CRANFIELD UNIVERSITY

ANNA LEDWOCH

Resilience of complex supply networks

School of Aerospace, Transport and Manufacturing (SATM)
Department of Manufacturing

Doctor of Philosophy
Academic year: 2016–2017

Thesis restricted

Supervisors:
Dr Alexandra Brintrup
Prof. Ashutosh Tiwari
Prof. Jörn Mehnen

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This thesis is submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

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Abstract

During recent decades supply chains have grown, and became increasingly interconnected due to globalisation and outsourcing. Empirical and theoretical studies now characterise supply chains as complex networks rather than the hierarchical, linear chain structures often theorised in classical literature. Increased topological complexity resulted in an increased exposure to risk, however existing supply chain risk management methodologies are designed based on the linear structure assumption rather than interdependent network structures. There is a growing need to better understand the complexities of supply networks, and how to identify, measure and mitigate risks more efficiently.

The aim of this thesis is to identify how supply network topology influences resilience. More specifically, how applying well-established supply chain risk management strategies can decrease disruption impact in different supply network topologies. The influence of supply network topology on resilience is captured using a dynamic agent-based model based on empirical and theoretical supply network structures, without a single entity controlling the whole system where each supplier is an independent decision-maker. These suppliers are then disrupted using various disruption scenarios. Suppliers in the network then apply inventory mitigation and contingent rerouting to decrease impact of disruptions on the rest of the network. To the best of author's knowledge, this is the first time the impact of random disruptions and its reduction through risk management strategies in different supply network topologies have been assessed in a fully dynamic, interconnected environment.

The main lessons from this work are as follows: It has been observed that the supply network topology plays a crucial role in reducing impact of disruptions. Some supply network topologies are more resilient to random disruptions as they better fulfil customer demand under perturbations. Under random disruptions, inventory mitigation is a well-performing shock absorption mechanism. Contingent rerouting, on the other hand, is a strategy that needs specific conditions to work well. Firstly, the strategy must be applied by companies in supply topologies where the majority of supply chain members have alternative suppliers. Secondly, contingent rerouting is only efficient in cases when the reaction time to supplier's disruption is shorter than the duration of the disruption.

It has also been observed that the topological position of the individual company who applies specific risk management strategy heavily impacts costs and fill-rates of the overall system. This property is moderated by other variables such as disruption duration, disruption frequency and the chosen risk management strategy. An additional, important lesson here is that, choosing the supplier that suffered the most from disruptions or have specific topological position in a network to apply a risk management strategy might not always decrease the costs incurred by the whole system. In contrast, it might increase it if not applied appropriately.

This thesis underpins the significance of topology in supply network resilience. The results from this work are foundational to the claim that it is possible to design an extended supply network that will be able reduce the impact of certain disruption types. However, the design must consider topological properties as well as moderating variables.

Keywords

complexity, supply network topology, supply chain risk management, resilience, agent-based modeling

Acknowledgements

First of all, I would like to thank my supervisor Dr Alexandra Brintrup for giving me the opportunity of being involved in the project, her invaluable support and advice, and hours of fruitful discussions. I would not be able to finish this thesis without her.

I would like to thank Professor Ashutosh Tiwari, Professor Jörn Mehnen and Marc Verelst for their help throughout the thesis.

I am grateful to Dr Hakan Yaşarcan for his patience and long hours of discussions and tutoring. He played a big role in my understanding of system dynamics and he always had time for me.

I would like to thank my sister and best friend Dr Katarzyna Ledwoch, for the whole life that we spent together inseparably, sharing all the joys and sorrows, and for all until dawn conversations. I am grateful to my parents Karina and Mariusz Ledwoch for their amazing support and unconditional belief that everything will go as planned.

Also, I would like to thank Dr Laura Gendre, Dr Alena Puchkova and all other friends, for being there for me when I needed.

This project has been sponsored by a company operating within a fast-moving consumer goods industry, which wished to remain anonymous.

List of Publications

Ledwoch, A., Brintrup, A., Mehnen, J., and Tiwari, A. (2016). Systemic Risk Assessment in Complex Supply Networks. *IEEE Systems Journal*, doi: 10.1109/JSYST.2016.2596999.

Ledwoch, A., Yasarcan, H., and Brintrup, A. (2018). The moderating impact of supply network topology on the effectiveness of risk management. *International Journal of Production Economics*, 197:13-26, doi: 10.1016/j.ijpe.2017.12.013.

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Nomenclature

α_S	stock adjustment time
α_{SL}	weight of supply line
δ	Kronecker delta
κ_1	largest eigenvalue of an adjacency matrix
$\Phi_{i,t}$	number of operational suppliers of an agent i in week t
$\phi_{i,t}$	operationality of an agent i in week t
σ	standard deviation
A	adjacency matrix
AF	acquisition flow
$B_{i,t}$	backlog of an agent i in week t
C	transitivity
c	mean degree
C_i	total costs generated by an agent i
C_{A_i}	authority of a node i
C_{BT_i}	betweenness centrality of a node i
C_{C_i}	closeness centrality of a node i

C_{E_i}	eigenvector centrality of a node i
C_{H_i}	hub centrality of a node i
C_{NET}	total costs generated by a network
C_{R_i}	radiality of a node i
$D_{i,t}$	customer demand of an agent i in week t
d_{ij}	geodesic distance between nodes i and j
$EL_{i,t}$	expected losses (forecasted demand) of an agent i in week t
FR_i	unit fill rate of an agent i
FR_{NET}	average unit fill rate of a network
$G(n,p)$	random network model
$I_{i,t}$	on-hand inventory of an agent i in week t
$IO_{i,t}$	indicated order of an agent i in week t
k_i	degree of a node i
k_i^{in}	in-degree of a node i
k_i^{out}	out-degree of a node i
l	mean geodesic distance
$L_{i,t}$	loss flow of an agent i in week t
m	number of links
mdt	mailing delay time
N	number of agents
n	number of nodes
$O_{i,t}$	submitted order (control flow) of an agent i in week t

$O_{ji,t}$	order of an agent i submitted to supplier j in week t
$p(\overline{\phi})$	disruption frequency
$P(k)$	degree distribution
r	assortativity
$S_{i,t}$	net inventory (stock) of an agent i in week t)
S_i^*	desired stock of an agent i
$SA_{i,t}$	stock adjustment of an agent i in week t
$SL_{i,t}$	supply line of an agent i in week t
SL_i^*	desired supply line of an agent i
$SLA_{i,t}$	supply line adjustment of an agent i in week t
st	shipment time
$st_{j,k}$	number of geodesic paths between nodes j and k
$st_{j,k}(i)$	number of geodesic paths between nodes j and k going through i
$UD_{i,t}$	unmet customer demand of an agent i in week t
x_i	characteristic of a node i

Abbreviations

CN	complex network
CAS	complex adaptive system
CR	contingent rerouting
DC	distribution centre
FMCG	fast moving consumer goods
IM	inventory mitigation
JADE	Java Development Environment
NP	non-deterministic polynomial-time
OEM	original equipment manufacturer
SCM	supply chain management
SCR	supply chain risk
SCRM	supply chain risk management

Chapter 1

Introduction

1.1 Supply Chains as Complex Systems

Over the past decades supply chains have grown longer, became interconnected as a result of globalisation and rising cost pressures (Basole and Bellamy, 2014b, Diehl and Spinler, 2013, Garvey et al., 2015, Mizgier et al., 2013). These inter-firm dependencies are the cause of complexity implying counter-intuitive behaviour and emergence (Bezuidenhout et al., 2012).

Supply chains have been observed to share common properties with Complex Adaptive Systems (Choi et al., 2001), where a *complex system* or *network* denotes a structure that has numerous interconnected components with non-trivial interactions (Estrada, 2014, Ghadge et al., 2013, Pettit and Fiksel, 2013). Supply chains are believed to be better represented and modelled as networks rather than linear structures (Bellamy and Basole, 2013, Garvey et al., 2015). Terms "supply network" and "supply chain" are used interchangeably throughout the thesis.

1.2 Need for Supply Chain Risk Management

Complexity and uncertainty in supply chains have increased (Adhitya et al., 2009, Gaonkar and Viswanadham, 2004, Mizgier et al., 2013, Stecke and Kumar, 2009) and so has risk exposure (Harland et al., 2003, Stecke and Kumar, 2009, Wagner and Bode, 2006). Risk assessment has thus become an important part of successful supply chain management (Goh et al., 2007, Mizgier et al., 2013, Stecke and Kumar, 2009). The complexity of inter-firm relationships and higher frequency of disruptions have increased supply network vulnerability (Cagliano et al., 2012, Choi and Krause, 2006, Diehl and Spinler, 2013, Ghadge et al., 2013, Guertler and Spinler, 2015), since a failure in one supply chain entity can potentially propagate across the whole network (Basole and Bellamy, 2014a,b, Garvey et al., 2015, Yang and Yang, 2010). Under normal operations these risk interdependencies remain hidden without clear knowledge of where the vulnerability lies and make risk mitigation and monitoring challenging (Ghadge et al., 2013, Guertler and Spinler, 2015). Supply Chain Risk Management (SCRM) tools and methods rarely consider effects of risk management actions on the extended supply network, focusing mostly on the local perspective. Moreover, these tools were designed when supply chains were relatively stable and do not account for current volatility (Christopher and Holweg, 2011). There is a need for better methods to identify, measure and mitigate risks (Schmitt and Singh, 2012, Stecke and Kumar, 2009, Wagner and Neshat, 2012) that include extended supply chain interdependencies (Juttner et al., 2003). Christopher and Holweg (2017) argue that instead of eradicating the volatility completely the focus should be put on designing the supply chain structure so that it mitigates risk.

1.3 Thesis scope

Due to increased supply chain risk exposure and lack of managerial focus on extended supply chain, there is an emerging need for understanding the role that network topology plays in defining supply chain resilience. This thesis builds on complex adaptive systems theory and supply chain risk management, to identify how extended supply chain topology affects supply chain's ability to absorb disruptions and how effective are risk management strategies in reducing impact of disruptions. The considerations about resilience are extended further, by investigating how network's ability to withstand disruptions is affected if only specific suppliers have capabilities to apply risk management strategy. To capture complex interaction between suppliers and emulate disruptive scenarios in an extended supply chain setting, a simulation is developed as a part of the thesis.

1.4 Thesis Outline

The thesis is structured as follows. First, literature review is carried out to present common approaches to supply chain risk, including what risks supply chains face and what SCRM practices exist. Furthermore, as extended supply chains are shown to be better represented as networks rather than linear structures, interdisciplinary field of network science is studied as a tool for analysing topology of supply networks in the context of supply chain risk. Considerations about risk management are extended to complex supply networks and the knowledge gap is highlighted.

Knowledge gap leads to Chapter 3, presenting aim, objectives of the thesis, research methodology, and design of experiments. This chapter explains how objectives address knowledge gap. Research methodology presents tasks carried out in the thesis to fulfil research aim, and explains the choice of agent-based simulation as a methodological tool for experimentations. Design of experiment section discusses the main variables that are considered in this work: topologies, risk profiles, management strategies, risk management strategy level and targeting strategies. Chapter 4 focuses on design, implementation and validation of a simulation method suitable to emulate real-world scenarios in the extended supply network setting. Simulation consists of four main components: (a) agent-based model; (b) generic stock management structure; (c) disruptions module; and (d) implementation of risk management strategies.

Chapters 5, 6, 7 and 8 contain experiments carried out to fulfil research aim. Chapters 5 and 6 present how supply network topologies absorb disruptions and how effective are risk management strategies in reducing impact of disruptions with varying the risk profile and the level at which specific strategy is implemented. Chapters 7 and 8 focus on understanding whether choosing specific suppliers embedded in the supply network to apply risk management strategies can benefit the whole system. The thesis is finalised with Chapter 9 summarising the findings, highlighting contribution to knowledge, and suggesting further extensions to the work carried out. Thesis outline is presented in Figures 1.1 and 1.2.

Figure 1.1: Thesis outline for Chapter 2: Literature Review.

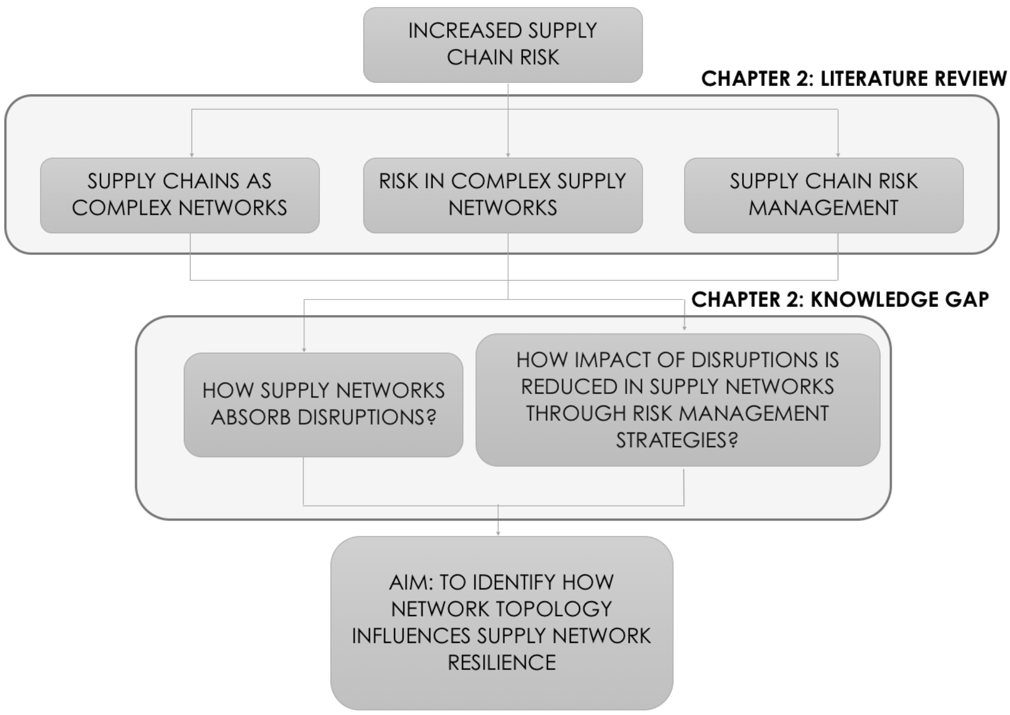
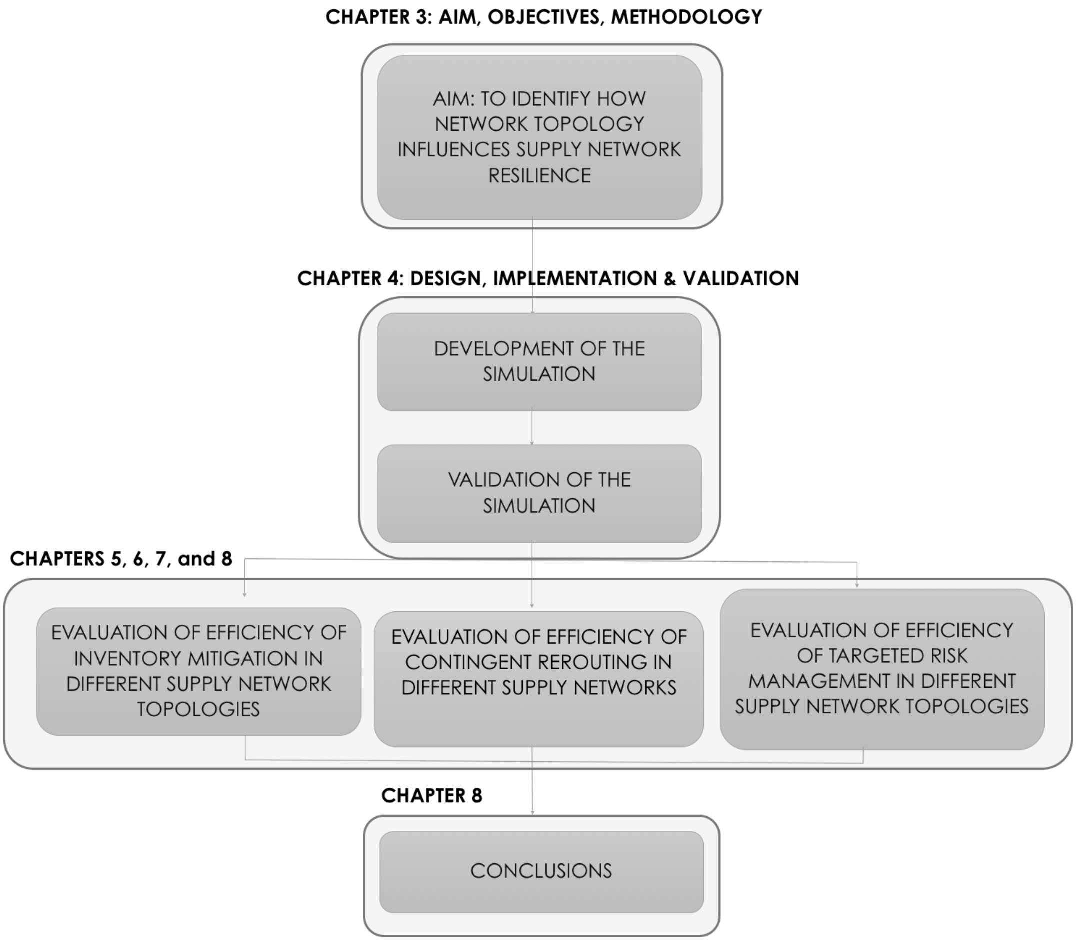


Figure 1.2: Thesis outline for Chapters 3, 4, 5, 6, 7 and 8.



Chapter 2

Literature Review

A *supply chain* can be defined as a set of companies that share the production and delivery responsibility of the material flow, from raw materials to the finished product delivered to end-users (Londe and Masters, 1994). Over the years supply chains have grown, to provide products and services globally rather than locally. Globalisation resulted in increased competition, which led to pressure to decrease costs through practices, such as reducing inventory or supplier base, outsourcing, or factories tending to focus on core capabilities (Adhitya et al., 2009, Akyuz and Erkan, 2010, Chopra and Meindl, 2010, Diehl and Spinler, 2013, Kleindorfer and Saad, 2005, Mizgier et al., 2013, Vlajic et al., 2013). Global sourcing encouraged to locate manufacturing in sites in few places in the world, which made companies vulnerable to disruptions such as natural disasters and terrorism (Kleindorfer and Saad, 2005). The complexity of supply chains have resulted in volatility and increased exposure to risk (Christopher and Holweg, 2011).

The list of highly visible incidents that severely affected the continuity of supply chain operations includes: Kobe earthquake (1995), fire in Philip's plant in 2000, 9/11 terrorist attack (Sheffi, 2005), hurricane Katrina (2005), Tohoku earthquake (2011) and Thailand flooding (2011). Two of these disasters are detailed below.

Tohoku earthquake has occurred in Japan on the 11th March 2011, recorded to have the magnitude of 9.0 and being classified as one of the most powerful ones in Japan's and World's history. The tragedy was magnified by following tsunamis and nuclear facilities failure, resulting in the highest death toll caused by an earthquake in a developed country and giving economic losses of over $300 billion USD (Canis, 2011). Electricity shortages across the country affected not only Japan's production, but had an international impact since overseas companies relied upon timely deliveries of goods from Japan. The combined impact of the earthquake, tsunamis and nuclear facilities failure affected the automakers such as Volkswagen, BMW, Toyota and GM, and the electronics producers including Renesas, Panasonic, Toshiba and Hitachi[1].

In the period of July - November 2011, following Japan's tragedy in Tohoku, in Thailand occurred an excessive rainfall. The rainfall resulted in flooding, which has been characterised as the fourth most expensive disaster until 2011, surpassed only by Kobe earthquake (1995), hurricane Katrina (2005) and Tohoku earthquake (2011). The economic losses has been estimated as $45.7 billion USD (Koontanakulvong and Santitamnanon, 2013). The flooding affected Western Digital's (WD) plant, causing severe shortages of hard drives across the world. The international market has been affected because Thailand was accounted for 40% of global hard drive assembly[2]. The multitude of events that threat the supply chain bring to attention the shortcomings of prioritising supply chain efficiency with just-in-time practices, and neglecting supply chain risk (Goh et al., 2007, Mizgier et al., 2013, Stecke and Kumar, 2009).

This chapter is focused on the importance of considering supply chain risk in business plans and operations, and presents methods to deal with that risk. First, the term risk is defined and various risks that supply chains face today are given. Next, the concept of Supply Chain Risk Management (SCMRM) is described as the set of tools and methods that deal with supply chain risk. These methods can be separated into categories: identification, assessment, implementation and monitoring. The thesis considers mostly risk assessment and risk implementation processes, therefore particular attention to these was paid in the literature review.

Nowadays supply chains are no longer linear, they have evolved into networks consisting of multiple interconnected entities. Current risk management methods have in mind supply chain linearity, therefore perform poorly when applied to supply

[1]https://www.newscientist.com/blogs/shortsharpscience/2011/03/powerful-japan-quake-sparks-ts.html, accessed on 12^{th} January 2017

[2]http://spectrum.ieee.org/computing/hardware/the-lessons-of-thailands-flood, accessed on 12^{th} January 2017

networks. The systemic risk concept is presented as the risk of an event affecting multiple interconnected entities. The methods drawn from network science and applied having in mind systemic risk are shown to be a successful proxy in assessing risk in a supply network. Next, well-known strategies for risk management are presented. However, it is not known what is the effectiveness of these risk management methods applied in a supply network, which is highlighted by the knowledge gap section at the end of the chapter.

The literature review process was performed by searching Scopus, Science Direct and Web of Science databases. Two themes informed the literature review: identification of risks and challenges that supply chains face today, and identification of supply chain risk management strategies to deal with the risks identified. To understand the risks and challenges of supply chains, and get an understanding of the supply chain risk management process the following keywords were used: *supply chain risk management*, *supply chain risk assessment*, *supply network risk assessment*, *supply network risk management*, and *supply chain risk identification*.

Articles were selected based on the relevance to the topic captured in the abstract, and quality of the journal. Since this thesis is concerned with topology, the review further focused on risk management in complex supply networks. In order to understand how to manage the risk in a complex system, the literature has been expanded beyond the field of supply chain management with the special attention to network science literature. Databases were searched for *robustness*, *resilience*, *supply chain robustness*, *supply chain resilience*, and *complex supply network*. Journals were selected based on their abstract's relevance to the topic with the specific focus on supply chains being seen from the complex system perspective, and understanding how risk is analysed and managed in systems beyond supply networks. To identify strategies that companies apply to manage the risk, databases were searched for *supply chain risk management*, *supply chain risk mitigation*, *supply chain contingency*, *inventory mitigation*, *safety stock*, *contingent rerouting*, and *rerouting* keywords. Articles were selected based on their abstract, having in mind whether the paper contains a discussion on evaluation of the performance of risk management strategy, preferably in a complex network setting.

2.1 Risks that supply chains face today

Risk has been defined as the variability from the possible outcomes (March and Saphira, 1987); and a measure that enables to evaluate the potential losses (Scholz et al., 2012, Scholz and Siegrist, 2010). A similar approach has been adopted by Juttner et al. (2003), where the risk is "the variation in the distribution of possible supply chain outcomes, their likelihood and subjective values". Another popular definition defines risk as a product of probability and severity, where probability refers to probability of the event to occur, and severity as the negative business impact (Christopher and Peck, 2004). Although the majority of the literature considers risk as a negative event, some sources recognise that risk could be seen as an opportunity (Diehl and Spinler, 2013). Risk that is seen as an opportunity will not be considered in this thesis, as the main focus is on the negative consequences of the disturbances.

The risk, being a threat for the system under consideration, is closely related to *vulnerability*. Being vulnerable, according to the Oxford English Dictionary, is defined as:

> "*exposed to the possibility of being attacked or harmed, either physically or emotionally*" (Stevenson, 2010, p. 1992)

A supply chain is vulnerable, when some part of it is at risk (Peck, 2005). In the Supply Chain Risk Management Literature vulnerability is defined by Svensson (2000) as:

> "*the existence of random disturbances that lead to deviations in the supply chain of components and materials from normal, expected or planned schedules or activities, all of which cause negative effects or consequences for the involved manufacturer and its sub-contractors.*" (Svensson, 2000, p. 732)

Pettit et al. (2010) links vulnerability with the susceptibility to disruptions. Similarly, Sheffi and Rice (2005) write that reducing vulnerability means reducing the likelihood of disturbances. Svensson (2002) highlights that vulnerability is composed of two components: "a disturbance and the negative consequence of disturbance", and Sheffi and Rice (2005) take similar stand.

Supply chains are exposed to numerous risks, potential disturbances, which can be separated into various categories. The literature often divides risks according to their source of origin, such as environmental, network or organisational risk sources (Juttner et al., 2003). Environmental risks are uncontrollable events resulting from the external environment, such as terrorists attacks or extreme weather. Operational risks are occurring within the supply chain boundaries, therefore can be directly influenced by the organisation. They include labour strikes or IT system failures. Network-related risks refer to the effects of interconnectedness of business partners within the supply chain; examples of drivers of such risks include distorted information, or stock-outs. Juttner et al. (2003) highlight that this kind of risk can be amplified when passed on from the supplier to the customer, therefore the supply chain-wide risk awareness is of critical importance. More detailed categorisation of risks according to risk drivers, include demand risks, supply risks, product/service management risks, or legal risks (Christopher and Peck, 2004, Diabat et al., 2012, Harland et al., 2003, Manuj and Mentzer, 2008a, Oke and Gopalakrishnan, 2009). Tang and Musa (2011) categorise risks according to the type of flow, such as material, financial and information flow risks. Supply chain risk classifications are summarised in Table 2.1.

