Our results suggest that we can enable companies and decision-makers to develop and create new risk mitigation strategies using our novel SNRS. In doing so, we are making a significant contribution to the important research on endemic outbreaks and how they affect supply chains. Our defined approach adds significant value to companies and can be one of the first steps to build enterprises' supply network intelligence capabilities. The results not only provide insights for the short to medium term implementation of risk mitigation measures or for increasing the resilience of the supply network but also allow company executives to make long-term supply network design considerations. In addition, we have enhanced the understanding of supply network theory and decision support tools through the use of graphical representations of global supply networks, their mathematical computation using graph theory, and the application of simulation tools. Answering the second RQ thus contributes to the supply network research community and the existing pool of decision support models by presenting a novel approach to combine social network analysis, graph visualisation, and MCS that provides a holistic view and enables companies and researchers to study supply risk factors that shape supply networks in a scale-free network.

The answer to the third RQ (*What is the optimal inventory policy for a supply chain system facing stochastic demand and stochastic lead time, and how does it depend on factors such as inventory holding costs, stockout costs, lead time variability, and demand variability to minimise total costs while maintaining satisfactory service levels?*), is the third and final building block that completes our work. Our approach to answering the last RQ was to identify optimal inventory policies for stochastic demand and lead times at different service levels using advanced simulation optimisation. To the best of our knowledge, we were the first to perform this depth of different optimisation simulations and to compare optimal inventory policies for three service levels and inventory scheduling policies. Despite the easing of the COVID pandemic, our research contribution and findings are relevant to practitioners and academics as delivery times remain disrupted, unpredictable and stochastic due to further global conflicts and geopolitical tensions. Deterministic and largely predictable delivery times remain the exception in many industries. The results, especially those obtained using sensitivity analysis, also reveal a fundamental weakness of companies and managers focusing on inventory holding costs. Our findings show that the commonly held belief that lower service levels result in lower inventory holding costs is incorrect under certain conditions and inventory policies. Our results can support practitioners in selecting the optimal stocking and replenishment strategy for their product groups on the basis of the different inventory policies, lead time cases and service levels we have analysed. An essential contribution of our work on the relevant research field concerns the four different inventory policies, different service levels and lead time cases, which have not been sufficiently analysed in the relevant literature reviewed. In particular, we make a contribution to the dual replenishment strategy, which refers in our work to regular (base-stock level) or expediting (expediting-base-stock level) orders. Typically, companies only use expediting in crisis situations or late deliveries. Our analysis shows that dual replenishment strategies can make a significant contribution to overall cost and service level optimisation. Companies should, therefore, consider implementing dual replenishment strategies systematically and strategically. Furthermore, we used our results to compare the comparatively high computational complexity of simulating stochastic demand and lead time model with a simplified simulation of stochastic demand and deterministic lead times model. Our results suggest that deterministic lead time data is a good approximation during a long simulation run in a steady-state condition as long as the stochastic data are not too spread out and random. Our results are particularly interesting for market participants and researchers in areas with a very low tolerance threshold for delivery deviations. These include, in particular, the areas of healthcare, where the rapid delivery of medical products and supplies is crucial to patients, the automotive industry, particularly those that operate on a just-in-time inventory management system, and the aerospace and defence industry, which requires strict adherence to delivery schedules to avoid any disruption to the operation of military and commercial aircraft. Therefore, our results, especially for market participants in the latter field, provide important research results.

5.2 Critical Review

Our work is not without limitations. In all three essays, we had to make assumptions to reduce the complexity of the analyses and calculations due to the high complexity of supply chains, network structures, and the real world.

Assumptions for the first essay in Chapter 2. Our partner company produces hundreds of different antibodies. Each has different production steps, processes, and delivery times. Representing all SKUs and optimising the simulation is highly complex and not realistically feasible. We have therefore focused our research on only one variant and transferred all the necessary information for these variants into the digital twin to be as close to reality as possible. We have also assumed that the variability in delivery times and process times follows a triangular distribution, which is close to reality but cannot fully represent it. Finally, we assume that raw material supplies are not restricted.

Assumptions for the second essay in Chapter 3. In our second essay, we look at risk mitigation strategies for the supply network of a complex organisation. It will be evident to the reader that there are many different types of risk and risk factors that a company may need to prepare for. In our study, however, we use only one of these risks - the WRI - which focuses on social, infrastructure, and environmental risks. We also have to acknowledge that the risk we calculate for each node and, therefore, each supplier is based on the data provided by the partner company. Although we have validated the data with the partner company, it is still not possible to say whether, for example, a supplier that we have identified as critical is actually critical or whether the supplier itself has already taken measures to mitigate the risk. The most restrictive assumption is that we only demonstrate one possible risk mitigation measure - dual sourcing - although there are various ways to mitigate the risk. Finally, it was only possible to study the network for which the data was available. Although these data are extensively compared to other research in this area, we do not have insight into the deeper supply structures of suppliers.

Assumptions for the third essay in Chapter 3. For the purposes of our research and various simulation optimisations, we have studied customer demand with a Poisson distribution. We used a triangular distribution for the stochastic lead time, which is stochastic and independent and identically distributed, but we did not use a completely random distribution function that would imply order crossing. Our focus was on minimising the total cost of a system, so we had to include the calculated backlog costs. This assumption and our calculation are correct, but recent research shows that a significant proportion of customers do not wait, and a lost sale is significantly more expensive than a backlog cost consideration. We have not included this case in our analysis. Additionally, we only consider the cost aspect of our work and not the revenue and potential profit resulting from the sale of goods. The study is based on theoretical data, and we have not been able to test what impact our findings would have on a real case.

5.3 Outlook

Given the broad scope of research in SCM, many research questions can be posed and investigated. This is also true for our work and the three essays. In the following, we address only a few important points from our point of view. Therefore, we have selected a few points for each of the three parts representing the clearest extension, given the diversity of the main themes of the three essays.

For essay number one, extending the model and increasing the complexity of the simulation is where we see the most significant added value for research and practice. Companies no longer operate in an environment where only one variant and configuration can be sold. Companies must respond to different customer needs, including different variants. Therefore, we see an important element and building block for further research and investigation approaches in the future in extending our model by increasing the SKU level complexity. This also means that for each new SKU, the process times, delivery times, and order point policies in the model have to be adjusted accordingly, which leads to an increase in complexity, but represents reality better and more reliably.

For essay number two, in our opinion, it is important to incorporate additional risk types to exploit the full potential of our novel concept SNRS. For nodes with correspondingly high-risk scores, different risk mitigation strategies, not only dual sourcing, should be used to mitigate the risk and increase resilience. Subsequently, a holistic SNRS calculation on the supply network would be possible, leading to considerable added value in research and practice.

Regarding essay number three, we see two important points that should be considered in future research. First, there could be variations in the demand distribution and the use of probability distributions other than the Poisson distribution. Secondly, it would be interesting to investigate the issue of order crossing. This could arise in the case of a stochastic distribution with independent and identically distributed demand and random lead times. Finally, it would be interesting to implement the theoretical results based on a real case in cooperation with a company and to analyse and study the results.

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