Table 2.1: Supply Chain Risk classification according to various sources

Reference	**Risk Categories**
Juttner et al. (2003)	environmental risks, network risks, organisational risks
Harland et al. (2003)	strategic risks; operations risks; supply risks; customer risks; asset impairment risks; competitive risks; reputation risks; financial risks; fiscal risks; regulatory risks; legal risks

Table 2.1 – *Supply Chain Risk classification according to various sources*

Reference	**Risk Categories**
Chopra and Sodhi (2004)	disruptions; delays; systems risks; forecast risks; intellectual property risks; procurement risks; receivables risks; inventory risks; capacity risks
Christopher and Peck (2004)	process risks; control risks; demand risks; supply risks; environmental risks
Kleindorfer and Saad (2005)	operational contingencies; natural hazards, earthquakes, hurricanes and storms; terrorism and political instability
Manuj and Mentzer (2008a)	supply risks; operational risks; demand risks; security risks; macro risks; policy risks; competitive risks; resource risks
Wagner and Bode (2008)	demand side risks; supply side risks; regulatory, legal and bureaucratic risks; infrastructure risks; catastrophic risks
Oke and Gopalakrishnan (2009)	supply risks; demand risks; miscellaneous risks increasing costs-of-doing-business
Tang and Musa (2011)	material flow risks; financial flow risks; information flow risks
Diabat et al. (2012)	macro-level risks; demand management risks; supply management risks; product/service management risks; information management risks

According to World Economic Forum (2012), the top external risks are natural disasters, conflict and political unrest, sudden demand shocks, export/import restrictions, and terrorism; the top network-related problems are reliance on oil, availability of shared data/information, fragmentation along the value chain, extensive subcontracting and supplier visibility. Dobie (2015) report that natural disasters, accidents, political, economic and security threats are the most worrying issues in current times. Juttner et al. (2003) highlight that vulnerability in supply chains has increased resulting in problems like labour strikes, terrorism and epidemics.

2.2 Supply Chain Risk Management

The multitude of risks necessitates diverse methods to deal with them. These methods and practices are gathered under the term *Supply Chain Risk Management* (SCRM), which is defined as:

> "*the identification and management of risks for the supply chain, through a co-ordinated approach amongst supply chain members, to reduce supply chain vulnerability as a whole*" (Jüttner, 2005, p. 124)

Tuncel and Alpan (2010) have distinguished four phases of SCRM:

1. *Risk identification*, which is a process of recognition of potential risks. Supply chain risks has been identified and classified by Chopra and Sodhi (2004), Christopher and Peck (2004), Diabat et al. (2012), Harland et al. (2003), Kleindorfer and Saad (2005), Manuj and Mentzer (2008a), Oke and Gopalakrishnan (2009), Tang and Musa (2011), Wagner and Bode (2008).

2. *Risk assessment*, which is a process of evaluation of the probability of risk to occur and its consequences. An example of risk assessment methods are conceptual frameworks (Pettit et al., 2010, Scholten et al., 2014). However these are usually subjective and time-consuming. Other methods include risk optimisation or modelling. Roncoli et al. (2013) developed a model for minimising transportation risk. Raj et al. (2015) developed a method measuring resilience using Cox-PH model. These approaches are usually NP-hard (Zhao et al., 2011), and become computationally expensive as supply networks can reach to thousands of nodes and tens of thousands of links (Kito et al., 2014).

3. *Risk management implementation*, which can be separated into risk mitigation and contingency (Tomlin, 2006). *Risk mitigation* are actions that aim at reducing the probability of the risk to occur, or minimise risk consequences.

Contingency actions are focused on reducing the impact of the risk that has already materialised. For example, Tomlin (2006) and Dong and Tomlin (2012) assessed performance of inventory mitigation and contingent rerouting strategies. Qi and Lee (2015) evaluated drawbacks and advantages of expedited shipping.

4. *Risk monitoring*, which is a process of continuous risk detection. For example, Fernandez et al. (2015) developed a supply chain disruption monitoring service using an agent-based model.

The categorisation of SCRM into different phases is presented also by Juttner et al. (2003), where four phases are identified: assessing risk sources, defining risk consequences, tracking risk drivers, and mitigating risks. A separation of SCRM into five steps, adopted from Manuj and Mentzer (2008a), is as follows:

1. *Risk identification*, which includes classification of risks into supply, operations, demand, and security
2. *Risk assessment and evaluation*, which includes estimating risk probability distributions when historical data is available, or questionnaires when such data in unavailable
3. *Selection of appropriate risk management*, where strategies might include avoidance, postponement, speculation, hedging, control, sharing/transferring, and security.
4. *Implementation of supply chain risk management strategy*, which includes the following enablers of risk strategy implementation: complexity management, organisational learning, information technology, and performance metrics
5. *Mitigation of supply chain risks*, which includes preparing for unforeseen risk events

Hallikas et al. (2004), similarly to Tuncel and Alpan (2010), separates risk management into: risk identification, risk assessment, decision and implementation of risk management actions, and risk monitoring.

Finch (2004), Adhitya et al. (2009) and World Economic Forum (2012) highlight the importance of SCRM practices to maintain operational supply chains. Risk management in a supply chain context brings numerous benefits, including better decision-making, lower operating costs, and optimised insurance coverage and insurance premium (Auer et al., 2014).

Risk and vulnerability are multidisciplinary terms, which have been used in the context of supply chains for long time (Chopra and Sodhi, 2004, Juttner et al., 2003, Svensson, 2000). Recently, the discussion has been extended to concepts of robustness and resilience, which are constructs adopted from fields of ecology, psychology and engineering (Ponomarov and Holcomb, 2009).

The Oxford English Dictionary defines the term *robust* as:

> "*(Of a system, organisation, etc.) able to withstand or overcome adverse conditions*" (Stevenson, 2010, p. 1537)

Robustness, as defined in ecology literature, is the reduced sensitivity of a system's output to shocks (Anderies et al., 2013). A robust immune response system is able to resist a disease even when the small part of the system is not active (Chowdhury and Chakrabarti, 1990).

In operations management, robust supply chain is a system that is able to resist disruptions and still operate without reorganising (Aven, 2011, Scholz et al., 2012, Wieland and Wallenburg, 2012). According to Goetschalckx et al. (2012), robustness is:

> "*The capability of the supply network to adapt to (...) changing conditions and execute its function efficiently under a variety of future conditions*" (Goetschalckx et al., 2012, p. 121)

As Goetschalckx et al. (2012) mentions the adaptation to changing conditions, Aven (2011) highlights that adaptation is restricted to known treats and disruptions. Aven (2011), Scholz et al. (2012), Wieland and Wallenburg (2012) state that the system does not need to reorganise to be able to maintain properties of being robust, whereas Brandon-Jones et al. (2014) highlight that this change is sometimes required to maintain functionality.

The Oxford English Dictionary defines the term *resilient* as:

> "*(Of a system, organisation, etc.) able to withstand or overcome adverse conditions*" (Stevenson, 2010)

In ecology, *resilience* is defined as the ability to persist the relationships within the ecological system and absorb changes (Holling, 1973). In the supply chain literature resilience is seen as the capability of the system to go back to its stable state after the disruption (Sheffi, 2005); the ability to absorb shocks and reorganising its structure according to circumstances; readiness of the system to deal with unknown risks (Scholz et al., 2012). Resilience is seen as a broad concept that includes flexibility, robustness and adaptation (Soni et al., 2014). Many sources identify the speed of system reorganisation and adaptation to changing circumstances as a key component of resilience (Aven, 2011, Sheffi, 2005). Peck (2005) defines resilience as:

> "*ability of the system to return to is original or desired state after being disturbed*" (Peck, 2005, p. 221)

Aven (2011) defines the term as following:

> "*[Resilience] is defined as the ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time, and composite costs, and risks.*" (Aven, 2011, p. 515)

According to Christopher and Peck (2004), resilience is "the ability of a system to return to its original state or move to a new, more desirable state after being disturbed".

Often, robustness and resilience are treated simultaneously, which makes it hard to draw accurate boundaries between these two terms. As Anderies et al. (2013) writes:

> "*Are robustness and resilience the same? The short answer is yes and no.*" (Anderies et al., 2013, p. 5)

In the SCRM literature, both robustness and resilience are accounted for the ability to adapt to the changing circumstances; although a resilient system is a system which is not only able to adapt, but also to reconfigure to a new state after being exposed to disruptions (Asbjornslett, 1999). The literature highlights the significance of time in the change process, as a resilient system should be able to undergo the changes within an acceptable time-frame. Juttner and Maklan (2011) relate risk, vulnerability, supply chain risk management, and resilience as follows: vulnerability is the susceptibility of a supply chain to disruptions; and SCRM is a set of techniques aiming to reduce this vulnerability, increase resilience, manage and mitigate risks.

During recent decades supply chains became global and intertwined, increasing their complexity and risk exposure. In this context the term *complexity* denotes a structure that has numerous interconnected components with non-trivial interactions (Ghadge et al., 2013, Pettit and Fiksel, 2013). In a complex topology risks resulting from complexity and infrastructure are believed to be of higher threat than the other ones (Pettit and Fiksel, 2013).

SCRM literature shows that structural characteristics of supply chains significantly influence vulnerability, highlighting an importance of supply network topology (Adenso-Diaz et al., 2012, Craighead et al., 2007, Juttner et al., 2003, Wagner and Neshat, 2010), supplier-customer dependencies (Peck, 2005, Wagner and Neshat, 2012), network density and criticality of supply chain members (Craighead et al., 2007). Mari et al. (2015) proxied supply network resilience with structural characteristics of supply chains. This fact necessitates extended supply network visibility, where the term *extended* refers to visibility beyond direct business partners. There is a need for better methods to identify and measure risks (Stecke and Kumar, 2009, Wagner and Neshat, 2012), including supply chain interdependencies (Juttner et al., 2003). The following sections describe approaches to extended supply chain risk management.

2.3 Supply chain as the complex network

Supplier-buyer relationships for many years were considered mainly as dyads. When supply chains have grown, it has been shown that suppliers and buyers are interdependent and influence each other's decision-making. For example, buyer can exert pressure on its suppliers and make them cooperate or compete (Wilhelm, 2011). However, supply chains are no longer linear and they have become *Complex Adaptive Systems* (CAS), emerging without a single entity controlling it (Choi et al., 2001). It has been proposed that supply chains are better represented as *networks* (Choi and Wu, 2009), rather than a linear chain.

2.3.1 What is a network?

According to Newman:

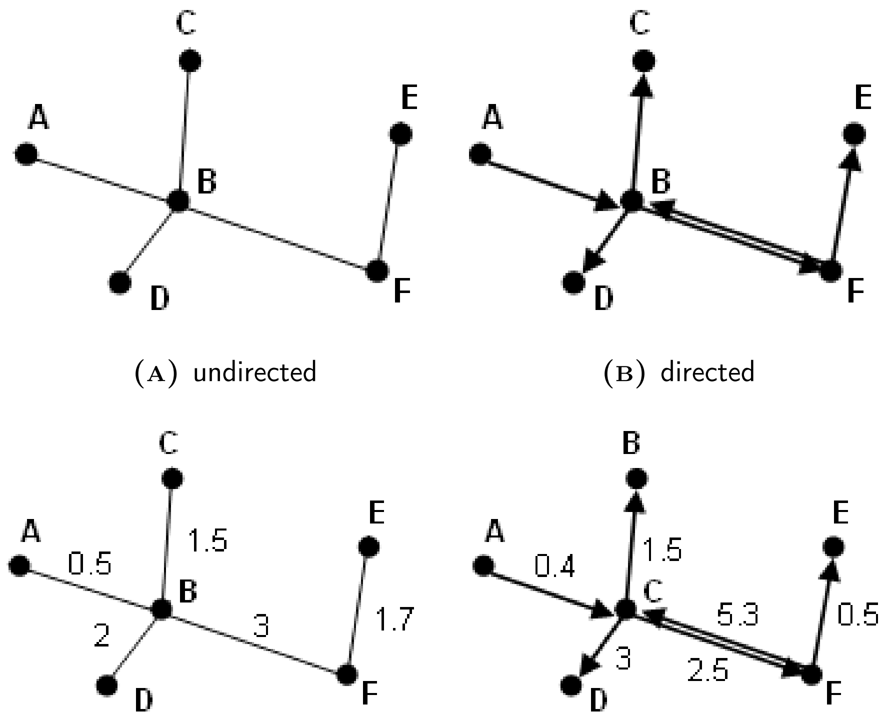
> "*A network is, in its simplest form, a collection of points joined together in pairs by lines.*" (Newman, 2010, p. 1)

A network is an abstract representation of the system, where nodes refer to elements of this system, and links represent relationships between these elements. There are various examples of ways of representing a network: undirected, directed networks, weighted, and many others (Figure 2.1).

An undirected network represents a system with relations in both directions. A link between a node A and B implies that there is a link from A to B, and from B to A (Figure 2.1 A). In a directed network, the relationship have a direction. A link from A to B, does not imply that there is a link from B to A (Figure 2.1 B). In a weighted network there is a numerical value defining either the relationship between two nodes, or the node itself (Figures 2.1 C and 2.1 D). For example, in a social network the weight associated with a node could be a person's age or social status, and a weight associated with a link could be the number of years that two people have known each other.

Examples of real world networks are: the Internet (Faloutsos et al., 1999), transportation networks (Kansky, 1963), social networks (Milgram, 1967, Travers and

FIGURE 2.1: Network types



(A) undirected

(B) directed

(C) undirected weighted

(D) directed weighted

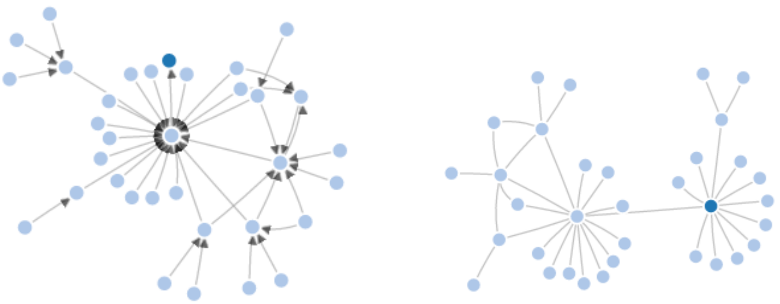
Milgram, 1969), protein-protein interaction networks (Jeong et al., 2001), neural networks (White et al., 1986), food webs (Cohen, 1989) and many others. Networks are studied to capture the patterns of interactions, which have significant effect on behaviour of the system. Milgram's study on the social friendship networks in America resulted in discovery of *small-world effect*. Small world implies that any person in the world can be reached from any other person by following the net of its acquaintances in fewer steps compared to randomly organised network of the same size (Milgram, 1967). This property of the social network has been called six degrees of separation. White et al. (1986) analyse brain of *C. elegans*, network of less than 300 neurons, revealing the structure of the neural network of an organism. Another study by (Faloutsos et al., 1999) reveals that the Internet consists of few highly connected nodes, called *hubs*, and many poorly connected ones.

Analysis of supply chains through lens of network science is a relatively new concept, starting from Choi et al. (2001), Borgatti and Li (2009), and Lomi and Pattison (2006) claiming that supply chains are CASs and that network science is appropriate for supply chain analysis. The broad picture of the supply network has not been revealed for a long time. Analysis beyond direct customers and suppliers was difficult due to long and laborious data collection. First examples of empirical studies on the large-scale include Brintrup et al. (2016, 2015), Choi and Hong (2002), Kim et al. (2011), Kito et al. (2014). Figure 2.2 A presents Honda Acura's material flow, where each node corresponds to a single supplier and each link corresponds to the flow of products from the supplier to the customer. Figure 2.2 B is an undirected network presenting Honda Acura's contractual flow, where a link between two nodes indicate that there is a business relation between two connected suppliers. Both networks are empirical examples taken from Choi and Hong (2002) and Kim et al. (2011).

2.4 Systemic risk in complex supply networks

Supply networks can comprise thousands of suppliers (Basole and Bellamy, 2012, Brintrup et al., 2016, 2015), implying that a disruption that originates in one supply chain entity can affect other upstream or downstream companies. These interdependencies necessitate increased risk awareness beyond direct suppliers and customers.

Figure 2.2: Directed material flow and undirected contractual network of Honda Acura. Honda is marked by dark blue.



(a) Honda Acura's material flow (b) Honda Acura's contractual flow

The idea of local risk is thus replaced by the concept of systemic risk, which is defined as:

> *"the risk of having not just statistically independent failures, but interdependent, so-called 'cascading' failures in a network of N interconnected system components"* (Helbing, 2013).

Systemic risk analysis techniques involve relating topology to cascading failures by asking questions such as: *Who is most likely to fail in a given system?*, *Who will fail next if x fails?*, and answer them utilising tools taken from field of network science (Vespignani, 2012, Watts, 2002). The *topology* is a specific connection pattern, in which suppliers of multiple tiers are tied together. Studies on network topology, regarded as *network science*, unveil systems' behavioural phenomena, which cannot be well understood from the perspective of a single entity. Systemic risk assessment has become popular in financial systems mainly after the 2008 financial crisis (Chen et al., 2013, Hu et al., 2012, Zhang et al., 2014). The systemic risk concept is one of many network science topics, regarded from the network-level and node-level perspectives.

2.4.1 Network-level metrics

Network-level metrics analyse characteristics of the overall system, and include methods such as cascading failures, percolation or epidemiology. It has begun with the field of social sciences and biology, where phenomena such as *information cascades*, *diffusion of innovations* or *spread of diseases* are studied. In these systems an individual in a society is able to influence other's behaviour, decisions, beliefs (Banerjee, 1992, Easley and Kleinberg, 2010) or health (Coleman et al., 1996). Other methods originate from graph theory, which is the origin of network science. The methods incude mean degree, mean geodesic distance (Correa and Yusta, 2013, Correa-Henao and Yusta-Loyo, 2015, El-Rashidy and Grant-Muller, 2014), degree distribution (Laxe et al., 2012, Tang, 2013), clustering coefficient (Tang, 2013), transitivity, and assortativity (Newman, 2010).

2.4.1.1 Cascading failures

Cascading failure happens when a disruption in one node triggers failures in neighbouring nodes (Tang et al., 2016, Zeng and Xiao, 2014, Zhu et al., 2014). The concept of cascading failures has been applied across range of domains such as transportation networks (Zhao et al., 2015), power-grids (Zhu et al., 2014) or supply networks (Tang et al., 2016, Zeng and Xiao, 2014). It was observed that cascades in many systems happen rarely, yet with surprisingly high impact. Also, cascading failures are more likely to occur in certain topologies (Watts, 2002). There are multiple risk propagation models available in the literature (Lorenz et al., 2009).

2.4.1.2 Epidemiology

Another view on systemic risk in complex systems can be taken from *epidemiology*, the science of understanding the propagation of infectious diseases. It has been applied across numerous disciplines ranging from biological systems, power-grid failures or computer viruses spread. Epidemiology studies how network topology influences propagation of a disease and answers the question what is the possibility of an outbreak in the system (Newman, 2010). It expanded its view from disease spread to systemic risk profiles, especially in financial networks studying unexpected shocks and bankruptcy propagation (Battistion et al., 2007, Gai and Kapadia, 2010). In supply networks, Hertzel et al. (2008) studied the effects of customer and supplier bankruptcy; Basole and Bellamy (2014b) used classical epidemic model to measure risk diffusion in supply networks.

2.4.1.3 Percolation

Percolation is the process of removing some part of the network: nodes, links or both (Dinh and Thai, 2010), to determine network robustness and resilience (Newman, 2010), but can be successfully applied as a systemic risk proxy. It has been used in numerous applications including networks in general (Trajanovski et al., 2013), communication networks (Jorgic et al., 2004) and supply chains, where Thadakamalla et al. (2004) and Zhao et al. (2011) used percolation for supply network survivability and resilience assessments.

2.4.1.4 Mean degree

The connection patterns of nodes and links are represented by an *adjacency matrix* A_{ij}, where A_{ij} is equal to 1 when the node j is connected to node i (Equation 2.1).

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge from } j \text{ to } i \\ 0 & \text{otherwise.} \end{cases} \tag{2.1}$$

The number of connections the single node has is called a *degree* k and is represented by sum of corresponding adjacency matrix entries (Equation 2.2), where n indicates number of nodes.

$$k_i = \sum_{j=1}^{n} A_{ij} \tag{2.2}$$

In directed networks, the node has *in-degree* k_i^{in} and *out-degree* k_j^{out}, which correspond to incoming and outgoing connections, respectively (Equations 2.3 and 2.4).

$$k_i^{in} = \sum_{j=1}^{n} A_{ij} \tag{2.3}$$

$$k_j^{out} = \sum_{i=1}^{n} A_{ij} \tag{2.4}$$

The average of node degrees in the network is denoted by *mean degree* c (Equation 2.5).

$$c = \frac{1}{n}\sum_{j=1}^{n} k_j \tag{2.5}$$

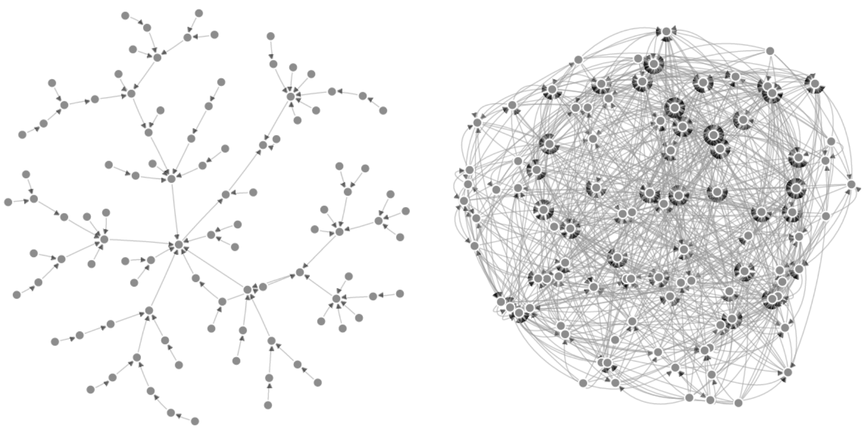
The mean degree defines how many connections there are on average between nodes. When the mean degree is low, the network is *sparse* implying lowly interconnected network; when it is high, the network is *dense* implying highly interconnected network. Theoretical results highlight that more densely connected biological networks are more robust than sparse topologies (Siegal et al., 2007, Wagner, 1996), although there is an empirical evidence that biological networks with sparse connectivity patterns also exhibit robustness (Leclerc, 2008). Examples of sparse and dense networks are presented in Figure 2.3.

2.4.1.5 Transitivity

Transitivity, also called *clustering*, is a measure of immediate connectivity; in social networks would imply how likely it is that a friend of my friend is also my friend. If there are nodes u, v and w in the network, the connected triple is a relation where there is a connection between nodes u and v, v and w, but there does not have to be necessarily a connection between v and w (Figure 2.4 A). A triangle (Figure 2.4 B) is a relation where all nodes u, v and w are connected (a friend of my friend is also my friend). Transitivity counts the number of triangles divided by the number of triples (Equation 2.6).

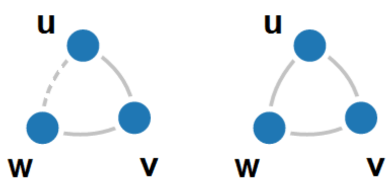
$$C = \frac{\text{(Number of triangles)} \times 3}{\text{(Number of connected triples)}} \tag{2.6}$$

FIGURE 2.3: Sparse and dense network topologies



(A) sparse network ($c = 1$) (B) dense network ($c = 8$)

FIGURE 2.4: Triples and triangles in a network



(A) triple (B) triangle

Triangles in a cause-and-effect network have been identified to result in increased supply chain complexity (Bezuidenhout et al., 2012).

2.4.1.6 Assortativity

Assortativity is a measure of connection patterns with regard to their similarity; whether nodes tend to connect to other nodes with similar properties. For example, in social networks we tend to be friends with people that are somewhat similar to us, have the same age, beliefs or nationality (Newman, 2010). The *assortativity coefficient* r denotes whether nodes in the network connect to other nodes with similar characteristic x (Equation 2.7).

$$r = \frac{\sum_{ij}(A_{ij} - \frac{k_i k_j}{2m})x_i x_j}{\sum_{ij}(k_i \delta_{ij} - \frac{k_i k_j}{2m})x_i x_j} \tag{2.7}$$

Assortativity coefficient is composed of adjacency matrix A_{ij}, degree k, number of links m, numerical characteristic x_i, and Kronecker delta δ_{ij}. δ_{ij} is equal to 1 if $i = j$, 0 otherwise. The coefficient is in the range of -1 to 1, where 1 indicates high assortativity and -1 denotes high disassortativity. Disassortativity is regarded as pattern where nodes tend to connect to other nodes with distinct characteristics. For example, in a material flow of a supply network, high assortativity would imply large firms sourcing from large suppliers rather than small enterprises.

2.4.1.7 Mean geodesic distance

The *mean geodesic distance* l is the average of the shortest path lengths d_{ij} between all nodes in the network. The geodesic distance between node i and j is denoted by d_{ij} (Equation 2.8). It indicates how long one needs to travel on average from one node to another in the network. The smaller the mean geodesic distance, the shorter the average distance between nodes (Newman, 2010). In a supply network, a mean geodesic distance indicates the average path goods travel, and if short it is associated with high responsiveness and increased robustness (Nair and Vidal, 2011). Reniers et al. (2012) have developed a systemic risk index based on the mean geodesic distance.

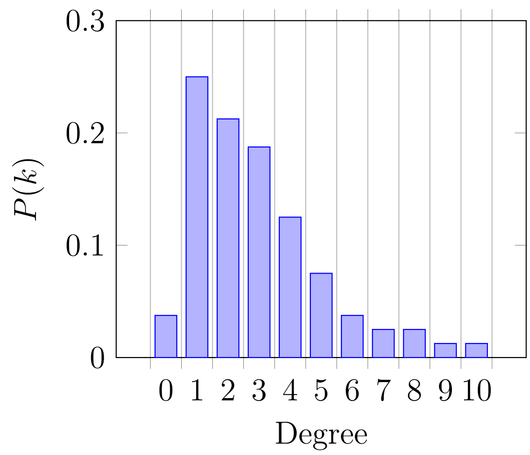
$$l = \frac{1}{n^2} \sum_{ij} d_{ij} \tag{2.8}$$

2.4.1.8 Degree distribution

Until two decades ago, theoretical studies assumed that the topological properties of the majority of real world networks were random in nature (Barabasi, 2009). Mapping large-scale structures of networks such as the World Wide Web revealed that not only the connectivity patterns are not random, but also that the way nodes are wired with each other gives rise to unique system characteristics (Barabasi, 2009). Particular attention has been given to degree distribution, which defines the probability of a randomly selected node having a certain number of connections with its neighbours (Newman, 2010). Figure 2.5 presents the exemplary degree distribution P_k, indicating that there is 0.25 probability that the node randomly chosen from this specific network will have a degree equal to one. The degree distribution is the most commonly used measure determining topological properties of complex systems (Newman, 2005) and a key feature that determines their vulnerabilities (Barabasi, 2009, Watts, 2002) including vulnerability of supply chains (Basole and Bellamy, 2014a, Nair and Vidal, 2011, Zhao et al., 2011). Two most characteristically distinct network topologies based on degree distribution are:

- *random networks*, which are networks with Poisson degree distribution. There are two popular models: G(n, m) and G(n, p), where the latter is referred to as the *Erdős Renyi* random graph. G(n, m) is a model which assumes that m links are placed amongst n nodes at random; G(n, p) network assumes that connections between n nodes are chosen according to the probability p (Newman, 2010).
- *scale-free networks*, which are networks with power-law degree distribution. They consist of "hub" nodes that have very large number of connections, and many small nodes, which connect to these "hubs". The degree, to which nodes can obtain links, has an exponential relationship to the number of a node's

Figure 2.5: Degree distribution *P(k)* of a network



existing links. There are numerous examples of networks that exhibit scale-free properties, such as physical internet or World Wide Web (Barabasi and Albert, 1999).

There is an ongoing debate regarding the nature of supply network topology. Few theoretical studies consider supply networks as scale-free (Hearnshaw and Wilson, 2013, Thadakamalla et al., 2004), whereas empirical observations do not support this claim (Brintrup et al., 2016, 2015, Kito et al., 2014). Brintrup et al. (2015) and Brintrup et al. (2016) mapped the empirical networks of global automotive industry and Airbus supply network: The global automotive network displayed an exponential distribution, which means there is a limitation to which the hubs can grow; whereas the Airbus network had too small sample size to determine significant patterns in scale. The scarcity of empirical examples and their conflicting results prevent one from opting for methods that depend on a priori assumptions on topology.

These models inherit different properties that lead to various strengths and weaknesses (Kim et al., 2015). Random networks are vulnerable against random disruptions and robust against targeted ones. Scale-free networks are vulnerable against targeted disruptions and robust against random disruptions (Barabasi and Albert, 1999). These claims have been supported by the supply chain literature (Nair and Vidal, 2011, Thadakamalla et al., 2004, Zhao et al., 2011). Kim et al. (2015) state that the closer the supply network degree distribution to power-law, the more resilient supply network is. Thadakamalla et al. (2004) and Zhao et al. (2011) removed supply nodes in a process called percolation and observed increased robustness of scale-free topologies to random disruptions. Nair and Vidal (2011) linked topology with network's ability to reduce impact of disruptions, highlighting that scale-free networks show lower vulnerability and respond quicker to disruptions.

2.4.2 Node-level metrics

Node-level metrics describe characteristics of an individual embedded in the complex system. The most common node-level methods are centrality metrics. *Centrality metrics* are statistical measures that enable one to explain the role that the node plays in the general structure of a given network (Lozares et al., 2015, Newman, 2010). In addition, there are various types of interpretations for centralities such as power, exposure, risk, control, autonomy or other (Borgatti and Everett, 2006). Centralities have been used for vulnerability and risk assessment in various fields, ranging from electrical grids and financial systems to supply networks. Borgatti and Everett (2006) mention that these metrics complement each other and are needed for creating a complete picture of various roles played by each node in the network.

2.4.2.1 Degree centrality

The *degree* of a node is the number of nodes connected to it (Newman, 2010). It depicts the connectivity and immediate chance for a node to exert its influence to the rest of the network (Wang et al., 2010). In literature the degree is associated also with prestige, status (Newman, 2010) or access to knowledge (Rana and Allen, 2015). It is represented by the Equation 2.2.

The measure has been applied in vulnerability assessment in various domains including power-grids, disease networks and supply chains. Wang et al. (2010) used degree with the domain related information to find the vulnerable nodes in power-grid network. Bell et al. (1999) used the metric to assess the vulnerability of individuals defining it is a probability of being infected by HIV. Laxe et al. (2012) linked degree with the operational capacity of each port in transportation networks. Correa and

Yusta (2013) used the measure to define the operational functionality of the power grid components, e.g. low-degree nodes are capacitors, high-degree are buses. Borgatti and Everett (2006) related to the degree centrality as the volume measure and discuss that it is associated with certainty of arrival. There are many applications for this centrality measure, which has a fair background in vulnerability assessment (Chopra and Khanna, 2014), being a good indicator of the exposure of the node to whatever is flowing through the network (Kuzubas et al., 2014, Wang et al., 2010).

In a supply chain context, degree specifies the number of business partners. It has been used to identify specific roles of firms within the supply network: integrators and allocators. An integrator is a company assembling or transforming materials into value-added products, whereas an allocator's responsibility is resource distribution (Kim et al., 2011). It has been used by Bezuidenhout et al. (2012) and Mizgier et al. (2013) for bottleneck identification, and by Dong (2006) to assess supply chain robustness.

Although a useful measure to assess the vulnerability, it might not be enough to assess the systemic risk, since it accounts only partially for network topology (Mizgier et al., 2013). Niu et al. (2015) mentioned that the degree consider limited information and there are better metrics that include the global information.

2.4.2.2 Eigenvector centrality

Eigenvector centrality measures node importance based on the importance of its neighbours (Bonacich, 1972). It is represented by Equation 2.9.

$$C'_{EI_i} = \kappa_1^{-1} \sum_j A_{ij} C_{EI_j} \tag{2.9}$$

where A is an adjacency matrix, C_{EI_i} is eigenvector centrality of the node i and κ_1 is the largest eigenvalue of the adjacency matrix.

High eigenvector centrality means that a node has more power (Kuzubas et al., 2014, Niu et al., 2015). Borgatti and Everett (2006) related eigenvector centrality with certainty of arrival and highlight the link with risk assessment. It was used in pattern analysis in fMRI data of the human brain (Lohmann et al., 2010) and applied to electric power grid for vulnerability analysis (Wang et al., 2010).

Eigenvector centrality has drawbacks when applied in directed networks, since it relies on number of in-coming or out-going links. In directed networks, the peripheral nodes usually have zero in-degree. Zero in-degree causes eigenvector centrality to converge to zero after a number of iterations. For further information, reader is directed to Newman (2010). To prevent this from happening eigenvector centrality has been modified so that a small amount of centrality β is assigned for each node. The modified version of eigenvector centrality is called Katz centrality and is presented in the Equation 2.10 (Katz, 1953).

$$C'_{K_i} = \kappa_1^{-1} \sum_j A_{ij} C_{K_j} + \beta_i \tag{2.10}$$

where C_{K_i} is Katz centrality of a node i, A is the adjacency matrix of the network, α and β are constants.

2.4.2.3 Hub and Authority Centrality

Hubs are nodes that point to many authorities. *Authorities* are nodes that are pointed to by many hubs (Kleinberg, 1999). These centralities are represented by Equations 2.11 and 2.12.

$$C_{H_i} = \beta \sum_j A_{ji} C_{A_j} \tag{2.11}$$

$$C_{A_i} = \alpha \sum_j A_{ij} C_{H_j} \tag{2.12}$$

where α and β are positive constants, A is an adjacency matrix, C_A is authority centrality and C_H is hub centrality.

Hub and authority centrality have been used in financial systems to identify which banks need a capital injection in order to stop contagious failures (Hu et al., 2012). Carlos (2013) argues that authority and hub centralities are successful proxies to measure systemic risk and are able to identify different systemic risk types: coming from the out-going and in-coming links.

2.4.2.4 Closeness centrality

Closeness centrality is the inverse of the mean distance from a node to other nodes (Newman, 2010), introduced by Bavelas (1950). It is denoted by Equation 2.13.

$$C_{C_i} = \frac{n}{\sum\limits_{j} d_{ij}} \tag{2.13}$$

where C_C is closeness centrality, n is number of nodes and d_{ij} is length of the shortest path between nodes i and j (Newman, 2010).

Closeness centrality indicates how long it takes for information to spread from the node to the rest of the network (Niu et al., 2015), and is associated with the influence on other nodes (Kuzubas et al., 2014) or independence (Rana and Allen, 2015). It is regarded as a proxy for social capital and information spread (Borgatti et al., 1998, Otte and Rousseau, 2002). Closeness centrality-like measures are natural choice when dealing with risk of something arriving on time (Borgatti and Everett, 2006). Closeness is used by Nguyen and Thai (2013) for the vulnerability analysis in the electric power network.

The highest closeness value for a company embedded in the supply chain indicates that the firm has the smallest average distance to the other parts of the network. Companies with high centrality have been classified as navigators, who collect information more autonomously (Kim et al., 2011).

2.4.2.5 Radiality centrality

Radiality centrality is a measure of how a node is connected and reachable within a network (Valente and Foreman, 1998), and is denoted by Equation 2.14.

$$C_{R_i} = \frac{\sum\limits_{j} d - d_{ij} + 1}{n - 1} \tag{2.14}$$

where d is the network diameter, d_{ij} is the length of the shortest path between nodes i and j, and n is the number of nodes.

In a supply chain context, radiality centrality denotes how closely the company is located to its partners in the neighbourhood. It is a natural choice when dealing with risk of something not arriving on time (Borgatti and Everett, 2006). Mizgier et al. (2013) used radiality to identify suppliers that if disrupted affect the most companies.

2.4.2.6 Betweenness centrality

Betweenness centrality measures the extent to which a node lies on paths between other nodes (Freeman, 1977). It can be denoted by:

$$C_{BT_i} = \sum_{j,k} \frac{st_{j,k}(i)}{st_{j,k}} \tag{2.15}$$

where $st_{j,k}(i)$ indicates number of shortest paths between j and k going through i and $st_{j,k}$ number of all shortest paths between j and k.

Betweenness centrality is associated with the global importance of the node and the influence it has over the flow in the network (Chopra and Khanna, 2014, Niu et al., 2015) including spread (Kuzubas et al., 2014) and cut-off of information (Rana and Allen, 2015). Bompard et al. (2011) argue that the higher the betweenness, the higher number of geodesic paths coming though the node and therefore higher criticality. Laxe et al. (2012) relates betweenness centrality to relative geographical importance. Nguyen and Thai (2013) use the metric for vulnerability assessment in power networks, whereas Tang (2013) for IP multimedia subsystems.

Betweenness centrality in a supply chain context might indicate companies that act as a middleman, important in passing a product from a supplier to a customer. Those companies are intermediaries, controlling the flow of goods (Kim et al., 2011). Mizgier et al. (2013) used it to identify bottlenecks in the supply network; Basole and Bellamy (2014b) used betweenness as a risk measure in their visualisation model.

2.5 Risk management strategies

There are a multitude of supply chain management techniques aiming at reducing risk exposure in supply chains. Examples of risk management strategies are presented in Table 2.2, including strategies such as safety stock, multi-sourcing strategies, information sharing, collaboration, and contingent rerouting. These strategies usually focus on adding redundancy or flexibility (Chopra and Sodhi, 2004, Talluri et al., 2013, Yang and Yang, 2010).

Supply Chain Management literature refers to supply chain risk management strategies mainly as *risk mitigation*, however in this work risk mitigation is restricted to be a strategy performed before the occurrence of the disruption. The reactive strategy, which is performed after the occurrence of the disruption to remedy the effect is called *contingency strategy*. The distinction of risk management techniques into risk mitigation and contingency is taken from Tomlin (2006).

Stecke and Kumar (2009) divides risk mitigation in proactive strategies, advanced warning strategies and coping strategies. *Proactive strategies* are actions the purpose of which is to decrease likelihood of a disruption and overall vulnerability; *advanced warning strategies* are actions aiming at predicting a disruption and preparing for it in advance; *coping strategies*' purpose is to minimise the impact of disruptions and build on flexibility and redundancy. Colicchia et al. (2010) divide management approaches into: operational buffers, mitigation, and contingency plans. Pettit et al. (2010) introduce supply chain capabilities, which are defined as "attributes that enable an enterprise to anticipate and overcome disruptions"; by increasing these capabilities the supply chain resilience increases. Although rerouting is classified as contingency strategy by Tomlin (2006), Stecke and Kumar (2009) include rerouting in coping strategies category under risk mitigation. In this thesis, the rerouting strategy is treated as a contingency strategy. Although Colicchia et al. (2010) separates additional inventory from mitigation strategies, in this thesis inventory is classified as a mitigation strategy, following the distinction made by Tomlin (2006).

Stecke and Kumar (2009) highlight the importance of applying mitigation strategies to reduce risk, as these reduce lead time and lead time variability, enhance inventory management, reduce bullwhip effect. Tang (2006) raises few concerns related to application of supply chain management strategies such as: possible additional costs related to strategy implementation; or that the strategy might not fit with the company's overall business strategy.

Table 2.2: Supply chain risk management strategies according to various sources

Reference	Risk management strategies
Juttner et al. (2003)	avoidance; control; cooperation; flexibility
Chopra and Sodhi (2004)	additional capacity, additional inventory, redundant suppliers; increase responsiveness; increase flexibility; aggregate or pool demand; increase capability; multiple customers
Tang (2006)	postponement; strategic stock; flexible supply base; make-and-buy; economic supply incentives; flexible transportation; revenue management via dynamic pricing and promotion; assortment planning; silent product rollover
Khan and Burnes (2007)	supplier collaboration; purchasing partnerships; risk sharing/knowledge transfer; strategic alliances; inventory management; focus on core competence; proactive supply management; buffers; product differentiation
Manuj and Mentzer (2008a), Manuj and Mentzer (2008b)	avoidance; postponement; speculation; hedging; control; transferring/sharing risk; security
Oke and Gopalakrishnan (2009)	better planning and co-ordination of supply and demand; flexible capacity; having contingency plans; multiple sourcing; educate customers; identification of supply chain vulnerability; cost reduction in operations; lobbying; finding alternative raw materials; managing demand

Table 2.2 – *Supply chain risk management strategies according to various sources*

Reference	**Risk management strategies**
Stecke and Kumar (2009)	proactive strategies: select safe locations, choose robust suppliers and transportation media, establish secure communication links, enforce security, use efficient human resource management; advance warning strategies: enhance visibility and coordination, increase transportation visibility, monitor weather forecasts, monitor trends; coping strategies: carry extra inventory, alternative sourcing arrangement, flexible transportation, maintain redundant critical components, standardise various processes, redesign products to pool risks.
Colicchia et al. (2010)	operational buffers: excess inventory, productive capacity, backup sourcing, multiple sourcing; mitigation: reducing risk likelihood and impact; contingency planning: business continuity management
Pettit et al. (2010)	flexibility in sourcing; flexibility in order fulfilment; increase capability; increase efficiency; increase visibility; increase adaptability; increase recovery capability; increase dispersion; increase collaboration; increase organisation capability; increase security; increase financial strength

Effectiveness of various risk management actions has been a subject of broad discussion, including effectiveness of inventory policies (Constantino et al., 2014, Kurano et al., 2014), collaboration and information sharing techniques (Constantino et al., 2014, Sarkar and Kumar, 2015, Yang and Fan, 2016), production rescheduling (Paul et al., 2015), insurance (Dong and Tomlin, 2012), order quantity optimisation (Giri, 2011, Hu and Kostamis, 2015), re-planning multi-stage supply chain (Ivanov et al., 2016), rescheduling procurement (Kirilmaz and Erol, 2016) or change of transportation modes (Colicchia et al., 2010).

Talluri et al. (2013) suggests that no strategy is a one-fits-all solution; Chopra and Sodhi (2004) highlight that while decreasing risk in one area, risk mitigation and contingency actions might increase risk in the other. Also, Harland et al. (2003) brought to attention that some risks might not be possible to eliminate, especially external ones such as political, economic or climate risks. Risk has been managed using different sets of methods, although current risk practices are developed for supply chains having in mind their hierarchical properties and simplicity. Lack of awareness on how certain risks propagate across the network creates an uncertainty about how to mitigate their effects.

2.6 Scope and knowledge gap

The study focuses on disruption risks, since these risks are often top-ranked across supply chain literature. *Disruption risks* are considered as supply chain interruptions which are unpredictable. These can be considered in two dimensions: likelihood and severity (Sheffi and Rice, 2005). Examples of low-likelihood and high-impact events are natural disasters, labour disputes, supplier bankruptcy, war, or terrorism (Chopra and Sodhi, 2004). Examples of high-likelihood and low-impact events are machine breakdowns or transportation link disruption (Sheffi and Rice, 2005). There are events that have both likelihood and impact either high or low and examples of such events include: loss of key supplier, quality problems, or computer viruses. Hendricks and Singhal (2005) showed in his study on 827 disruptions between 1989 and 2000, that companies that have experienced disruption have showed average 40% lower stock returns than their non-disrupted industry peers. The decrease in stock returns happened regardless of disruption type or industry.

The choice of risk management strategies includes inventory mitigation and contingent rerouting as these are identified as effective in reducing impact of supply network disruptions (Chopra and Sodhi, 2004). *Inventory mitigation* is considered a redundancy based strategy, where additional amount of inventory is kept to prevent the focal company from stocking out in case of a disruption. Kurano et al.

(2014) claimed that the amount of additional inventory needed is dependent on the risk profile. Additional inventory is expensive. Nonetheless, it also ensures production continuity during disruptions (Kamalahmadi and Parast, 2017) and absorbs shocks (Mishra et al., 2016). Tomlin (2006) highlighted that inventory mitigation is not an attractive strategy in rare and long disruptions if other options are available because the costs associated with excessive inventory kept for long periods of time do not balance the risk. Colicchia et al. (2010) claim that operational buffers, like additional inventory, might decrease operational performance and could negatively impact competitive advantage.

Contingent rerouting is considered to be a flexibility based approach, where the focal company reorganises its volumes after the disruption so as to minimise the disruption's impact. Literature highlights dominance of flexibility based strategies over redundancy based ones (Talluri et al., 2013). It is claimed that flexibility creates a competitive advantage in the marketplace (Sheffi and Rice, 2005). Carvalho et al. (2012) found that flexible transportation capacity performs better than inventory mitigation in an automotive supply network. Dong and Tomlin (2012) claimed that contingent rerouting is more effective in cost reduction than inventory mitigation for rare and long disruptions.

The performance of inventory mitigation and contingency rerouting has been broadly investigated by the literature. Tomlin (2006) and Qi and Lee (2015) used a two echelon setting with 1 manufacturer and two suppliers: one reliable and the other not, to investigate performance of inventory mitigation and contingency sourcing. Qi (2013) evaluated different sourcing strategies under disruptions at the primary supplier. Chen et al. (2012) evaluated the performance of contingency rerouting strategy with a backup supplier that has limited capacity and optimises the inventory management policy. Iakovou et al. (2015) explored emergency sourcing and determined the optimal capacity level to be reserved from the emergency supplier. They consider contingent rerouting, backup capacities, alternative transportation channels, increased order quantities and increased warehouse storage.

SCRM literature focuses mostly on the focal company and its direct business partners rather than the extended supply network. Nonetheless, there are exceptions where studies are extended to multi-tiered supply network. Seok et al. (2016) developed an intelligent contingent sourcing, where each supply tier is independent and self-interested. They perform the study on the beer-game supply network topology. The intelligent contingent sourcing is based on the idea that each agent decides itself whether to cooperate or not. Benaicha and Hadj-Alouane (2013) assessed the performance of adding additional location to the supply network as a backup plan in case of a disruption. Silbermayr and Minner (2014) evaluated performance of single and dual-sourcing strategies in suppliers that are subject to disruptions, highlighting advantages of the dual-sourcing strategy. Schmitt and Singh (2012) developed a simulation to optimise inventory to minimise total costs and meet required service levels. Talluri et al. (2013) investigated the effectiveness of different risk mitigation strategies proposed by Chopra and Sodhi (2004). They highlighted the benefits of flexibility approaches over keeping additional inventory because they characterised the latter as costly and not effective in reducing disruption impact. Wang et al. (2010) investigated the performance of dual sourcing and process improvement strategy. Carvalho et al. (2012) used redundancy and flexibility strategies in an automotive supply network to assess their performance against disruptions. They found that additional transportation capacity works out better than inventory mitigation strategy. These studies extend to multi-tiered topologies, although they consider linear structures and account for only one topology at the time.

Regardless of the strategy applied, SCR managers often need to decide on the trade-offs between robustness and effectiveness (Christopher and Peck, 2004). Others argue that the right balance might lie in the strategic decision-making process. Schmitt and Singh (2012) and Kleindorfer and Saad (2005) highlighted that in order to strengthen the whole system, the performance of the weakest link needs to be improved. This assumption brings to life considerations about targeted mitigation and contingency, where applying the strategy in the suppliers located in a critical position might substantially improve performance of the overall system.

In summary, the following research gaps have been identified:

1. While studies on the influence of supply network topology on supply network's ability to absorb disruptions exist, they usually do not consider supply network dynamics, or network costs and fill-rates. The term dynamics refer here to changes over time.

2. The effectiveness of risk management strategies on a focal company has been explored, however the effectiveness of mitigation and contingency in different supply network topologies have not been considered yet.

3. There is a lack of understanding of how strengthening the weakest supplier can benefit supply network performance. There is little evidence supporting the statement that targeting low-performing supply chain members to apply certain risk management strategy will increase the overall system performance.

Chapter 3

Research Aim, Objectives and Methodology

To the best of author's knowledge, little attention has been given to how performance of various supply network topologies is influenced by random disruptions. Moreover, the ability of risk management strategies to decrease impact of disruptions in different network topologies has not been investigated so far. There is a lack of knowledge on how targeted risk management can benefit the overall supply network with distinct topologies.

3.1 Aim

Therefore, the aim of this thesis is as follows:

> *To identify how network topology influences supply network resilience to random disruptions.*

Within the context of this thesis *supply network topology* refers to supplier connection patterns measured by degree distribution (Thadakamalla et al., 2004, Zhao et al., 2011).

Supply network resilience refers to the ability of the system to absorb shocks (Scholz et al., 2012), withstand a disruption (Aven, 2011), and the extent to which the network can return to its desired state after being disturbed (Peck, 2005). It is operationalised in the context of this thesis as the ability of the system to fulfil customer demand while a part of the supply network is being perturbed.

While SCRM literature highlights that a resilient company can undergo a transition, or a structural change when facing a disruption (Christopher and Peck, 2004, Scholz et al., 2012), the contextualisation of structural changes is beyond the scope of this thesis as the key area of interest is the relationship between existing supply network topology and its resilience. Finally, following the literature review presented in Chapter 2, two key risk management strategies that have been found to be commonly applied in SCRM are considered: inventory mitigation and contingent rerouting.

3.2 Objectives

The aim leads to the following objectives:

1. To evaluate how costs and fill-rates are influenced by random disruptions in different supply network topologies.
2. To evaluate an ability of a random inventory mitigation strategy to decrease costs and increase fill-rates in supply networks under random disruptions.
3. To evaluate an ability of a random contingent rerouting strategy to decrease costs and increase fill-rates in supply networks under random disruptions.
4. To evaluate an ability of a targeted inventory mitigation strategy to decrease costs and increase fill-rates in supply networks under random disruptions.
5. To evaluate an ability of a targeted contingent rerouting strategy to decrease costs and increase fill-rates in supply networks under random disruptions.

Here *random inventory mitigation* and *random contingent rerouting* refer to the random choice of companies embedded in supply network applying risk management strategy; and *targeted inventory mitigation* and *targeted contingent rerouting* indicates strategic choice of companies applying risk management strategies. The strategic choice might be informed by a company's topological position, or its declining performance, proxied by its costs or fill-rates.

In this work, disruptions are considered in two dimensions, namely disruption frequency which corresponds to likelihood, and disruption duration which corresponds to severity.

1^{st} research objective relates to 1^{st} knowledge gap and is addressed in Chapters 5 and 6. 2^{nd} and 3^{rd} research objectives relate to 2^{nd} knowledge gap and are addressed in Chapters 5 and 6. 4^{th} and 5^{th} research objectives relate to 3^{rd} knowledge gap and are addressed in Chapters 7 and 8. The simulation, presented in Chapter 4, is chosen as a methodological step to fulfil research objectives and emulate disruptive scenarios.

3.3 Overview of existing simulation techniques

The thesis focuses on the effectiveness of risk management strategies on distinct supply network topologies, therefore the methodology applied needs to fulfil the following criteria:

- *Quantitative*: Because costs and fill-rates of various networks will be benchmarked, the method needs to be able to measure these in a way where numerical comparison can be applied.
- *Dynamic*: Because the effectiveness of risk management strategies can be only observed over time, the method needs to simulate supply network's dynamics.
- *Flexible*: Because different topologies are compared, the method needs to be suitable for connecting companies in different topological configurations without substantial effort.
- *Distributed*: Because there is a need to model the supply network as composed of entities that can make decisions independently, without a single entity controlling the whole system, the method needs to enable distributed decision-making.

Complexity of many supply chain-related problems results in risk management methods being hard to apply (Gjerdrum et al., 2001). Supply networks can exhibit possible conflicts between local and global interests (Terzi and Cavalieri, 2004), which imply that what is good for a single entity might not prove to be optimal for the whole system. Most analytical models and empirical studies focus on the focal firm perspective, rarely considering how a firm embedded in a complex adaptive supply network influences other firms and its environment (Li et al., 2010). Simulation is a useful tool in supply chain modelling because it enables to investigate the information, cash and material flow over time. Simulation supports the identification of performance gaps between the desired and actual state of the system, enabling one to design scenarios to reduce the vulnerability to disturbances (Carvalho et al., 2012). De Sensi et al. (2008) highlighted that simulation plays a crucial role in defining trade-offs between experimental variables, such as inventory or costs. The most popular supply chain simulation techniques are discrete-event simulation and agent-based modelling.

According to Brialsford et al. (2014), *Discrete event simulation* models queueing systems as they progress through time. It is comprised of entities, activities and events, where the *entity* is an object that flows trough the system of queues, an *activity* is a process performed on the entity, and an *event* is a discrete point in time which triggers the change of the system state (Brialsford et al., 2014). Discrete-event simulation allows to assess the system's performance prior to its implementation by enabling what-if analysis and possibility of incorporating new features without interruptions to the real system (Chang and Makatsoris, 2001).

Multi-agent modelling is a simulation technique which comprises of multiple entities, called *agents*, which are computer systems capable of independent actions, communicating and interacting with each other (Costas et al., 2015). Agents are: reactive, proactive and social. *Reactiveness* imply that agents perceive environment and react according to the observed input. *Proactiveness* imply that agents can exhibit goals and can take the initiative to fulfil those goals. They have *social abilities*, which implies that they interact with other agents in order to meet their objectives and goals (Wooldridge, 2009).

Multi-agent systems are claimed to be the best methodology for modelling distributed decision-making problems in supply chains, where entities embedded in this system do not have the perfect knowledge about the surrounding environment (Costas et al., 2015, Gjerdrum et al., 2001, Julka et al., 2002). Gjerdrum et al. (2001) claims that multi-agent modelling is appropriate for order fulfilment process modelling. Literature advocates the use of multi-agent systems to model supply networks since it enables one to represent supply chain members as autonomous, interdependent, adaptive and self-organizing entities (Swaminathan et al., 1998). Agent based modelling methods are especially valuable since they enable one to capture complex phenomena at network-level (Pathak et al., 2007), which could not be obtained by traditional analytical approaches (Chatfield et al., 2013).

Due to the ability to model entities as autonomous individuals and to model dynamic processes, the agent-based modelling has been chosen as a method to fulfil the research aim. Java Agent Development Environment (JADE) has been chosen as the software environment employed for agent-based simulation due to: 1) compliance with Foundation for Intelligent Agents (FIPA) specifications and 2) scalability and flexibility, since agents can be distributed across different machines[3].

3.4 Research Methodology

This section contains steps undertaken to meet the research aim and objectives, described as research methodology (split into two parts and shown in Tables 3.1 and 3.2). Phases contain: information acquisition and analysis, simulation design and development, data collection, experimentation, discussion, conclusions and writing-up.

During the initial part of the project, scoping activities have been carried out. They enabled the establishment of the initial project scope, identification of the knowledge gap, aims and objectives, and selection of tools and methods that are applied to fulfil the aim. Next, the agent-based model has been designed and developed using JADE programming environment. There are multiple network topologies considered as the basis for creating a structure in which firms are connected in the agent-based simulation. These topologies can be divided into two categories: empirical and theoretical networks.

Empirical networks indicate network topologies informed by real supply networks. There are two empirical networks considered: the Maserati automotive supply network and logistics network of the company operating within fast-moving consumer

[3] http://jade.tilab.com/, accessed on 19^{th} January 2017

Table 3.1: Research Methodology: Information Acquisition and Analysis, Simulation Design and Implementation, and Data Collection phases.

Phase Name	**Description**	**Outcome**
Information Acquisition and Analysis	Literature Review	Define knowledge gap, aims, and objectives; Identification of applicable methods and techniques
	Requirement Assessment	Project scope, project success and failure criteria
Simulation Design, Development & Validation	Software Requirements Analysis	List of requirements
	Literature review	Identification of suitable software: JAVA based JADE programming environment chosen
	Software Design	Software architecture design
	Software Development	Agent-based model implemented
	Identification of performance metrics	Total costs and unit fill rates chosen
	Validation	Validate model
Data Collection	Collecting supply network data on companies in different industries, generation of theoretical networks	auto-maker supply network, FMCG internal logistics network, random and scale-free topologies

goods industry. These empirical topologies were chosen due to their different topological characteristics and data availability. The Maserati network is an automotive supply network, and it is a classical example of the diamond shaped upstream supply chain (Kito et al., 2014), with single auto maker and numerous middle-tier suppliers. The Maserati supply network has been retrieved from Marklines[4], online automotive database. FMCG network is a logistics network, which has been obtained from the company operating within FMCG industry, where the company has been anonymised. The logistics network, even if is not the supply network, still

[4]http://www.marklines.com/en/supplier db/, accessed on 1^{st} March 2014

Table 3.2: Research Methodology: Carrying out Experiments, Discussion and Conclusions phases.

Phase Name	Description	Outcome
Carrying out Experiments	assessing ability of supply networks to withstand disruptions	Meeting 1^{sr} research objective
	assessing effectiveness of random inventory mitigation and random contingent rerouting	Meeting 2^{nd} and 3^{rd} research objectives
	assessing effectiveness of targeted inventory mitigation and targeted contingent rerouting	Meeting 4^{th} and 5^{th} research objectives
Discussion and Conclusions		Critical academic discussion and conclusions on managerial implications
Thesis writing		Thesis document

represents the firm material flow, from the plants to distribution centres through logistics terminals.

Theoretical networks refer to the topological extremes informed by the literature: The one of non-existent hubs and the one with hubs, which are regarded as random and scale-free networks, respectively. Random and scale-free networks have been used to characterise supply networks because: (1) this thesis concurs with theoretical studies that point out the existence of hubs in supply networks; (2) multiple sources use these to model supply networks, including Nair and Vidal (2011), Thadakamalla et al. (2004), Zhao et al. (2011); and (3) these models are well documented in the literature to have various strengths and weaknesses to different disruption types. Degree distribution has been chosen as the basis for distinguishing theoretical networks since it has been identified as critical in assessing robustness.

The data collection process has been carried out to obtain empirical networks of the automotive and fast-moving consumer goods industry; random and scale-free topologies informed by the empirical networks have been generated. The phrase "informed by" refers to theoretical networks having the same number of nodes and links as empirical networks they relate to. The agent-based model performance metrics and targeted risk management selection criteria have been identified. The simulation has been validated with the work of Edali and Yasarcan (2014, 2016), Sterman (1989). Next, experiments have been carried out to answer five research objectives. These include the evaluation of the ability of empirical and theoretical networks to withstand disruptions and the evaluation of effectiveness of risk management strategies informed by the random and strategic choice of firms. The thesis is finalised with the critical academic discussion and conclusions on managerial implications.

The detailed design of experiments carried out to answer research questions is presented in the next section.

3.5 Design of experiment

There are two sets of experiments: one performed using risk management strategies applied by randomly chosen supply chain members, and the other using risk management strategies applied by supply chain members selected according to certain criteria, called random and targeted risk management, respectively. Experiments are carried out on empirical and theoretical networks informed by a real case study in the automotive and fast-moving consumer goods industries. Empirical and theoretical network topologies are used to create the structure in which firms are connected to each other. Each empirical network has its theoretical equivalents generated: For automotive network there are 5 random and 5 scale-free topologies generated with 565 nodes and 652 links, for fast-moving consumer goods network there are 5 random and 5 scale-free topologies generated with 103 nodes and 472 links. One by one, each network instance is then exposed to disruptions under different risk profiles (Tables 3.3 and 3.4). Five theoretical topologies were enough to conduct experiments as more would not significantly increase the accuracy of the results, as presented in Appendix A.

According to literature, risk profile can be expressed by two dimensions: likelihood and severity (Sheffi and Rice, 2005), which in this research is denoted as frequency and duration. *Frequency* is expressed by rare or frequent disruptions, and *duration* by short or long. In this thesis, a rare disruption is defined as the one having 0.5% chance of occurrence, meaning that disruption happens approximately once per four years per company. A frequent disruption is defined as the one having 10% chance of occurrence and indicate that it happens once per 10 weeks. Short and long disruptions last for 1 and 5 weeks, respectively. The combination of frequent and long disruptions is considered as a high risk environment, and the combination of rare and short disruption as a low risk environment. These values have been chosen guided by results obtained through trial and error and to express possible extreme real-world scenarios (Appendix A). It has been observed that there is a limit to which it is possible to disrupt suppliers in the model, since unnaturally high risk profiles result in increase in performance of all suppliers embedded in the network. This phenomenon occurs because when majority of suppliers are disrupted simultaneously, suppliers do not order nor sell their products resulting in the market freeze, as shown in Appendix A.

The final experimental variable consists of two risk management strategies: inventory mitigation and contingent rerouting. At any given run, only one strategy is available to all agents. The amount of agents applying a strategy is moderated by the mitigation level, which indicates the percentage of agents within the supply network that are chosen at random to perform mitigation or contingency actions. These consist of: 0%, 5%, 25%, 50%, 75%, and 100%, where 0% indicates that none of the agents apply mitigation or contingency and 100% indicates that all agents apply given strategy.

Thus, a single experimental run of random risk management scenarios consists of a given topology, risk profile, strategy, and the level at which that strategy is pursued by the firms. Each experimental run is repeated 30 times, giving a total 31,680 experiments. Scenarios are summarised in Table 3.3.

The next set of experiments focuses on targeted risk management to investigate whether strengthening the worst performing firms influences the overall network performance. The weakest firms are chosen according to centrality metrics and their performances obtained in scenarios without applying given strategies. Then,

Table 3.3: Experimental set-up for risk management in theoretical and empirical networks. There are in total 31,680 experiments which have been conducted using permutation of values in (A)-(D), each scenario includes 30 repetitions.

Nodes, links	(A) Topology	(B) Risk profile	(C) SCRM strategy	(D) Mit./Cont. level
565, 652	5 Scale-free	rare, short	Safety stock	0%,
	5 Random	rare, long		5%,
	Maserati	frequent, short		25%,
103, 472	5 Scale-free	frequent, long	Contingency re-routing	50%,
	5 Random			75%,
	FMCG			100%

for every topology and each risk profile, 5% of agents that obtained the highest C_{K_i}, highest C_{A_i}, highest C_{H_i}, highest C_{BT_i}, highest C_{C_i}, highest C_{R_i}, highest C_i and lowest FR_i are chosen. The improvements in targeted and random risk management performances are then compared. Thus a single experimental run consists of a given topology, risk profile, risk management strategy and targeting strategy. There are 616 experiments, summarised in Table 3.4.

TABLE 3.4: Experimental set-up for performance assessment of targeted mitigation and contingency. There are in total 616 experiments which have been conducted using permutation of values in (A)-(C) and (E).

Nodes, links	(A) Topology	(B) Risk profile	(C) SCRM strategy	(E) Targeting strategy
565, 652	5 Scale-free 5 Random Maserati	rare, short rare, long frequent, short frequent, long	Safety stock Contingent rerouting	random highest C_{K_i} highest C_{A_i} highest C_{H_i} highest C_{BT_i} highest C_{C_i} highest C_{R_i} highest C_i lowest FR_i

Chapter 4

Simulation design and validation

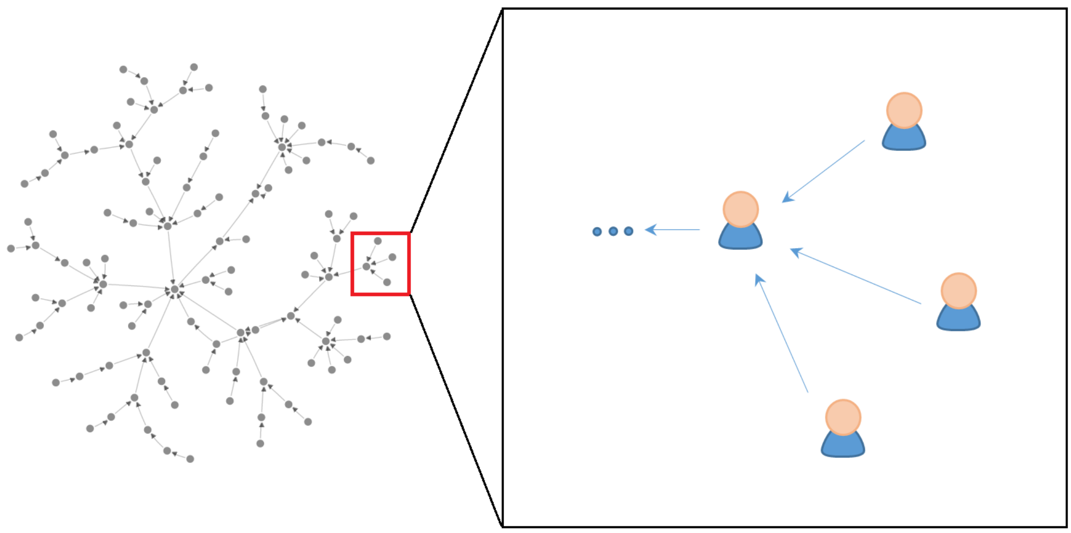
This section discusses the main components of the research design: (a) an agent-based model of the supply network; (b) the generic stock-management structure and its extension to complex supply networks; (c) disruptions; (d) risk management strategies and (e) performance metrics. Next, detailed input/output specifications are presented and the simulation is validated against the work of Edali and Yasarcan (2014, 2016) and Sterman (1989).

4.1 Agent-based model design

In this work, an agent-based model is composed of interconnected software entities, embedded in the complex supply network, as presented in Figure 4.1. There are five types of supply network members:

1. Agent
2. Logistic provider
3. Consumer
4. Raw Materials Supplier
5. Clock

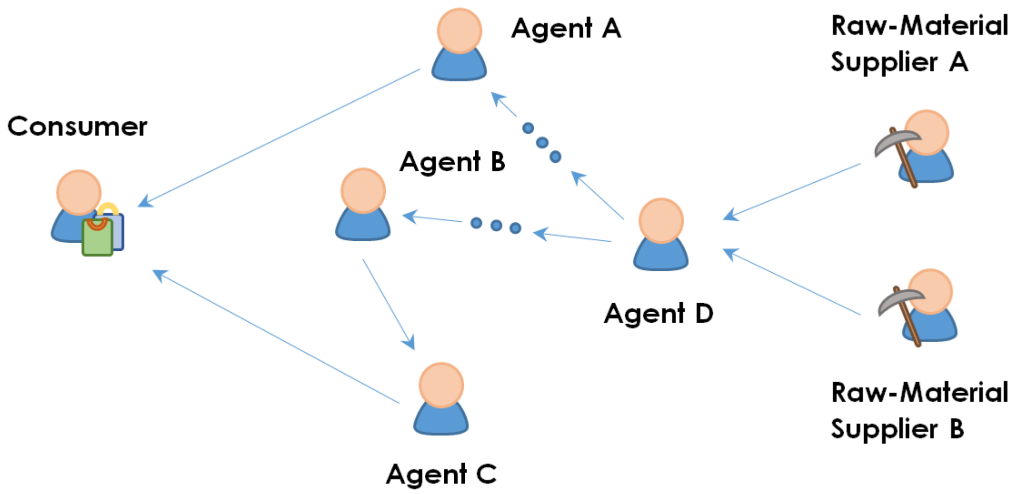
Figure 4.1: Agents embedded in a supply network topology. Solid arrows indicate material flow from the supplier to the customer.



Where each *agent* represents a member of the supply network controlling its own inventory, the *logistic provider* ships goods across the network, *consumer* and *raw material supplier* reside on the upstream and downstream ends of the supply network to pull the demand and provide infinite supply of raw materials (Figure 4.2), and the *clock* which synchronises all the supply network members to perform their tasks in a weekly manner. Usually, any software entity in an agent-based model is referred to as an agent, although in this work the term is restricted only to the decision-makers, the other members of the supply network are referred to by their respective names, if not stated otherwise. The functionality scope of agents includes:

1. Receive inventory
2. Fill orders
3. Record inventory and backlog
4. Ship products
5. Forecast demand and place orders

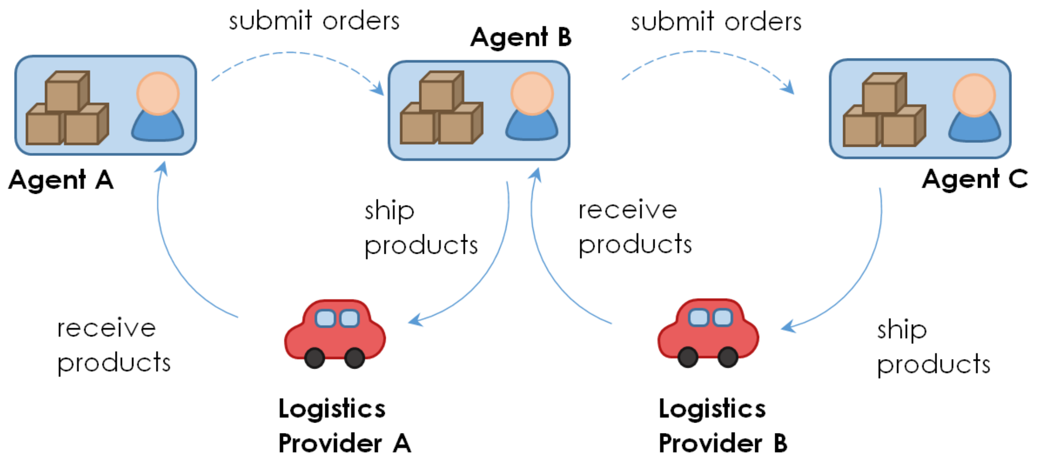
Figure 4.2: The upstream and downstream ends of a supply network are represented by consumers and raw material suppliers. Consumer pulls the demand and raw material supplier provide an infinite supply to agents. Solid arrows indicate the material flow from the supplier to the customer.



Each agent has their *suppliers* from whom it orders products and *customers* who order from the agent. Agents order from their suppliers and fill orders from their customers communicating via messages. Suppliers and customers are terms, which describe a relative position of an agent rather than a type of an agent. An agent embedded in a complex supply network can be some agent's supplier and other agent's customer at the same time. This implies high architecture flexibility because agents can be assembled in any topology chosen. Simulation runs in a discrete manner, where agents simultaneously perform ordering decisions each week, synchronised by the clock. It is assumed that all suppliers of an agent have perfectly substitutable goods.

Agents interact with their suppliers and customers each week in the following manner, an agent: (1) receives inventory from its suppliers; (2) receives orders from their customers; (3) subtracts order amount from inventory or register backlog; (4) ships available goods through logistics providers; and (5) forecast demand and place orders to its suppliers. The decision-making processes are taken from Sterman (1989). The diagram of how agents interact with each other is presented in Figure 4.3.

Figure 4.3: Agent interaction with its suppliers and customers. Solid arrows indicate material flow from the supplier to the customer, and dashed ones indicate information flow.

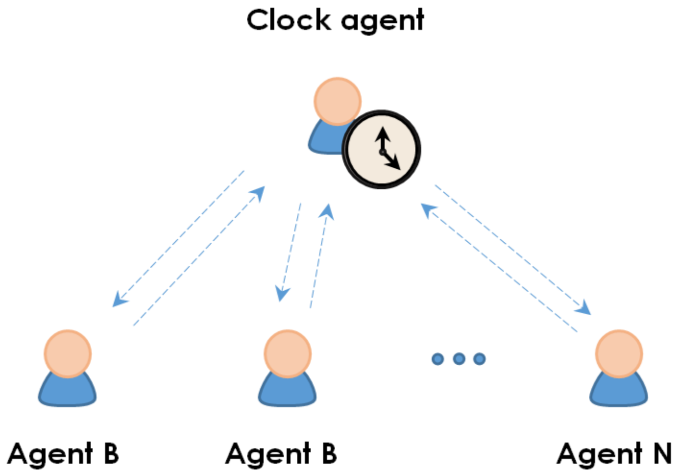


Each agent manages its inventory according to specific rules, as set out in Sterman (1989) in the beer distribution game. More details on ordering process are presented in the next section. An agent manages its inventory in the following manner: inventory is increased when goods are received; inventory is decreased when the products are shipped to customers; the backlog is registered when there is not enough inventory to fill the customer order. When the customer order is greater than the available inventory, the agent ships whatever is available and register the backlog of remaining amount. If an agent has multiple customers, it responds to their requests on a first-come-first-serve basis.

Logistics providers act as a transportation proxy between the customer and the supplier. When the logistic provider obtains goods from the supplier, it "keeps" products for the time in-transit and when this period is over, the goods are delivered to the customer. The clock synchronises all agents, logistics providers, consumers and raw material suppliers so that they perform each action according to the schedule. The simulation week is divided into the following phases:

1. Receive inventory, receive orders, manage inventory, record backlog and send shipments to customers (agents).

FIGURE 4.4: Clock synchronises all agents to perform actions weekly according to their schedule. Dashed arrows indicate information flow.



2. Forecast demand and order from suppliers (agents).

3. Advance logistics (logistic providers).

The consumers and raw material suppliers participate in the first two phases, although their responsibilities are restricted to: receiving orders, sending shipments (raw material suppliers) and ordering from suppliers (consumers).

After each phase, there is a message sent by the clock to indicate that a certain phase begins (Figure 4.4). The message is sent to agents, consumers, raw material suppliers or logistic providers, depending on the phase. When the agent finishes performing actions scheduled in a certain phase, it sends the message to the clock to communicate that all the necessary tasks have been carried out. When the clock receives the "done" message by all concerned agents, it proceeds to another phase, by sending appropriate initiation messages again.

4.2 Internal decision-making

4.2.1 Generic stock management

Each agent is assumed to control its inventory, which is modelled using the generic stock management structure (Figure 4.5). This generic structure encompasses both the physical aspects of the stock management task and the decision making processes of human decision makers (Sterman, 1989, Yasarcan, 2011). The orders are formed using the anchor-and-adjust ordering policy as suggested by Sterman (1989). There are other stock management systems, such as human resources, driving or social drinking (Sterman, 1989).

The parameters of the stock management system that refer to inventory management are as follows: *stock* (S) refers to net inventory, *supply line* (SL) refers to goods on order (past orders that have not arrived yet), *loss flow* (L) refers to shipments to customers, *acquisition flow* (AF) refers to arrivals from suppliers, *acquisition delay time* refers to the delay with which the supplies arrive, *control flow* (O) refers to order of goods. *Stock* (S) is composed of on-hand inventory and backlog, where *on-hand inventory* (I_t) is the amount of physically available goods in the stock and *backlog* (B_t) refers to customer orders which have been received, but could not be filled due to lack of on-hand inventory at the time (Equation 4.1).

$$S_t = I_t + B_t \tag{4.1}$$

The *expected loss* (EL) refers to forecasting customer demand[4]. The *indicated control decision*, called also *indicated order* (IO), represents the desired order amount to be placed to the supplier and is represented by the Equation 4.2. It is composed of three terms: losses which is an anchor term, stock adjustment and supply line adjustment which are adjustment terms. *Stock adjustments* (SA) are corrections made to the net inventory, *supply line adjustments* (SLA) are corrections made to goods on order.

[4]In this study, the expectation formation is performed using exponential smoothing methods with exponential smoothing fraction (θ) equal to 0.2, as suggested by Edali and Yasarcan (2014).

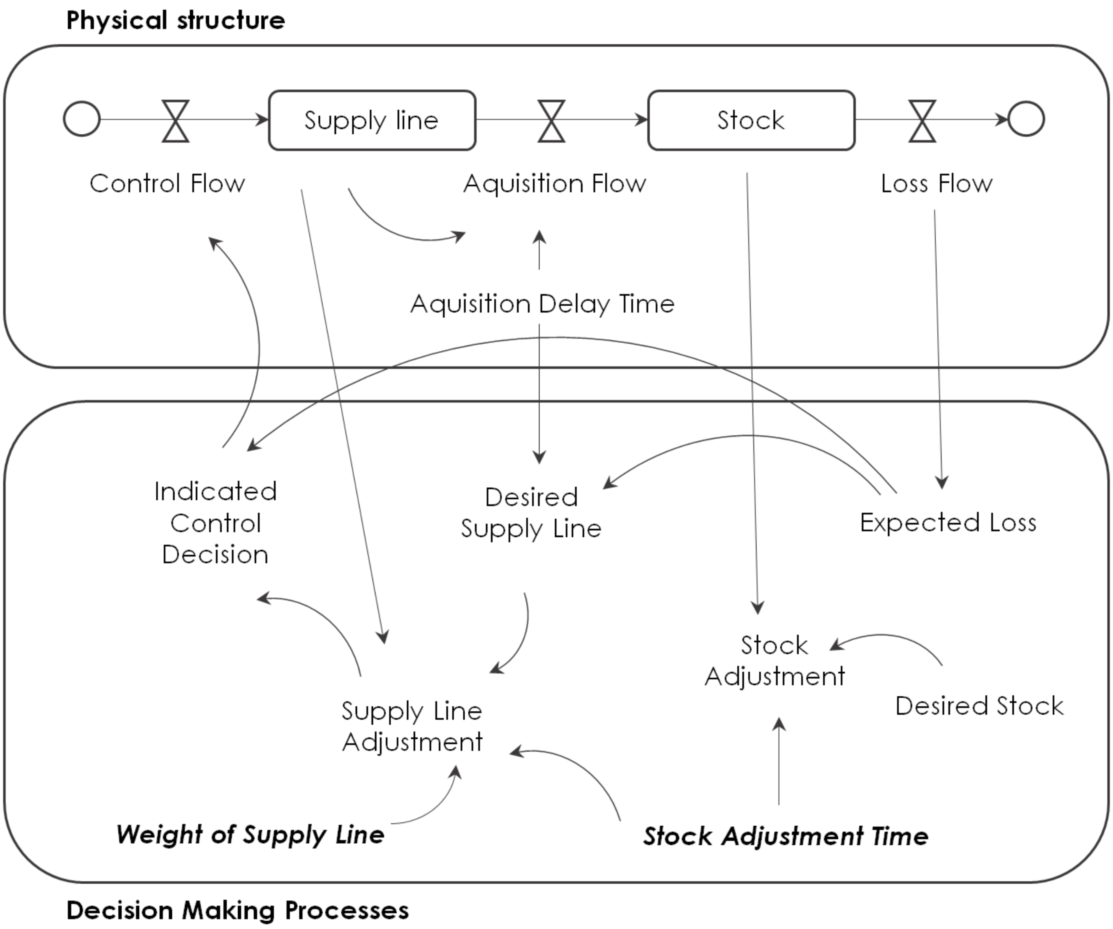


FIGURE 4.5: The generic stock management system (adopted from Sterman (1989))

$$IO_t = EL_t + SA_t + SLA_t \tag{4.2}$$

The Equation 4.2 can take negative values in some cases, e.g. when the amount of on-hand inventory and amount of goods on order is much higher than the expected demand. The assumption is made that negative orders are not possible, therefore the equation is modified as presented in the Equation 4.3, which always will take non-negative values.

$$O_t = MAX(0, IO_t) \tag{4.3}$$

The equations for adjustment terms are presented in 4.4 and 4.5. They are composed of stock adjustment time (sat), desired stock (S^*), stock (S), weight of supply line (wsl), desired supply line (SL^*) and supply line (SL). The *desired stock* and *desired supply line* correspond to the level which is required to prevent steady-state errors at equilibrium for stock and goods on order, respectively. The desired supply line is changing during the simulation run to close the discrepancies, the desired stock is chosen only once at the beginning. The *stock adjustment time* is a parameter, which defines the speed of closing the gap between the current and desired level of stock. The *weight of supply line* is the importance given to the supply line discrepancies.

$$SA_t = \frac{(S^* - S_t)}{sat} \tag{4.4}$$

$$SLA_t = \frac{wsl \cdot (SL_t^* - SL_t)}{sat} \tag{4.5}$$

The acquisition delay time is composed of mailing delay time and shipment time (Equation 4.6). *Mailing delay time* (mdt) is the time between submitting an order to the supplier and receiving that order by the supplier, and is equal to one week. *Shipment time* (st) is the time goods are in-transit and is equal to two weeks.

$$adt = mdt + st \tag{4.6}$$

4.2.2 Extension to the complex supply network

The generic stock management presented by Sterman (1989) and Edali and Yasarcan (2014) has been extended to complex supply networks and the main differences between these can be given as (1) in Edali and Yasarcan (2014) and Sterman (1989), the supply chain members are connected in series, the extended version is simulating complex network topologies; (2) their model describes four agents, whereas the extended model includes many more; (3) in their paper, the end-customer demand is around eight units per week, but in the extended study it is assumed to be equal to 1400 units per week for FMCG networks and and 14000 units per week for automotive networks, following empirical examples.

Agents applying anchor-and-adjust ordering policy are embedded in the complex network, therefore an ordering decision of a single agent has an effect on other agents. The equations of anchor-and-adjust policy are modified as presented in Equations 4.7, 4.8, 4.9, 4.10 and 4.11.

$$O_{i,t} = MAX(0, IO_{i,t}) \tag{4.7}$$

$$IO_{i,t} = EL_{i,t} + SA_{i,t} + SLA_{i,t} \tag{4.8}$$

$$SA_{i,t} = \alpha_S(S_i^* - S_{i,t}) \tag{4.9}$$

$$SLA_{i,t} = \alpha_{SL}(SL_{i,t}^* - SL_{i,t}) \tag{4.10}$$

$$S_{i,t} = I_{i,t} + B_{i,t} \tag{4.11}$$

Where i and t refer to a decision made by agent i in the week t. The other parameters are taken from Edali and Yasarcan (2014)[4].

[4] $\alpha_S = 1$, $\alpha_{SL} = 1$, $mdt = 1$, $st = 2$, inventory holding costs = \$0.5 per unit per week, backlog costs = \$1 per unit per week, $\theta = 0.2$

If an agent has multiple suppliers, the ordering decision is still made according to the original stock management structure, but the value is later split equally between all suppliers (Equation 4.12).

$$O_{ji,t} = \frac{A_{ij}O_{i,t}}{k_i^{in}} \tag{4.12}$$

where $O_{i,t}$ is an ordering decision made by agent i in week t, $O_{ji,t}$ indicates order submitted to agent j by agent i in week t, A_{ij} is an adjacency matrix, which takes value 1 when agent j is a supplier of agent i, and k_i^{in} is an in-degree of an agent i. The in-degree k_i^{in} will always be greater than zero because all agents always have suppliers. These suppliers might be other agents or the raw-material suppliers.

Each agent's desired stock is equal to 0, which implies that all agents try to optimise their inventory and keep its level equal to 0 (Equation 4.13). The time frame for the simulation is extended to 500 weeks to prevent the effect of the short-term transient dynamics dominating the overall results. The initial stock (S_{i,t_0}) of each agent i is equal to 0, as presented in Equation 4.14.

$$S^*_{i,t} = 0 \tag{4.13}$$

$$S_{i,t_0} = 0 \tag{4.14}$$

The initial order amount that an agent places to its suppliers is equal to the sum of initial orders of this agent's customers placed to that agent. The idea is presented in Equation 4.15, where the total number of agents in the network is equal to N and A_{ji} is an adjacency matrix. The adjacency matrix A_{ji} takes value 1 when agent j is the customer of agent i, 0 otherwise.

$$O_{i,t_0} = \sum_{j=0, j\neq i}^{N} A_{ji}O_{ji,t_0} \tag{4.15}$$

Initial supply line of each agent is equal to their initial order amount multiplied by the acquisition delay time, as presented in the Equation 4.16. If there are no internal (e.g. disruptions) or external (e.g. demand fluctuations) shocks applied to the system, this configuration enables stocks of all agents to be in an equilibrium and represent perfect just-in-time (JIT) system. The equilibrium implies, that inventories and ordering decisions will not change for all agents. In order to reach that equilibrium a setting up period is included in each simulation run and is not accounted in performance assessment. In case when shocks are present, the change in ordering decision of one agent will have an influence on the whole supply network.

$$SL_{i,t_0} = adt \times O_{i,t_0} \tag{4.16}$$

4.3 Disruptions

The agent-based model is subject to disruptions. According to the Oxford English Dictionary to disrupt means:

> *"interrupt (an event, activity, or process) by causing a disturbance or problem; drastically alter or destroy the structure of (something)"* (Stevenson, 2010, p. 507)

Therefore, a disruption is modelled in the agent-based simulation as a process that disables basic functionalities of a single agent, which can be equivalent to labour strike, natural disaster, or an accident such as fire or explosion. The effects of disabling the agent will be as follows:

- disrupted agent will not be able to order from its suppliers
- disrupted agent will not fill any orders from its customers
- disrupted agent will not receive inventory
- disrupted agent will not send shipments to its customers
- disrupted agent will notify its customers that it is disrupted

The duration of the disruption is dependent on the risk profile, and in this study it is equal to one or five ordering cycles, as specified in the Chapter 3 in Design of experiment section. All agents have the same probability $p(\overline{\phi})$ of being disrupted, where $\phi_{i,t}$ is the operationality of an agent i in week t. In simple words if the disruption probability $p(\overline{\phi})$ is equal to 0.5 it means that every agent will fail 50% of the time. The agent is disrupted, when its operationality ϕ is equal to 0. The disruption test is performed each week t for every agent i separately by drawing a sample $\omega_{i,t}$ from uniform distribution with values in the range $[0, 1]$. If $\omega_{i,t} \leq p(\overline{\phi})$, then the agent i is disrupted in a week t for number of cycles specified by the risk profile, as presented in Equation 4.17.

$$\phi_{i,t} = \begin{cases} 0 & \text{if } \omega_{i,t} \leq p(\overline{\phi}) \\ 1 & \text{if } \omega_{i,t} > p(\overline{\phi}) \end{cases} \tag{4.17}$$

$\phi_{i,t}$ is equal to 0 when the agent i is not operational in week t, and 1 otherwise. As the probability tests will be performed simultaneously in a certain week t for every agent in the network, it is possible that many agents will be disrupted at the same time, only one will be disrupted, or none will be disrupted.

4.4 Implementation of risk management strategies

4.4.1 Inventory mitigation

Inventory mitigation is a proactive risk management strategy aiming at reducing the impact of disruptions by holding an additional amount of stock at all times. In the extended model, an agent which applies inventory mitigation strategy keeps an additional amount of stock equal to its initial order amount. If and agent does not perform inventory mitigation, its desired inventory is equal to 0 (as presented in Equation 4.18).

$$S_i^* = \begin{cases} 0 & \text{if agent } i \text{ does not apply inventory mitigation} \\ O_{i,t_0} & \text{if agent } i \text{ applies inventory mitigation} \end{cases} \tag{4.18}$$

4.4.2 Contingent rerouting

Contingent rerouting is a reactive risk management strategy performed only when an agent has more than one supplier; the number of suppliers of a specific agent depends on the network topology in which it is embedded. When an agent reroutes, it stops ordering from the disrupted supplier and moves the disrupted volume to suppliers that are still operational. The agent sources equally from its operational suppliers at all times, as presented in Equations 4.19 and 4.20.

$$O_{ji,t} = \frac{\phi_{j,t} A_{ij} O_{i,t}}{\Phi_{i,t}} \tag{4.19}$$

$$\Phi_{i,t} = \sum_{j=0, j \neq i}^{N} \phi_{j,t} A_{ij} \tag{4.20}$$

$\phi_{j,t}$ is equal to 1 when an agent j is operational in week t, and $\Phi_{i,t}$ is the number of operational suppliers of agent i in week t. If none of the suppliers of i are operational ($\Phi_{i,t} = 0$), then the agent comes back to the original volume split, as indicated in Equation 4.12.

4.5 Performance metrics

Supply network performance has been evaluated using the following parameters: total costs incurred by all agents in the network denoted by C_{NET}; costs incurred by the end manufacturer denoted by C_{MAN}; average unit fill-rate of agents in the network denoted by FR_{NET}; and unit fill-rate of the end manufacturer denoted by FR_{NET}. These four metrics enable the evaluation of trade-offs between maintaining low costs and keeping high customer service at the end manufacturer and at the system's level. The end manufacturer (referred also as Original Equipment Manufacturer or OEM) is an agent which is located at the downstream end and is supplying products to end-consumer.

The total cost incurred by agent i is represented by the equation 4.21.

$$C_i = \sum_{t=1}^{T} I_{i,t} \times 0.5\$ + B_{i,t} \times 1\$ \tag{4.21}$$

$I_{i,t}$ denotes the on-hand inventory, $B_{i,t}$ indicates the backlog of an agent i in week t, and T is the number of simulation weeks. These values are multiplied by the inventory holding cost and backlog cost, which are 0.5$ and 1$ per unit per week, respectively (Edali and Yasarcan, 2014, Sterman, 1989). Inventory holding costs and backlog costs generated in each week are summed and show the total cost that agent i generated during T weeks of a single simulation run. The total cost incurred by the whole network is represented by C_{NET}, which is equal to the sum of costs generated independently by all agents (Equation 4.22).

$$C_{NET} = \sum_{i=1}^{N} C_i \tag{4.22}$$

The *unit fill-rate* can be described as a measure of customer service, *number of units (e.g. cases) filled as a fraction of units ordered* (Closs et al., 2010). This measure is referred later simply as fill-rate. Fill-rate of an agent i (FR_i) is a percentage of net demand in T simulated weeks (Equation 4.23).

$$FR_i = \frac{\sum_t^T D_{i,t} - \sum_{t=1}^T UD_{i,t}}{\sum_t^T D_{i,t}} \times 100\% \tag{4.23}$$

$D_{i,t}$ and $UD_{i,t}$ are the demand and unmet demand of agent i in week t, respectively. FR_{NET}, represented by equation 4.24, is an average of fill-rates of individual agents.

$$FR_{NET} = \frac{\sum_{i=1}^N FR_i}{N} \tag{4.24}$$

4.6 I/O specification

This section includes the detailed description of the input and output specification that is required for the simulation.

4.6.1 Input

The input to the agent-based model needs to include the following:

- Disruption frequency (rare or frequent)
- Disruption duration (short or long)
- Network topology
- Risk management strategy
- Agents' initial orders

Disruption duration, disruption frequency and risk management strategy applied are hard-coded into the simulation. Network topology and initial orders are included in a single text file, which has the following format:

```
agent_name:agents.AgentClass(additional_inventory##
                                initial_order##
                                list_of_suppliers##
                                list_of_customers);
```

additional_inventory is the amount of safety stock kept by that agent which is effectively S_i^*, *initial_order* is the value of initial order O_{i,t_0} of that agent. List of suppliers can be expanded in the following way:

```
supplier_A#supplier_B#supplier_C
```

List of customers can be expanded in the following way:

```
customer_A@logistics_provider_to_A#customer_B@logistics_provider_to_B
```

Sample input file is presented below:

```
agents=asyn:agents.Clock();
i0:agents.Agent(100.0##100.0##i1##c@t1);
i1:agents.Agent(0.0##100.0##s##i0@t2);
s:agents.RawMaterialSupplier(0.0##100.0####i1@t3);
c:agents.Consumer(0.0##14000.0##i0##);
t1:agents.LogisticsProvider();
t2:agents.LogisticsProvider()t3:agents.LogisticsProvider()
```

4.6.2 Outputs

Each agent logs its progress by writing parameters of each week into the text file. Sample log file of an agent is as follows:

```
I_t     S_t     D_t     O_t     A_t     EL_t    sum(O) sum(UD)  t
300.0   300.0   100.0   100.0     0.0   100.0     0.0    0.0     -2
200.0   200.0   100.0   100.0     0.0   100.0   100.0    0.0     -1
100.0   100.0   100.0   100.0     0.0   100.0   200.0    0.0      0
100.0   100.0   100.0   100.0   100.0   100.0   300.0    0.0      1
100.0   100.0   100.0   100.0   100.0   100.0   400.0    0.0      2
```

Where I_t is on-hand inventory in week t, S_t is stock in week t, D_t is customer demand in week t, O_t is order submitted to suppliers in week t, A_t is amount of goods that arrived in week t, EL_t is forecasted demand, $sum(O)$ is the total amount of goods ordered in previous weeks, $sum(UD)$ is the sum of unmet demands until week t.

Weeks -2, -1 and 0 are a part of the setting up period, therefore they are not included in the performance assessment. Each agent output file is then processed and summarized as follows:

```
agent_name:   total_costs   average_fill_rate
```

With an example:

```
i0:     25000.0 100.0
i1:         0.0 100.0
```

The results are further processed for the whole network by summing all individual agent's costs and averaging fill rates. Individual network results are averaged further, depending on which group the scenario belongs to. The results are grouped by topology, risk profile and strategy applied. Scenarios of theoretical networks are grouped by topology type creating an instance of 150 samples: 30 repetitions for 5 topologies. The topologies of the same type are grouped together e.g. all random automotive topologies. Scenarios of empirical networks create a group of 30 samples per topology. It has been observed that results from each sample within specific group have low standard error, as outputs of samples lie within similar ranges. These ranges are greater for higher disruption frequencies and durations, but in general still can be considered relatively small. All data points for a single topology are presented in Appendix A.

In the output file, the groups are decoded such that the topology type comes first (e.g. random automotive, scale-free automotive or empirical FMCG) and the mitigation/contingency level afterwards. $0IM$ indicates that 0% of agents applied inventory mitigation strategy, $75CR$ indicates that 75% agents applied contingent rerouting strategy. Results in that format are directly plotted in Chapters 5 and 6. Exemplary output file for rare and short disruptions can be as follows:

```
randomA_5IM:     20000.0  90.0   65.00   5.0     ...     75.0    2.0
randomA_25IM:    15000.0  80.0   70.00   5.0     ...     80.0    1.0
...
sfreeA_75CR:     4000.0  20.0    80.00   5.0     ...     92.0    1.0
sfreeA_100CR:    2000.0  10.0    85.00   5.0     ...     96.0    1.0
```

where the consecutive columns are represented as:

$group : C_{NET} \ \ \sigma C_{NET} \ \ FR_{NET} \ \ \sigma FR_{NET} \ \ C_{MAN} \ \ \sigma C_{MAN} \ \ FR_{MAN} \ \ \sigma FR_{MAN}$

C_{NET} and FR_{NET} are total costs and fill-rates for the whole network,C_{MAN} and FR_{MAN} are costs and fill-rates for the manufacturer only.

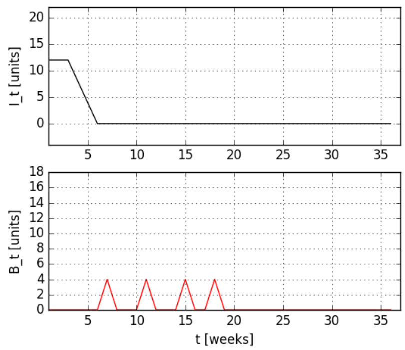
4.7 Simulation Validation

To validate the model, an agent-based simulation replicating conditions of Edali and Yasarcan (2014) and Sterman (1989) has been built. A supply network composed of fours agents connected in series and with the exact same parameters as reported in Sterman (1989) and Edali and Yasarcan (2014)[5], generated the same costs and inventories: \$204 total costs, \$46 for a retailer, \$50 for the wholesaler, \$54 for the distribution centre and \$54 for the factory. Inventory and backlog dynamics were compared with the output of the R source code published by Edali and Yasarcan (2014)[6] and the exact result was observed. The agent-based model dynamics are

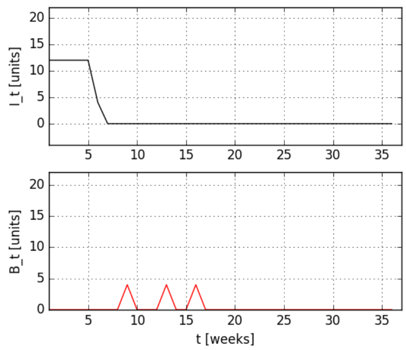
[5] $S^*_{r,w,d} = 16$, $S^*_f = 12$, $I_0 = 12$, $\alpha_S = 1$, $\alpha_{SL} = 1$, $mdt = 1$, $st = 2$, inventory holding costs = \$0.5 per unit per week, backlog costs = \$1 per unit per week, $\theta = 0$

[6] available at https://www.openabm.org/model/4166/version/1/view, accessed on 15^{th} July 2016

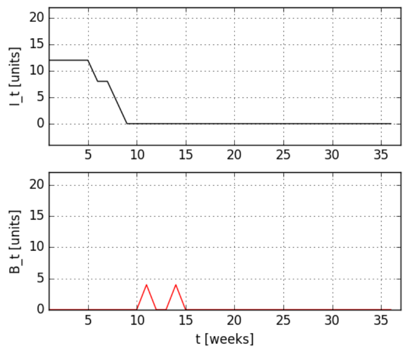
FIGURE 4.6: Inventory (I_t) and backlog (B_t) dynamics



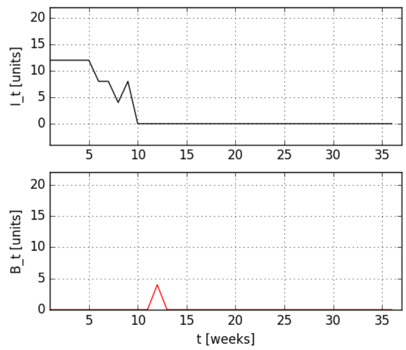
(A) retailer



(B) wholesaler



(C) distribution centre



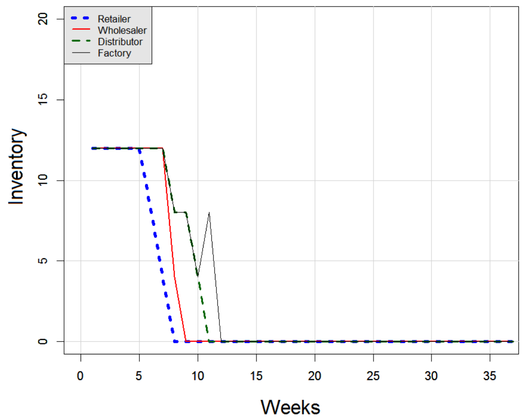
(D) factory

presented in Figure 4.6, the dynamics obtained by Edali and Yasarcan (2014) are presented in Figure 4.7.

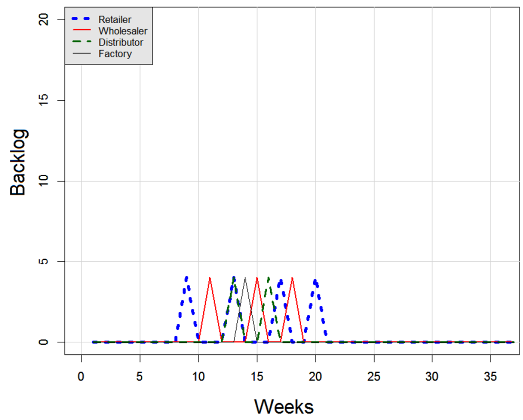
The empirical evidence of the dynamics of the model and data is presented in Appendices B, and C, where the simulation is run on an experimental supply network under four scenarios: (a) without disruptions, (b) with a disruption, (c) with a disruption applying inventory mitigation, and (d) with a disruption applying contingent rerouting. Scenarios contain a discussion on how a single disruption affects agents' stocks and customer demand.

In order to validate the extended model, the simulation was run for topologies without disruptions. Such a scenario is perfect just-in-time system, where whatever was delivered by a supplier is immediately sold to the customer, without accumulating

FIGURE 4.7: Inventory and backlog dynamics by Edali and Yasarcan (2014). On-hand inventory and backlog generated by retailer (blue), wholesaler (red), distributor (green) and factory (black) as reported by the R source code from Edali and Yasarcan (2014).



(A) inventory dynamics



(B) backlog dynamics

inventory. In this case C_{NET} has to be equal to 0, since agents do not generate costs because they do not have on-hand inventory nor backlog. FR_{NET} is equal to 100.0 because everything that is ordered is immediately filled from the stock.

The concept is shown in the Figure 4.8, where the inventory and backlog of an arbitrary agent are plotted against time. It can be seen that the dynamics of both parameters are equal to 0 at all times. The same pattern was recurring for all agents in the network and for all topology types, except the empirical case of FMCG company. C_{NET} and FR_{NET} of all topologies for the base scenario are presented in Table 4.1.

C_{NET} of FMCG empirical network is \$233,336,150.21 and FR_{NET} is equal to 51.09% because the logistics network contains cycles. A *cycle* in a directed network indicates that there is a path that starts at a node i and ends at the same node i. The cycles in the FMCG logistics network are paths of length two, where a node i links to node j, and node j links to node i. In practice, such behaviour means that a supplier of a company is this company's customer as well. These "ordering feedback loops" result in instabilities because when an agent i increases the order amount placed to agent j, agent j corrects its ordering decision by increasing its order amount placed

FIGURE 4.8: Visualisation of the inventory and backlog dynamics for the complex supply network, where the on-hand inventory (I_t) and backlog (B_t) of one agents are plotted against the time.

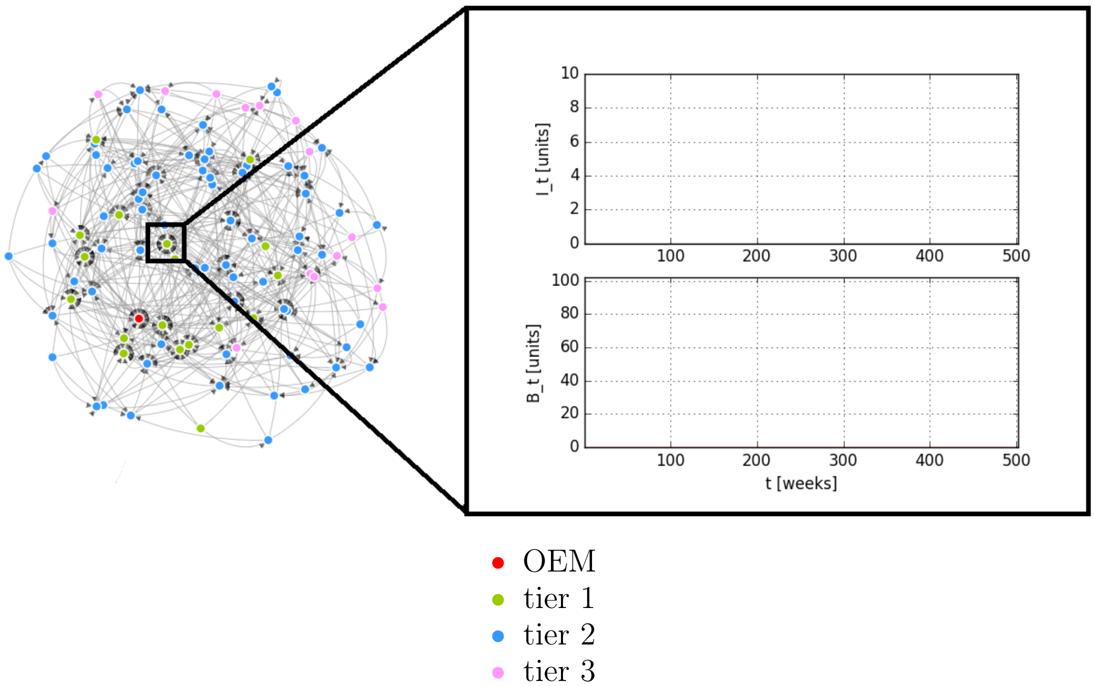


Table 4.1: Validation of agent-based model extended to supply networks

Topology (n, m)	Network	C_{NET}	FR_{NET}
Random FMCG (103,472)	random 1	0.00	100.00%
	random 2	0.00	100.00%
	random 3	0.00	100.00%
	random 4	0.00	100.00%
	random 5	0.00	100.00%
Random automotive (565,652)	random 1	0.00	100.00%
	random 2	0.00	100.00%
	random 3	0.00	100.00%
	random 4	0.00	100.00%
	random 5	0.00	100.00%
Scale-free FMCG (103,472)	random 1	0.00	100.00%
	random 2	0.00	100.00%
	random 3	0.00	100.00%
	random 4	0.00	100.00%
	random 5	0.00	100.00%
Scale-free automotive (565,652)	random 1	0.00	100.00%
	random 2	0.00	100.00%
	random 3	0.00	100.00%
	random 4	0.00	100.00%
	random 5	0.00	100.00%
FMCG (103,472)		233,336,150.21	51.09%
Maserati (565,652)		0.00	100.00%

to agent i in the next week. Then, agent i again increases its order decision and so on. In a perfect just-in-time system, as used for the validation purposes, the changes in agents' orders should not happen, although they still do because the agent-based model is subject to floating point arithmetic errors. For example, if an agent has three suppliers and its ordering decision is 1 unit, it will split the amount into three suppliers with 0.33333 each. In all acyclic supply networks, the floating point arithmetic errors are very small and are mitigated by agents. In the case of cyclic logistics network, these error build up resulting in a very unstable environment, high costs and low fill-rates. These instabilities are solely the result of an attempt to model the supply network on a logistics network topology. The cycles are present in logistics network because an inventory movement within the same organisation back and forth over some period of time has a justification. It makes the cycles valid in this case, although it would not usually happen in a supply network. The results of logistics network cannot be used to make conclusions on effectiveness of risk management strategies, nor be compared to other supply networks, although it is used rather as a curiosity and an exemplary show case which presents how cycles in a supply network could potentially hurt the performance.

Chapter 5

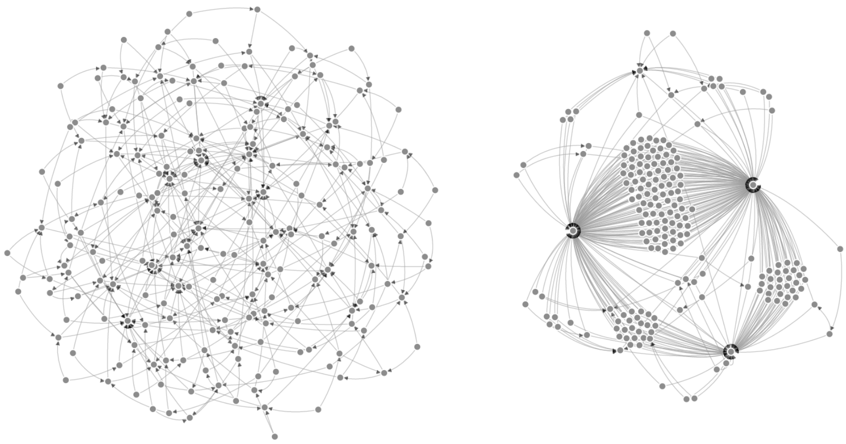
Risk management for theoretical networks

This section presents the ability of artificially generated random and scale-free networks to absorb disruptions and reduce the disruption impact through inventory mitigation and contingent rerouting. First, random and preferential generation models used to create theoretical networks are presented. Theoretical topologies are analysed using network-level metrics to gain insights into their potential vulnerabilities. Next, these networks are exposed to disruptions to investigate how topology affects costs and fill-rates. Mitigation and contingency strategies are applied in randomly chosen firms to assess their effectiveness in various topological configurations.

5.1 Network Generation Models

In order to create theoretical networks, two generation models have been used: random attachment model and preferential attachment model. A *generation model* is a set of rules which determine how network is created; ie. how nodes connect to each other. *Random attachment model* places m links between n nodes at random, generating random networks. *Preferential attachment model* places m links between n nodes, choosing each link with a probability proportional to the number of neighbours a node has, generating scale-free networks. The more neighbours, the higher probability of a specific node being chosen (Newman, 2010). Figures 5.1 A and 5.1 B present examples of topologies created using both generation models.

FIGURE 5.1: Exemplary networks generated with random and preferential attachment models



(A) random network (B) scale-free network

In order to generate networks which can represent realistic supply chains, there are certain limitations made on how the network is created. First, self-edges and multi-edges are not allowed. A *self-edge* is a link pointing to the same node it originates from, and is not a part of realistic supply network because a company cannot be supplying to itself products it is selling to others. *Mutli-edge* is a multiple instance of a link between the same pair of nodes. Because all goods are assumed to be perfectly substitutable, it is not allowed for a single supplier to deliver two or more different goods to the same customer. Both generation models avoid creating cycles. This is because a cycle implies that a single product has been transformed multiple times before it finally comes back to the starting node. To avoid cycles, all nodes in theoretical networks have links pointing downstream direction, never upstream. Moreover, there are no restrictions on the number of tiers or the number of nodes within the same tier.

5.2 Network-level characteristics of theoretical networks

There have been 20 distinct topologies generated: 5 random FMCG, 5 scale-free FMCG, 5 random automotive and 5 scale-free automotive networks. Random and scale-free networks have number of nodes and links corresponding to their respective empirical equivalents: 103 nodes and 472 links for FMCG networks, 565 nodes and 652 links for automotive networks. Random and scale-free network topologies for the automotive supply network are presented in Figures 5.4 and 5.5. Random and scale-free networks for FMCG logistics network are presented in Figures 5.2 and 5.3. Basic statistical properties of these networks are presented in Tables 5.1 and 5.2.

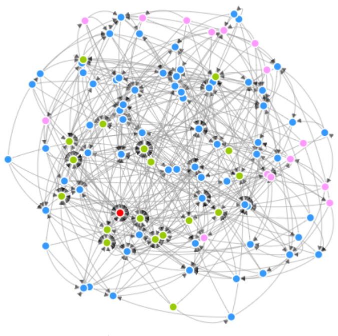
FMCG networks have higher mean-degree than automotive, with 4.58 for FMCG and 1.15 for automotive, implying that FMCG networks are more dense. Transitivity is equal to 0.1 for random and 0.48 for scale-free automotive topologies; 0.13 for random and 0.48 for scale-free FMCG topologies. Higher transitivity for scale-free FMCG and scale-free automotive networks implies that there are more triangles than in random topologies. High number of triangles in a supply network context would imply that given a firm having two suppliers, there is high probability that one of these suppliers is also supplying to the other one.

All scale-free networks have shorter mean geodesic distance than their random equivalents, with 0.723 for random FMCG and 0.060 for scale-free FMCG, with 0.057 for random automotive and 0.003 for scale-free automotive. This implies that there are less tiers in scale-free networks than in random ones, with approximately 7-8 tiers less for scale-free automotive networks and 1 tier less for scale-free FMCG networks (Figures 5.2, 5.3, 5.4 and 5.5). Lower mean geodesic distance for scale-free networks might lead to higher responsiveness and increased robustness.

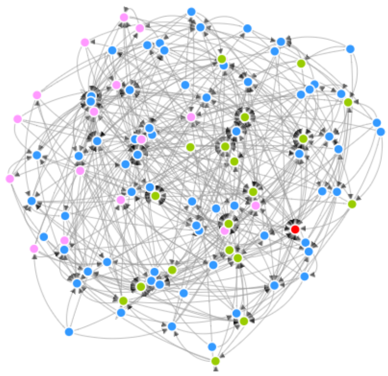
Random and scale-free FMCG networks are both slightly disassortative, which means that nodes tend to connect to other nodes with distinct characteristics. Random automotive topologies have assortativity close to zero and scale-free automotive topologies have high disassortativity. The differences in assortativity in random and scale-free automotive networks come from low mean degree. Low mean degree implies a restricted number of links per node, therefore scale-free networks tend to create star-like structures, with hubs in the center of the network and peripheral nodes connected to these hubs.

Topological characteristics, according to literature, suggest that scale-free networks absorb disruptions better than random networks (Barabasi and Albert, 1999, Kim et al., 2015, Nair and Vidal, 2011, Newman, 2010, Thadakamalla et al., 2004, Zhao et al., 2011).

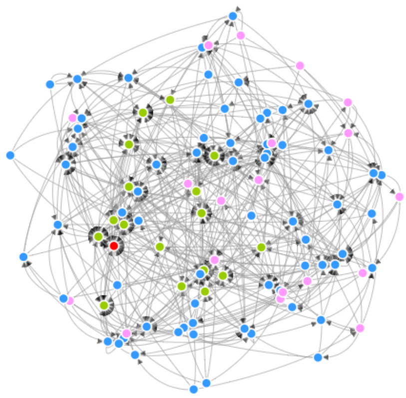
Figure 5.2: FMCG random networks generated using random attachment model ($n = 103$, $m = 472$)



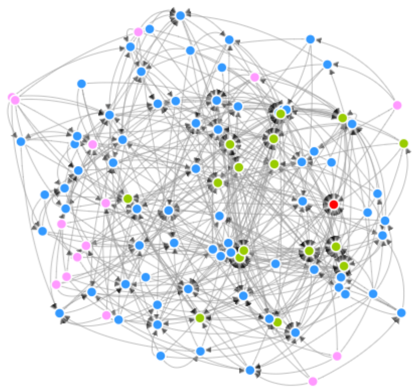
(a) random 1 (103, 472)



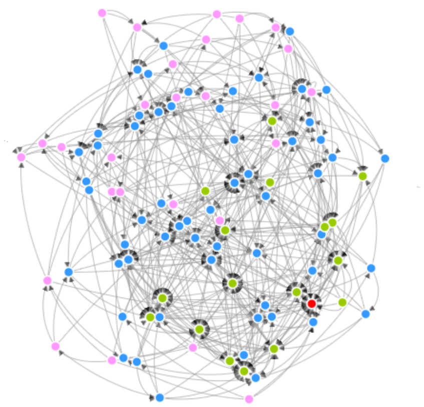
(b) random 2 (103, 472)



(c) random 3 (103, 472)

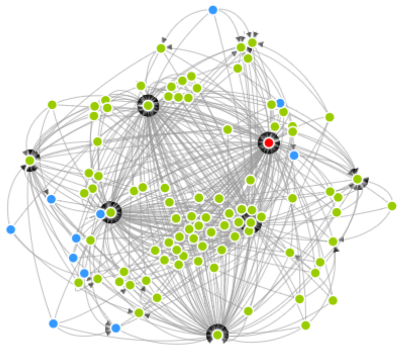


(d) random 4 (103, 472)

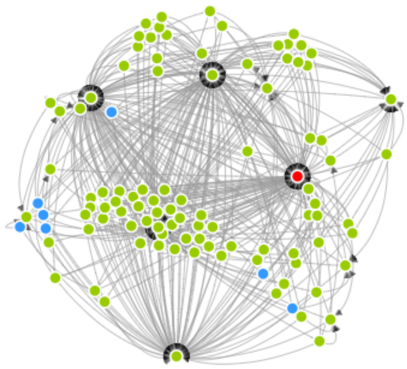


(e) random 5 (103, 472)

Figure 5.3: FMCG scale-free networks generated using preferential attachment model (n = 103, m = 472)



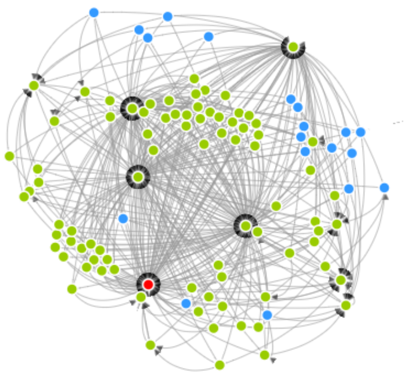
(a) scale-free 1 (103, 472)



(b) scale-free 2 (103, 472)

(c) scale-free 3 (103, 472)

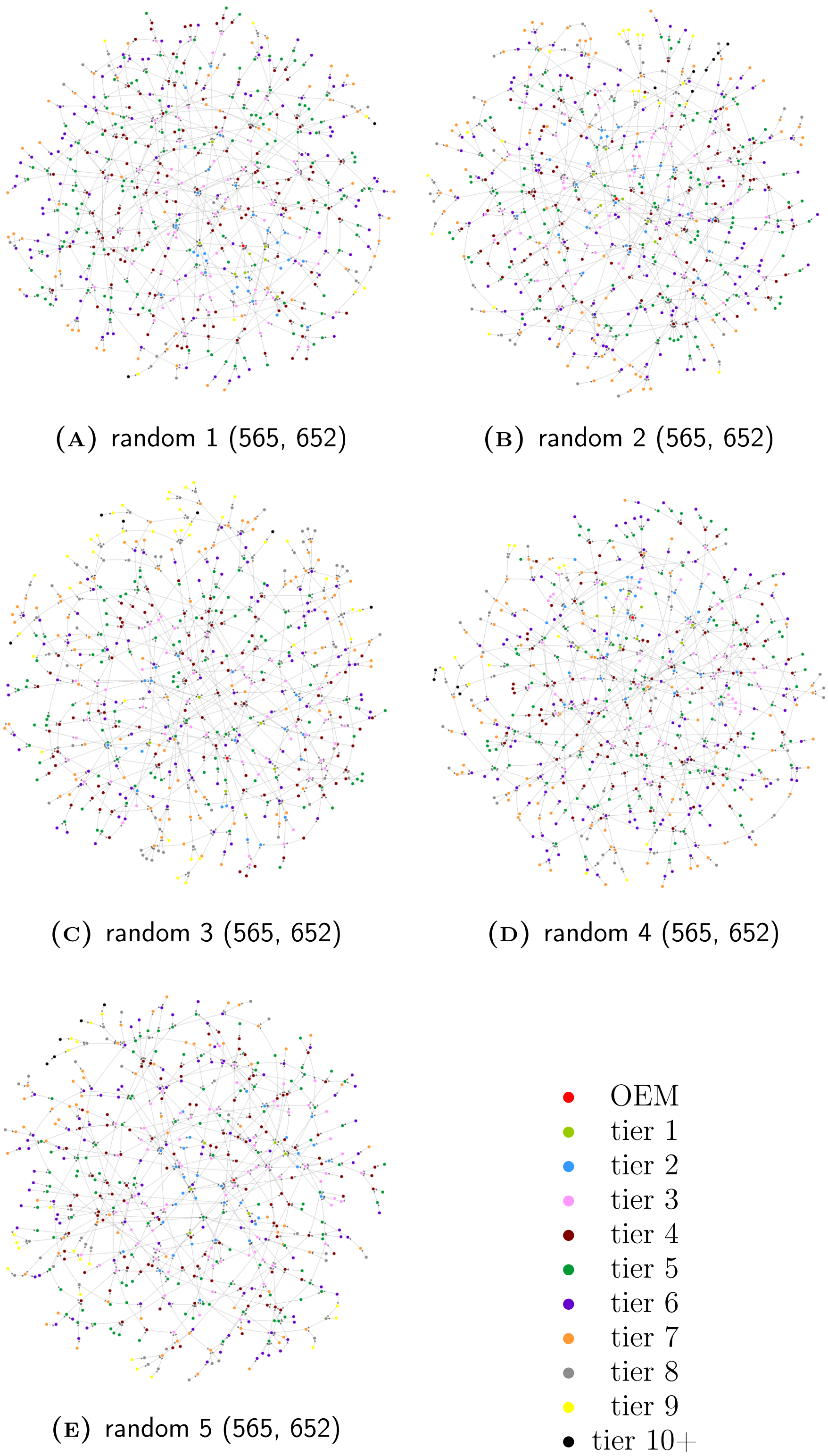
(d) scale-free 4 (103, 472)



(e) scale-free 5 (103, 472)

- OEM
- tier 1
- tier 2

FIGURE 5.4: Automotive random networks generated using random attachment model ($n = 565$, $m = 652$)



(A) random 1 (565, 652)

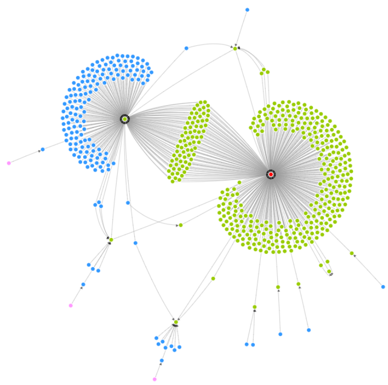
(B) random 2 (565, 652)

(C) random 3 (565, 652)

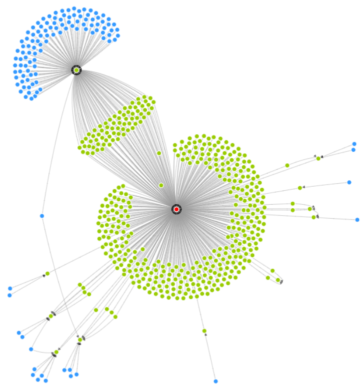
(D) random 4 (565, 652)

(E) random 5 (565, 652)

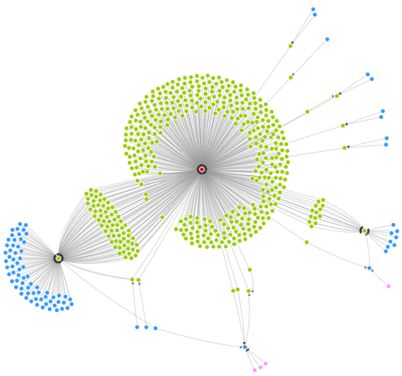
Figure 5.5: Automotive scale-free networks generated using preferential attachment model (n = 565, m = 652)



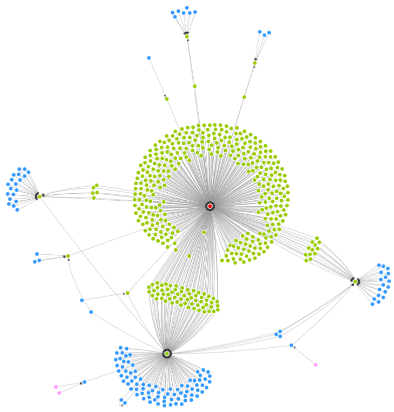
(A) scale-free 1 (565, 652)



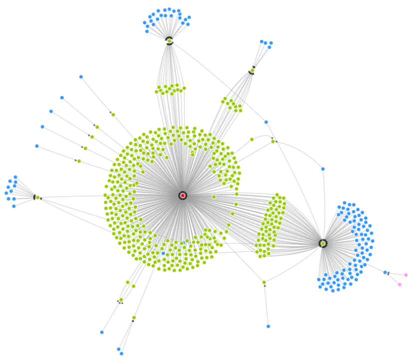
(B) scale-free 2 (565, 652)



(C) scale-free 3 (565, 652)



(D) scale-free 4 (565, 652)



(E) scale-free 5 (565, 652)

Table 5.1: Mean degree c and transitivity C of theoretical networks

Type	Topology	n	m	c^*	σc	C^*	σC
FMCG	Random	103	472	4.58	0.000	0.13	0.006
	Scale-free	103	472	4.58	0.000	0.48	0.012
Automotive	Random	565	652	1.15	0.000	0.01	0.009
	Scale-free	565	652	1.15	0.000	0.48	0.008

n number of nodes, m number of links, c mean degree, C transitivity, $\sigma c, \sigma C$ standard deviation of c, C
* average over 5 topologies

Table 5.2: Assortativity (r) and mean geodesic distance (l) of theoretical networks

Type	Topology	n	m	r^*	σr	l^*	σl
FMCG	Random	103	472	-0.096	0.054	0.723	0.045
	Scale-free	103	472	-0.088	0.054	0.060	0.006
Automotive	Random	565	652	-0.005	0.060	0.057	0.011
	Scale-free	565	652	-0.222	0.053	0.003	0.000

n number of nodes, m number of links, r assortativity coefficient, l mean geodesic distance, $\sigma r, \sigma l$ standard deviation of r, l
* average over 5 topologies

5.3 Disruption absorption in theoretical networks

When a supply network is exposed to disruptions, some agents experience problems in fulfilling the demand of their customers due to delayed deliveries of their suppliers. Inventory levels oscillate, and these oscillations travel upstream and downstream, causing lower fill-rates and higher costs (Table 5.3). The higher the risk profile, the higher costs C_{NET} and lower fill-rates FR_{NET}. For example, for random FMCG networks costs increase from \$1,180,475 to \$3,479,350.34 when duration of rare disruptions is increased from short to long; fill-rates decrease from 75.40% to 46.39%. The same pattern can be observed for random automotive, scale-free FMCG and scale-free automotive.

Random FMCG and random automotive networks generate higher costs than scale-free FMCG and scale-free automotive for all risk profiles. For example, for low risk profile costs are \$1,180,475.94 and \$82,834.50 for random FMCG and scale-free FMCG networks, respectively. This is 14 times higher costs for random networks than scale-free. For high risk profiles costs are \$13,615,533.95 and \$2,469,877.41, which is 5.5 times higher costs for random networks than scale-free. For low risk profile costs are \$10,615,611.69 and \$532,250.63 for random automotive and scale-free automotive networks, respectively. These are 20 times higher costs for random than scale-free. For high risk profiles costs are \$137,904,910.47 and \$20,256,150, which is 7 times higher. The cost difference between random and scale-free is decreasing for higher risk profiles, which implies that scale-free networks lose some of their resilience when heavily perturbed. When risk is high, there is a higher probability that the impact of the disruption reaches the hubs within the network. When hubs are impacted by the disruption, there is a chance that a phenomenon called cascading failure will occur.

Random FMCG and random automotive networks have lower fill-rates than scale-free FMCG and scale-free automotive. For low risk fill-rates are equal to 75.40% and 95.99% in random FMCG and scale-free FMCG networks, respectively. When risk is high, random FMCG network's fill-rates drop to 25.81%, which is half of the fill-rate obtained for scale-free FMCG networks under the same conditions. For low risk profile fill rates are 65.62% and 97.30% for random automotive and scale-free automotive networks, respectively. For high risk fill rates drop to 42.15% for random automotive and to 60.16% for scale-free automotive.

Random and scale-free automotive topologies generate higher costs than FMCG topologies because there are more nodes in the network and the end-consumer demand is higher. If the total cost is a biased metric because it depends on number of agents, fill-rates are normalised which makes it a good performance metric to compare topologies with different number of nodes or links. Automotive topologies have higher fill-rates for most of the cases compared with FMCG topologies. Higher resilience of automotive networks comes from its sparsity: When a disruption happens, there is a smaller damage spectrum and less immediate business partners affected.

In accordance with the literature, scale-free supply networks are more resilient to random disruptions (Nair and Vidal, 2011, Thadakamalla et al., 2004, Zhao et al., 2011). In addition, this work highlights that scale-free supply networks generate lower costs and have higher fill-rates.

5.4 Effectiveness of inventory mitigation in theoretical networks

The inventory mitigation strategy proves to be effective for scale-free and random topologies because it increases fill-rates and might decrease costs. However, the amount of cost reduction depends on risk profile and topology. Results are presented in Figures 5.6, 5.7, 5.8 and 5.9. Each data point plotted on these Figures is an average over 150 samples. Standard error of these samples is small because they fall within similar ranges. Even if plotted on all Figures, standard error is not always visible. All data points for a single topology are presented for chosen scenarios in Appendix A.

When all companies apply inventory mitigation for frequent and long disruptions, C_{NET} is decreased by 31.81% and 32.66% for random and scale-free FMCG topologies, respectively. For random and scale-free automotive topologies there was 16.25% and 33.71% C_{NET} reduction, respectively (Table 5.4). Cost reductions are caused

Table 5.3: Performance of theoretical networks exposed to disruptions. σFR_{NET} and σC_{NET} are standard deviations of fill-rates and costs, respectively.

Topology (n, m)	Risk profile	$FR_{NET}{}^{*}$	σFR_{NET}	$C_{NET}{}^{*}$	σC_{NET}
Random (103,472)	rare, short	75.40%	4.36%	1,180,475.94$	292,446.99$
	rare, long	46.39%	4.43%	3,479,350.34$	538,255.84$
	frequent, short	38.38%	2.17%	4,947,204.54$	370,403.37$
	frequent, long	25.81%	1.14%	13,615,533.95$	817,469.95$
Random (565,652)	rare, short	65.62%	1.55%	10,615,611.69$	2,668,248.99$
	rare, long	48.51%	1.14%	32,895,719.54$	8,192,217.54$
	frequent, short	54.59%	0.61%	42,389,538.93$	6,490,383.26$
	frequent, long	42.15%	0.91%	137,904,910.47$	22,247,087.01$
Scale-free (103,472)	rare, short	95.99%	1.15%	82,834.50$	24,859.64$
	rare, long	89.83%	2.67%	281,940.23$	86,665.64$
	frequent, short	75.96%	1.67%	707,977.39$	44,637.77$
	frequent, long	55.00%	1.85%	2,469,877.41$	130,703.55$
Scale-free (565,652)	rare, short	97.30%	0.97%	532,250.63$	186,739.11$
	rare, long	93.23%	2.27%	1,852,794.42$	609,556.81$
	frequent, short	78.79%	1.27%	5,909,025.48$	223,047.69$
	frequent, long	60.16%	1.87%	20,256,150.26$	503,290.62$

* average over 5 topologies and 30 trials

by the fact that the increase in inventory holding costs resulting from the additional inventory is less than the decrease in the backlog costs.

When disruptions are rare, the topology has a strong impact on the effectiveness of the inventory mitigation strategy. A decrease in cost can be observed only for random FMCG and random automotive topologies, where it occurs up to the specific mitigation level, e.g. the lowest costs for rare and short disruptions occur when around 25% of firms keep additional inventory. Cost reduction does not occur for rare disruptions in scale-free FMCG and scale-free automotive topologies, thus, they do not require as much inventory as random topologies. This is expressed by an increase in C_{NET} for scale-free FMCG topologies by 836.54% for rare and short disruptions when all companies apply inventory mitigation, and by 182.64% for rare and long disruptions (Table 5.4). Similarly to FMCG, scale-free automotive topologies have C_{NET} increased by 1242.93% for rare and short disruptions, and by 291.27% for rare and long disruptions.

Inventory mitigation strategy always improves fill-rates, regardless of topology (Figures 5.8 and 5.9). Increase in fill-rate is caused by the fact that companies keep additional inventory which absorbs any demand oscillations. The FR_{NET} improvement for frequent and long disruptions is 13.43% and 17.44% for random and scale-free FMCG topologies, respectively. The FR_{NET} improvement for frequent and long disruptions is 3.73% and 16.88% in random and scale-free automotive topologies, respectively. Scale-free topologies reduce disruption impact better because they reach higher FR_{NET} than random topologies for all risk profiles. For example, under frequent and short disruptions, in order to reach 75% FR_{NET} in random FMCG topology, there needs to be around 100% agents keeping additional inventory. For scale-free FMCG networks, the same result can be obtained with only 5% of agents applying inventory mitigation. Under frequent and short disruptions, in order to reach 65% FR_{NET} in random automotive topology, there needs to be around 100% agents keeping additional inventory. For scale-free automotive networks, FR_{NET} is already equal to 78.79% when 0% agents keep additional inventory. On average, the manufacturer reduces disruption impact better than the whole network for the majority of the risk profiles for FMCG and automotive topologies. This is because additional inventory prevents cascading failures across the network, stopping inventory oscillations from reaching the manufacturer. When risk is high, the amount of inventory is not enough to stop the failures and the impact of the disruption reaches the manufacturer.

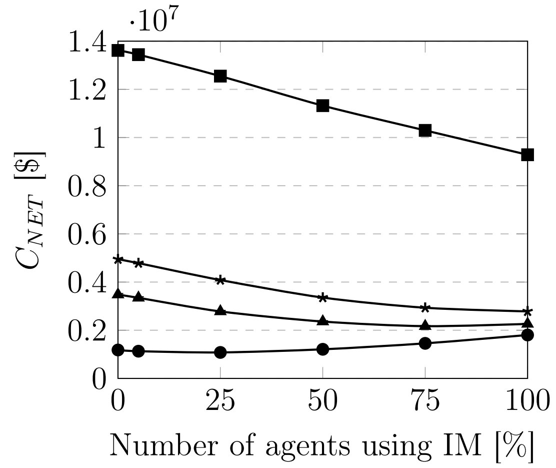
On average, scale-free networks are more resilient to random disruptions, they reduce disruption impact better using inventory mitigation, generate lower C_{NET} and C_{MAN}, and have higher FR_{NET} and FR_{MAN}. They have higher disruption thresholds and need less inventory than random topologies for the same risk profile. Keeping additional inventory is an effective risk mitigation strategy in a complex supply network environment as it always increases FR_{NET} and FR_{MAN}, and might decrease C_{NET} and C_{MAN} depending on the risk profile and topology. The same amount of inventory decreases total costs for random networks, but increases costs for scale-free networks under the same conditions.

5.5 Effectiveness of contingent rerouting in theoretical networks

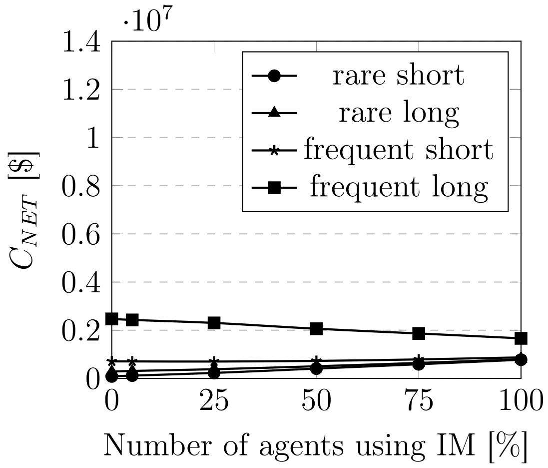
Contingent rerouting is not effective for short disruptions because of mailing delay time (*mdt*). If the disruption duration is short, the disrupted supplier is back to business before its customer applies contingent rerouting. Delay in application of contingency strategy causes unnecessary inventory oscillations and results in increased costs and decreased fill-rates for both the manufacturer and the whole network (Figures 5.10, Figures 5.11, 5.12 and 5.13).

Contingent rerouting is effective for long disruptions, but not in all cases. It increases random FMCG network performance, with an increase in FR_{NET} and FR_{MAN}, and with a decrease in C_{NET} and C_{MAN}. For scale-free FMCG networks, the strategy works only for the manufacturer with an increase in FR_{MAN} and a decrease in C_{MAN}. However, it does not improve the performance of the overall network (Table 5.4). This happens because the manufacturer has multiple alternative suppliers, whereas the majority of firms within scale-free network do not have many alternative sourcing options. Contingent rerouting is not effective even for long disruptions in automotive topologies. It results from the fact that these topologies have low mean degree, thus have an average small number of alternative suppliers. Contingent rerouting is effective for long disruptions in all manufacturers, regardless of topology. This is

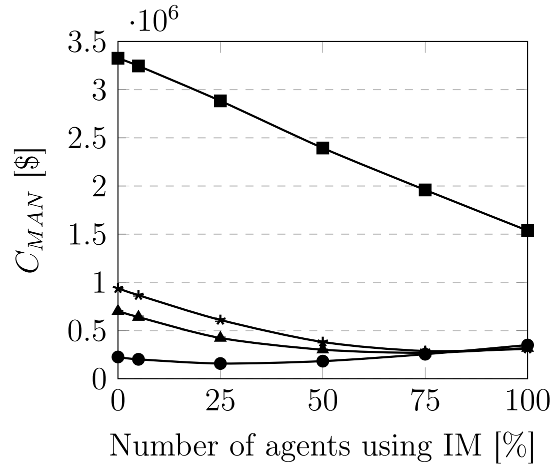
Figure 5.6: (a, b) Network and (c, d) manufacturer's costs for inventory mitigation (IM) strategy for FMCG random and scale-free networks (n=103, m=472)



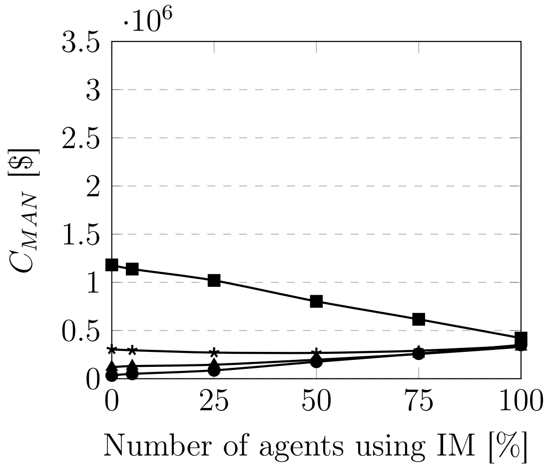
(a) C_{NET} for random networks



(b) C_{NET} for scale-free networks

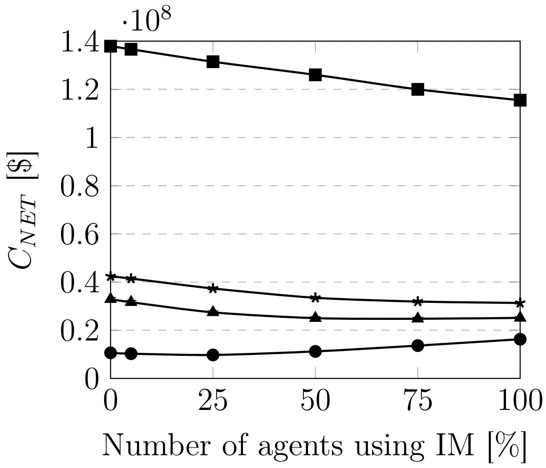


(c) C_{MAN} for random networks

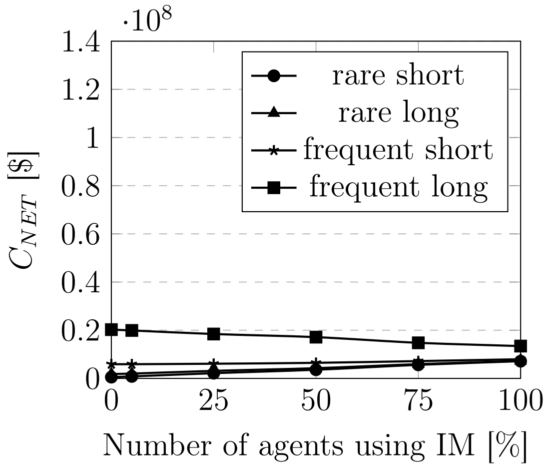


(d) C_{MAN} for scale-free networks

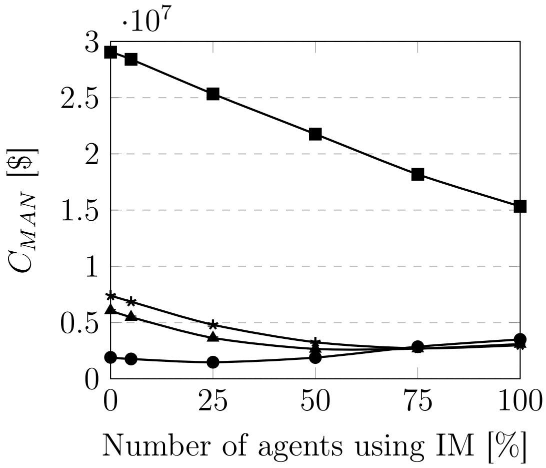
FIGURE 5.7: (a, b) Network and (c, d) manufacturer's costs for inventory mitigation (IM) strategy for automotive random and scale-free networks (n=565, m=652)



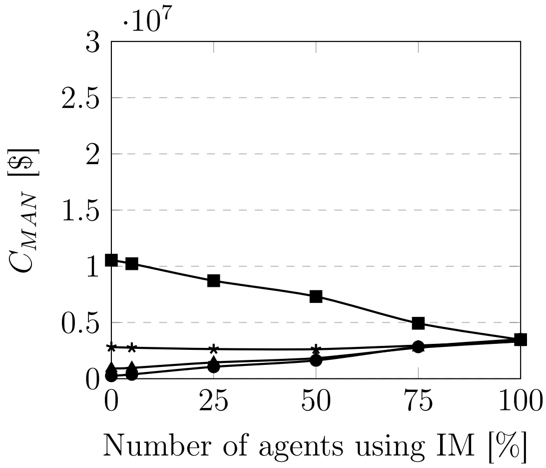
(A) C_{NET} for random networks



(B) C_{NET} for scale-free networks

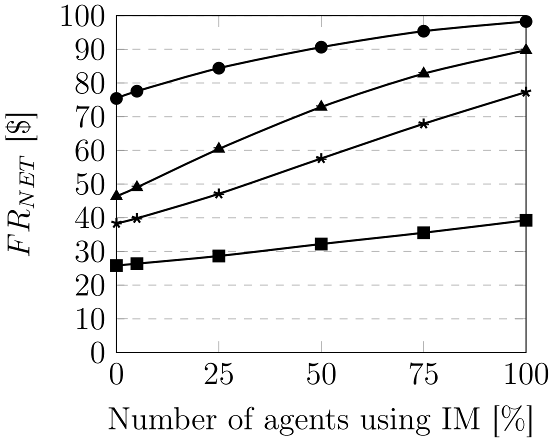


(C) C_{MAN} for random networks

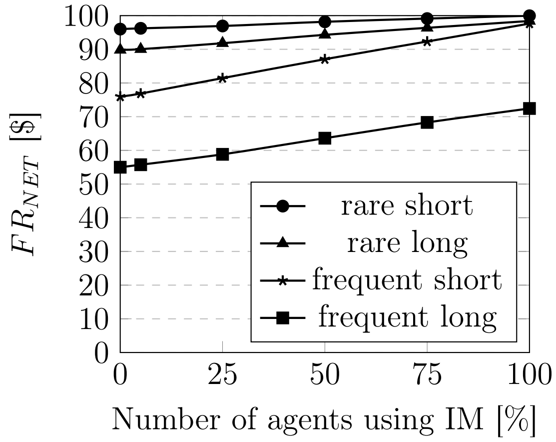


(D) C_{MAN} for scale-free networks

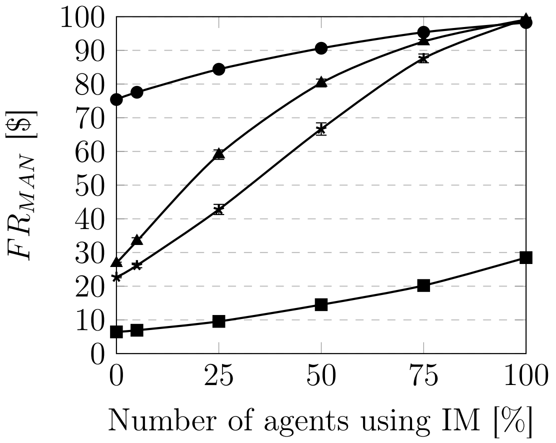
FIGURE 5.8: (a, b) Network and (c, d) manufacturer's fill-rates for inventory mitigation (IM) strategy for FMCG random and scale-free networks (n=103, m=472)



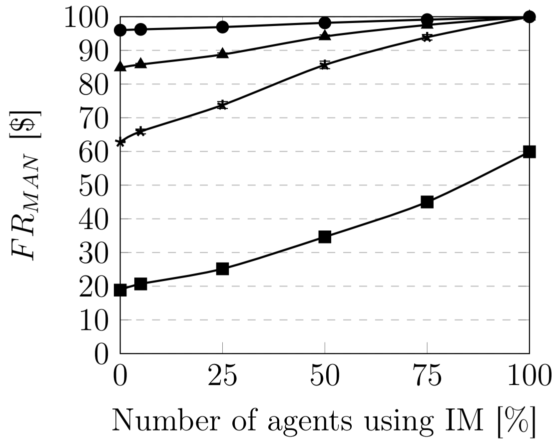
(A) FR_{NET} for random networks



(B) FR_{NET} for scale-free networks

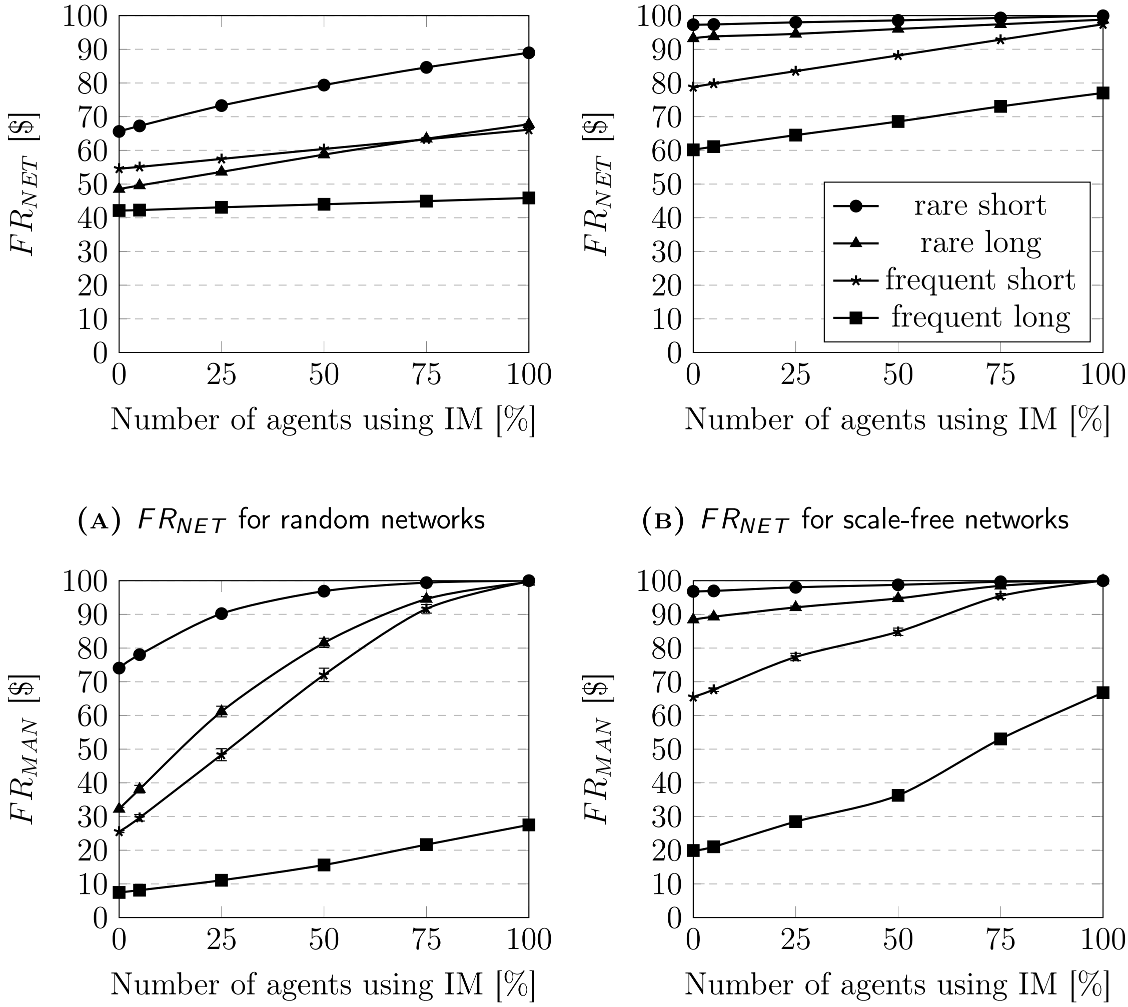


(C) FR_{MAN} for random networks



(D) FR_{MAN} for scale-free networks

FIGURE 5.9: (a, b) Network and (c, d) manufacturer's fill-rates for inventory mitigation (IM) strategy for automotive random and scale-free networks (n=565, m=652)



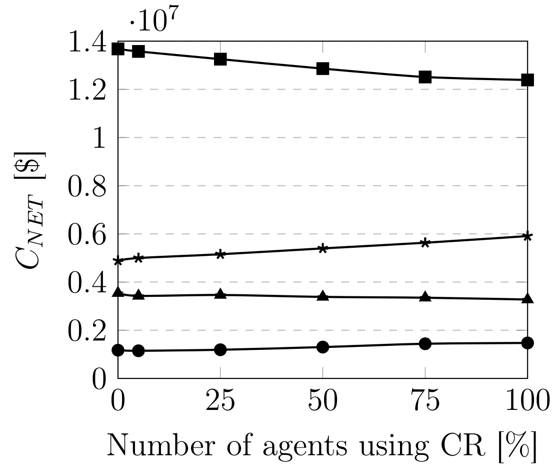
(A) FR_{NET} for random networks

(B) FR_{NET} for scale-free networks

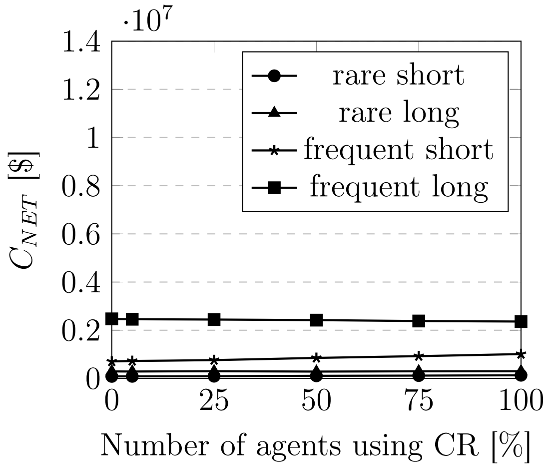
(C) FR_{MAN} for random networks

(D) FR_{MAN} for scale-free networks

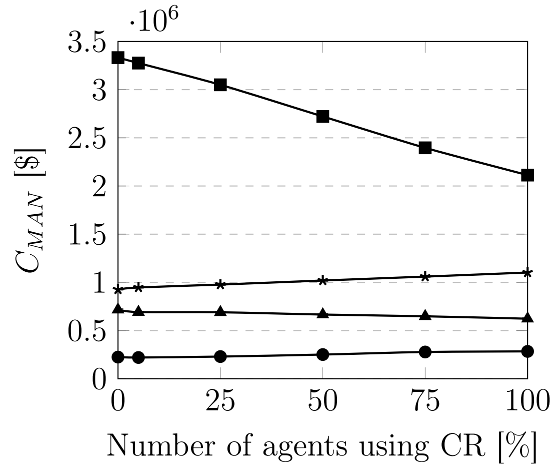
FIGURE 5.10: (a, b) Network and (c, d) manufacturer's costs for contingent rerouting (CR) strategy for FMCG random and scale-free networks (n=103, m=472)



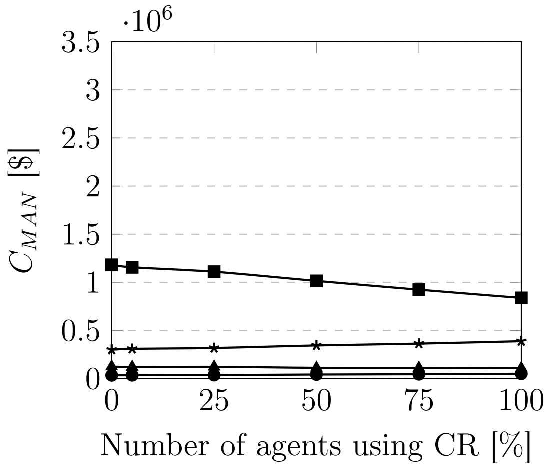
(A) C_{NET} for random networks



(B) C_{NET} for scale-free networks

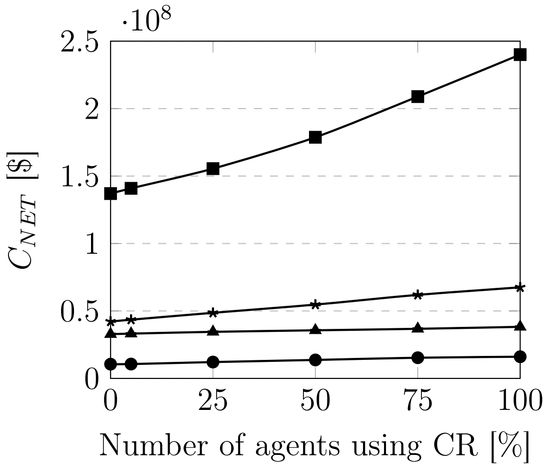


(C) C_{MAN} for random networks

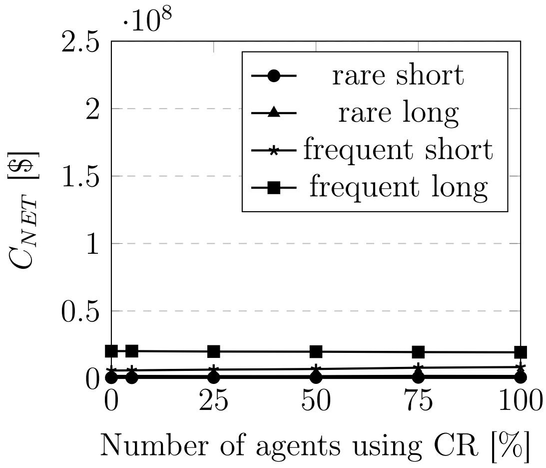


(D) C_{MAN} for scale-free networks

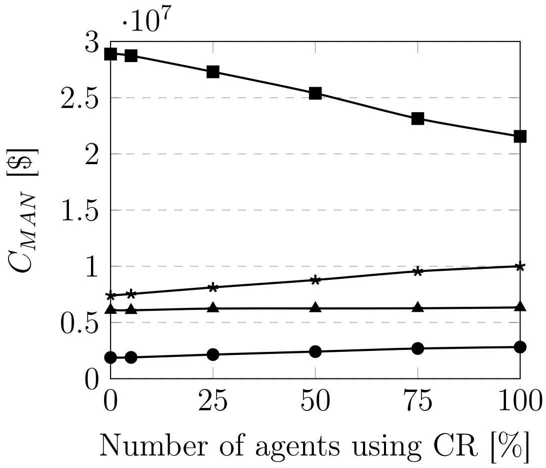
FIGURE 5.11: (a, b) Network and (c, d) manufacturer's costs for contingent rerouting (CR) strategy for automotive random and scale-free networks (n=565, m=652)



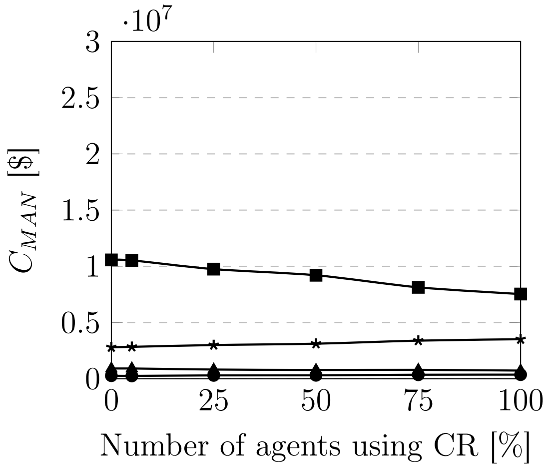
(A) C_{NET} for random networks



(B) C_{NET} for scale-free networks

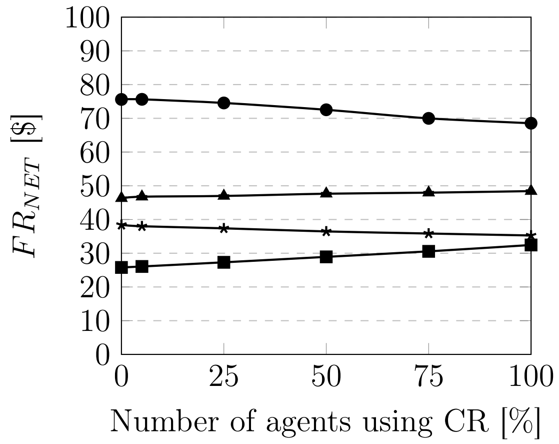


(C) C_{MAN} for random networks

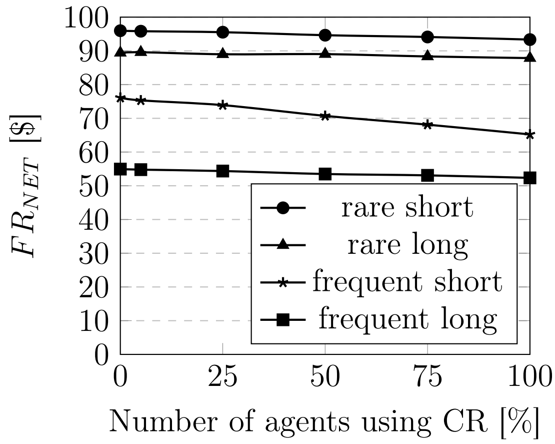


(D) C_{MAN} for scale-free networks

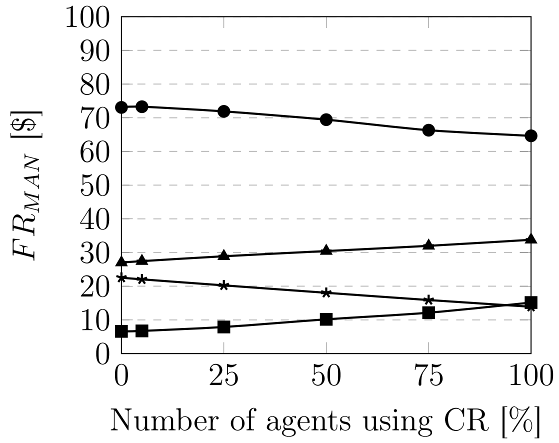
FIGURE 5.12: (a, b) Network and (c, d) manufacturer's fill-rates for contingent rerouting (CR) strategy for FMCG random and scale-free networks (n=103, m=472)



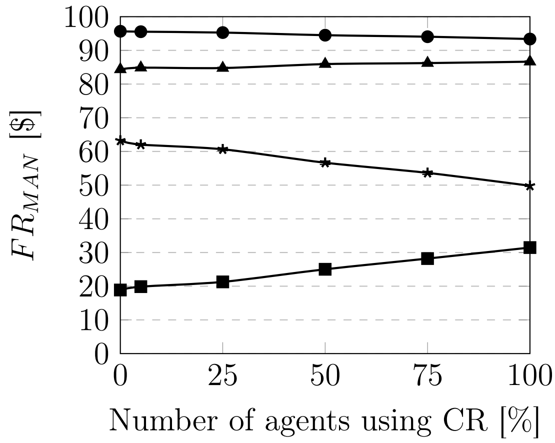
(A) FR_{NET} for random networks



(B) FR_{NET} for scale-free networks

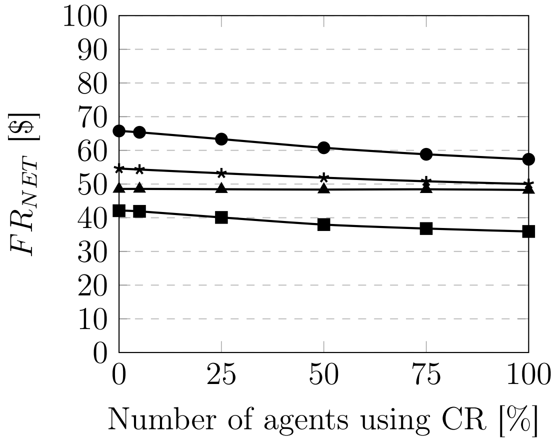


(C) FR_{MAN} for random networks

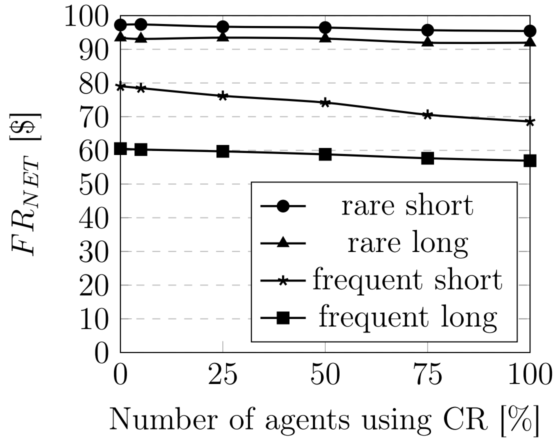


(D) FR_{MAN} for scale-free networks

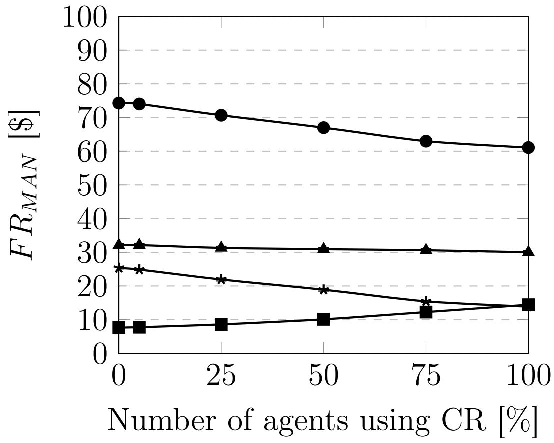
Figure 5.13: (a, b) Network and (c, d) manufacturer's fill-rates for contingent rerouting (CR) strategy for automotive random and scale-free networks (n=565, m=652)



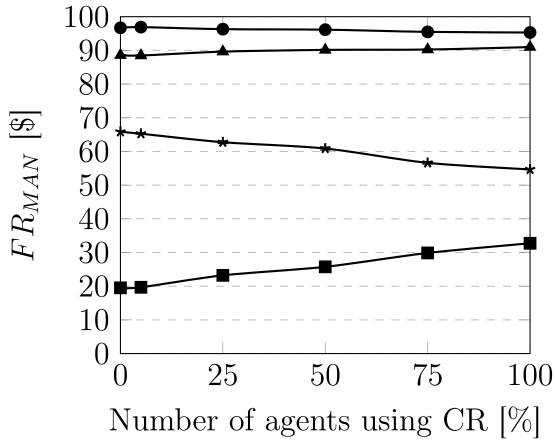
(a) FR_{NET} for random networks



(b) FR_{NET} for scale-free networks



(c) FR_{MAN} for random networks



(d) FR_{MAN} for scale-free networks

Table 5.4: Effectiveness of mitigation and contingency when all agents apply IM or CR strategies. % change from when no IM/CR strategy is applied.

Topology (n, m)	Risk profile	FR_{NET} IM*	FR_{NET} CR*	C_{NET} IM*	C_{NET} CR*
Random (103,472)	rare, short	22.84%	-6.84%	52.71%	24.50%
	rare, long	43.32%	2.03%	-34.95%	-5.88%
	frequent, short	38.93%	-3.11%	-43.75%	19.44%
	frequent, long	13.43%	6.63%	-31.81%	-8.87%
Random (565,652)	rare, short	23.33%	-8.42%	53.31%	52.19%
	rare, long	19.23%	-0.30%	-23.61%	16.47%
	frequent, short	11.54%	-4.59%	-26.09%	60.10%
	frequent, long	3.73%	-6.16%	-16.25%	75.19%
Scale-free (103,472)	rare, short	3.97%	-2.65%	836.54%	58.23%
	rare, long	8.58%	-1.96%	182.64%	5.53%
	frequent, short	21.69%	-10.72%	23.27%	42.70%
	frequent, long	17.44%	-2.65%	-32.66%	-4.37%
Scale-free (565,652)	rare, short	2.65%	-1.79%	1242.93%	47.67%
	rare, long	5.57%	-1.50%	291.27%	-0.13%
	frequent, short	18.64%	-10.44%	34.87%	43.44%
	frequent, long	16.88%	-3.59%	-33.71%	-4.12%

* IM (inventory mitigation); CR (contingent rerouting)

because all manufacturers have high number of suppliers, implying high number of alternatives when it comes to applying contingency strategy.

5.6 Summary

In this chapter it has been shown how random and scale-free topologies absorb disruptions and how inventory mitigation and contingent rerouting strategies are effective in reducing disruption impact.

It has been observed that: (1) scale-free networks generate lower costs than random networks; (2) scale-free networks generate higher fill-rates than random networks.

The results lead to the conclusion that an inventory mitigation strategy clearly outperforms contingent rerouting for all topology types and the majority of the risk profiles. The more additional inventory is kept in the network the higher the cost decrease will be. However, the amount of decrease occurs only up to some threshold value. When this threshold is passed, additional inventory causes costs to increase. The topology plays an important role in effectiveness of inventory mitigation because it influences the threshold value. Scale-free topologies have lower threshold values than random topologies, which implies that they need less inventory.

The following conclusions about inventory mitigation strategy has been drawn: (1) Additional inventory always increases fill-rate; (2) Additional inventory might decrease or increase costs depending on risk profile and network topology. The application of inventory mitigation for rare and long disruptions decreases costs in random networks and increases costs in scale-free networks; (3) Scale-free networks have higher disruption tolerance and need less inventory than random topologies for the same risk profiles.

Contingent rerouting changes costs linearly. Depending on the length of the disruption; it decreases the costs for long disruptions and increases the costs for short disruptions. The improvement for long disruptions is possible only in dense topologies, where agents have multiple alternative suppliers. In sparse topologies, this strategy did not prove to be effective. Inventory mitigation strategy always improves the fill-rate, whereas contingent rerouting decreases it for the majority of the cases.

The following conclusions about contingent rerouting strategy have been drawn: (1) Contingent rerouting is an effective strategy when disruption duration is long. It decreases costs and increases fill-rates. For short disruptions, there is an increase in costs and decrease in fill-rate due to inventory oscillations caused by order processing time; (2) Contingent rerouting is not an effective strategy for networks with low mean degree due to the low number of alternative suppliers; (3) Contingent rerouting is effective for firms that have high number of alternative suppliers.

The effectiveness of inventory mitigation and contingent rerouting has been a topic broadly discussed in the literature. It has been claimed that for long disruptions, the inventory mitigation does not prove to be an attractive strategy (Dong and Tomlin, 2012, Talluri et al., 2013, Tomlin, 2006), whereas results in this work show that the effectiveness of the strategy is highly dependent on the topology and performs better than contingent rerouting for the majority of the cases. The high effectiveness of inventory mitigation results from the absorption of inventory oscillations across the network (Mishra et al., 2016). Low performance of contingent rerouting applied in rare disruptions comes from high interconnectedness of the supply network; the supplier which receives the volume of the disrupted competitor has other supply obligations to meet. The short-term increase in demand in one supplier causes inventory oscillations to travel through the network creating the bullwhip effect and generates higher backlogs. Low performance of contingent rerouting in sparse topologies is caused by the fact that companies do not have alternative suppliers to source from in case one of them is disrupted.

Chapter 6

Risk management for empirical networks

This chapter extends robustness considerations to empirical networks. The effectiveness of two empirical networks is assessed and conclusions are made on its effectiveness in disruption absorption. Next, inventory mitigation and contingent rerouting strategies are applied. Their effectiveness on empirical networks is compared to their theoretical equivalents.

6.1 Network-level characteristics of empirical networks

Two empirical networks are considered: the automotive supply network of Maserati and a fast-moving consumer goods logistics network. The two networks have different types of supply entities. The Maserati network is a supply network, where each node represents an international company engaged in the supply of multiple parts used in a complex product assembly (Figure 6.2). Links between nodes indicate the material flow. The fast-moving consumer goods logistics network represents the internal firm operations, where nodes represent plants, distribution centres and rail terminals used to transport goods across the network (Figure 6.1).

Visualisations of Maserati and FMCG networks are presented in Figures 6.1 and 6.2. Basic topological properties of these networks are presented in Table 6.1. The Maserati network has a higher number of nodes, with 565 nodes and 652 links, compared with 103 nodes and 472 links in logistics network. The mean degree is lower almost four times for the Maserati network, which implies its sparsity. The

Table 6.1: Topological properties of empirical networks

Network type	n	m	c	C	r	l
FMCG	103	472	4.54	0.34	0.14	1.58
Maserati	565	652	1.15	0.11	-0.04	0.01

n number of nodes, m number of links, c mean degree,
C transitivity, r assortativity, l mean geodesic distance

mean degree is higher for FMCG topology, as expected from a logistics network, because products undertake less transformations and more movements from the plants to distribution centres etc. The rail terminals act as proxies between sites, transporting units across the network. Terminals playing the role of proxies also explain the high transitivity of the FMCG network. The Maserati network has very low negative assortativity, which implies that firms do not connect to other firms with a similar number of business partners. The logistics network is slightly assortative, which means that hub nodes tend to connect to other hub nodes. This is indeed the case because terminals which distribute the goods across the network are connected to other terminals.

Mean geodesic distance is equal to 0.01 for Maserati and 1.58 for FMCG network. The mean geodesic distances are so low for Maserati and other theoretical networks because they are acyclic. When there is no path between two nodes (e.g. a path from the manufacturer to raw-material supplier) a geodesic distance between these nodes is assumed to be zero. Since in acyclic supply networks only downstream links are allowed, there are many pairs of nodes which do not have the geodesic path. Non-existent paths between pair of nodes are not counted in the final sum, resulting in lower overall mean geodesic distance. The empirical FMCG network has cycles, with links pointing to upstream and downstream directions, therefore there are more paths available. Higher mean geodesic distance in the FMCG network does not practically mean that this distance is very high compared to other networks. Cycles in FMCG supply network have various effectiveness implications, as discussed later in this section.

Figures 6.3 and 6.4 present degree distribution for the Maserati and FMCG networks. Clearly, these networks distributions do not resemble each other mostly

FIGURE 6.1: FMCG company's logistics network

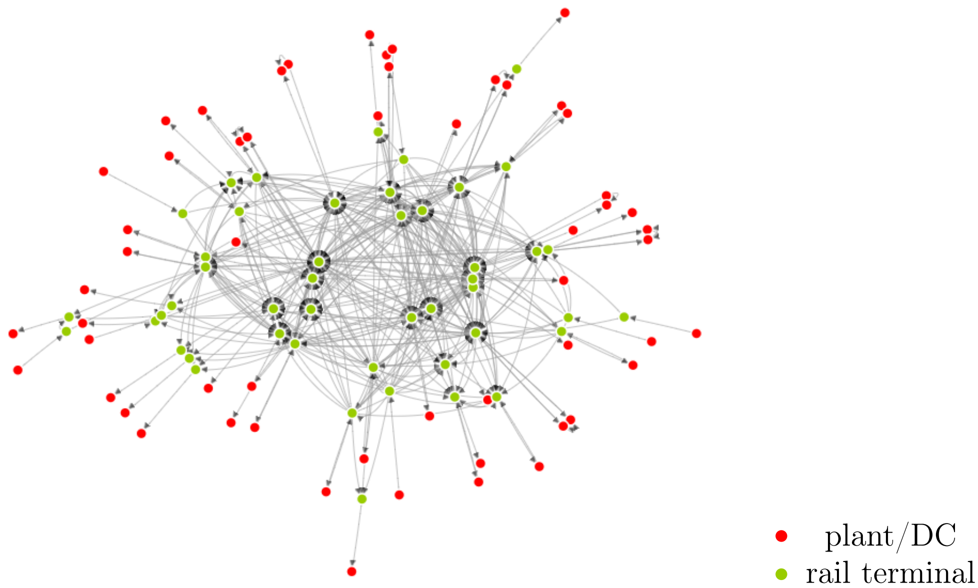


FIGURE 6.2: Maserati supply network

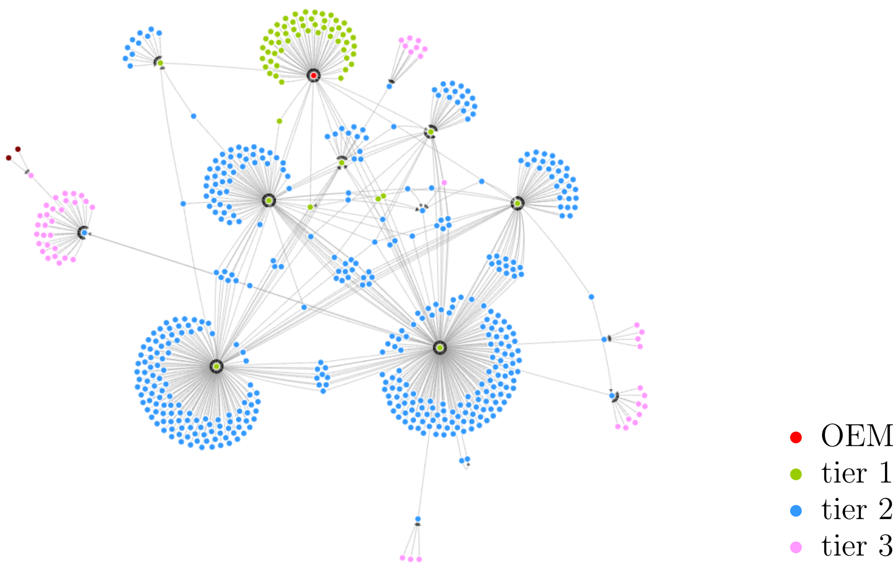
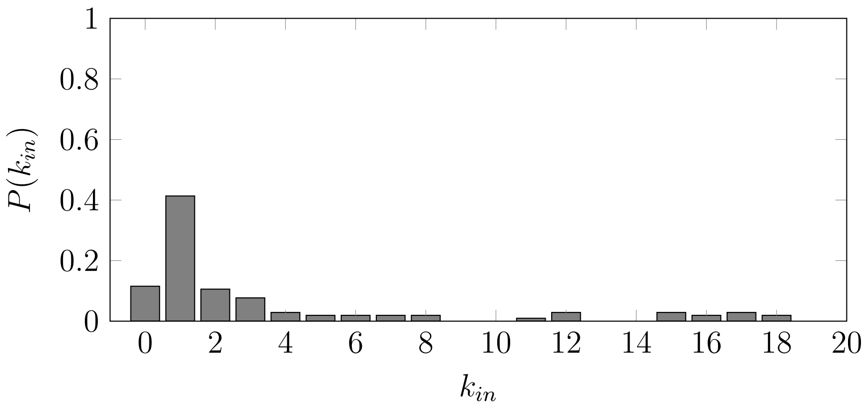
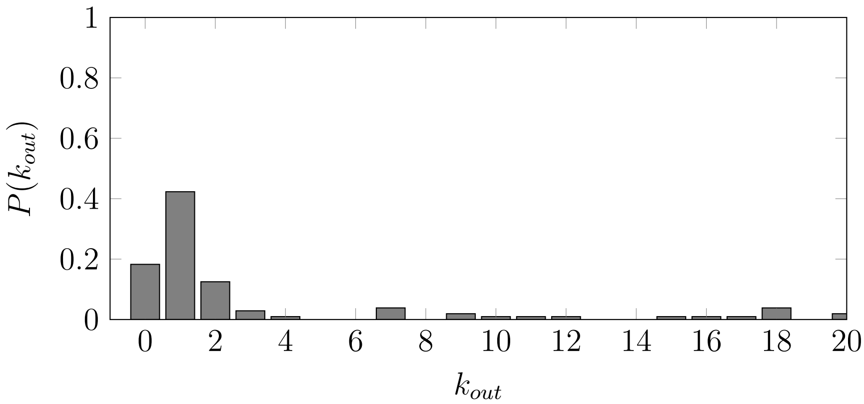


FIGURE 6.3: In-degree and out-degree distribution ($P(k_{in})$, $P_(k_{out})$) of FMCG network.

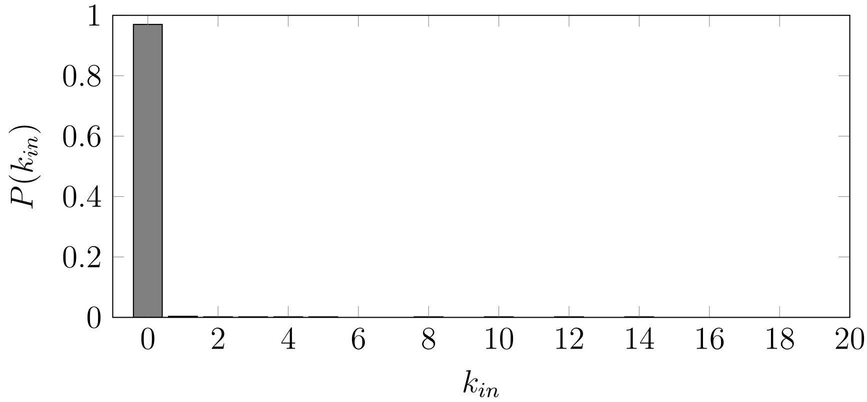


(A) $P(k_{in})$ of FMCG network

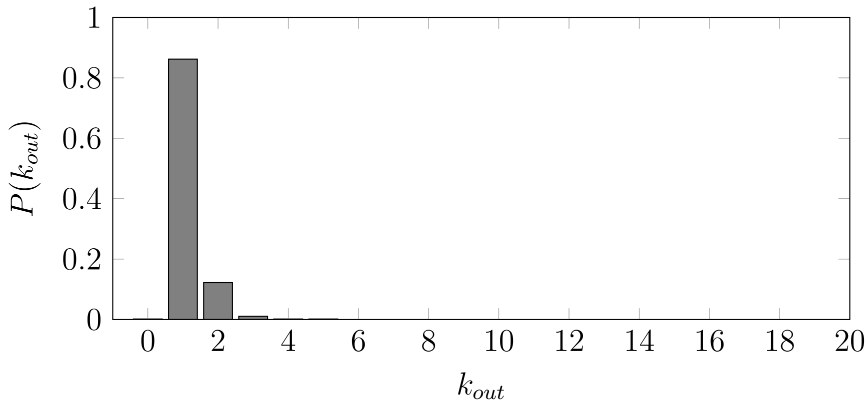


(B) $P(k_{out})$ of FMCG network

FIGURE 6.4: In-degree and out-degree distribution ($P(k_{in})$, $P_{(}k_{out})$) of Maserati.



(A) $P(k_{in})$ of Maserati



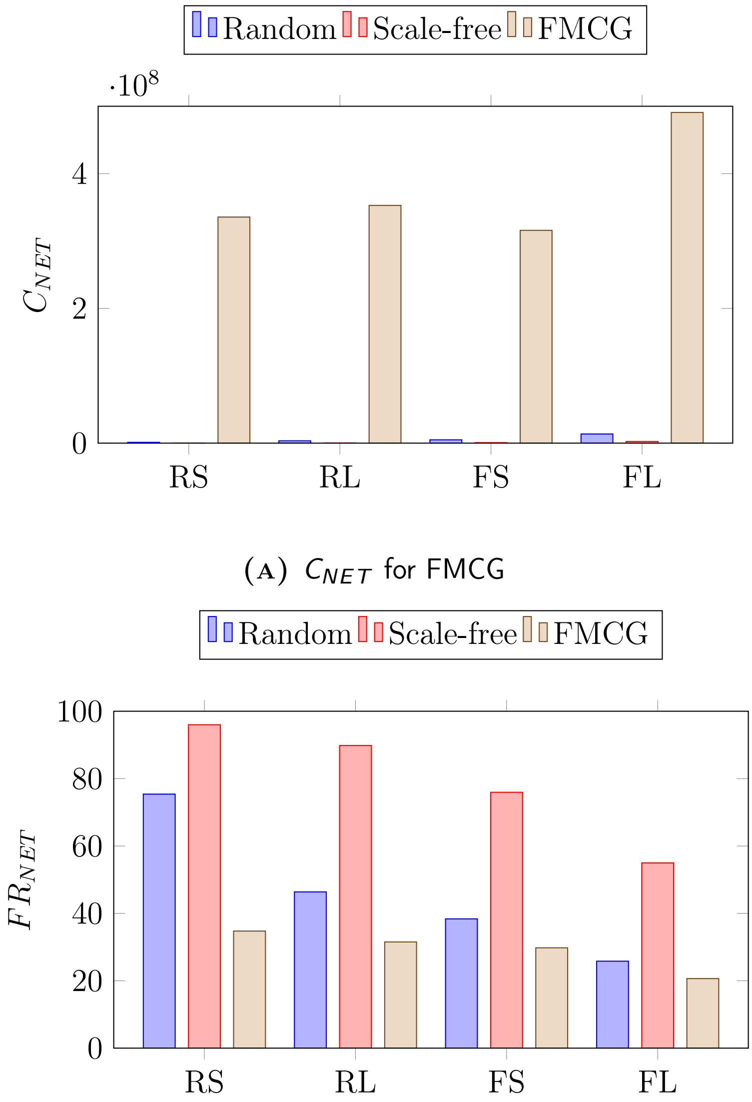
(B) $P(k_{out})$ of Maserati

because one is a supply network and the other is a logistics network. The FMCG logistics network has higher frequency of nodes with higher degree, as seen on Figure 6.3. Maserati, on the other hand, has much more low-degree nodes than high-degree nodes. Histograms in Figure 6.4 might resemble power-law, although it has been observed that scale-free automotive networks reach higher maximum degrees than Maserati do. Also, there are other differences between Maserati and scale-free networks as reported in Tables 5.1, 5.2, and 6.1. There is an ongoing debate as to the nature of supply network topology, although this is not the scope of this thesis therefore Maserati and FMCG networks will be treated as separate networks without being associated neither with scale-free nor random topologies.

6.2 Disruption absorption in empirical networks

This section describes how empirical supply networks react to disruptions. Table 6.2 presents C_{NET} and FR_{NET} of FMCG company and Maserati networks subject to disruptions. The higher risk, the higher costs and lower fill-rates for the majority of cases for both networks. The costs are 410 times more for FMCG than Maserati for rare and short disruptions and 20 times more for frequent and long disruptions. This is because the FMCG network contains cycles causing inventory oscillations as mentioned in the validation section in Chapter 4. Figures 6.5 and 6.6 present comparison between effectiveness of empirical networks under disruptions and their theoretical equivalents. Empirical FMCG topology generates much higher costs than random and scale free topologies (Figure 6.5 A), and has lower fill-rates (Figure 6.5 B). Maserati topology generates slightly higher costs and lower fill-rates than scale-free networks, which shows how close the dynamics of empirical supply networks might be to their scale-free equivalents. Additionally, scale-free automotive networks seem to have higher tolerance to disruption duration generating lower costs and higher fill rates than Maserati network. Empirical Maserati network has higher tolerance towards disruption frequency, generating lower costs and higher fill-rates than scale-free automotive network. Both phenomena are seen in Figures 6.6 A and 6.6 B. These results bring considerations about topologies being a key feature determining robustness to different characteristics of risk, such as duration and frequency.

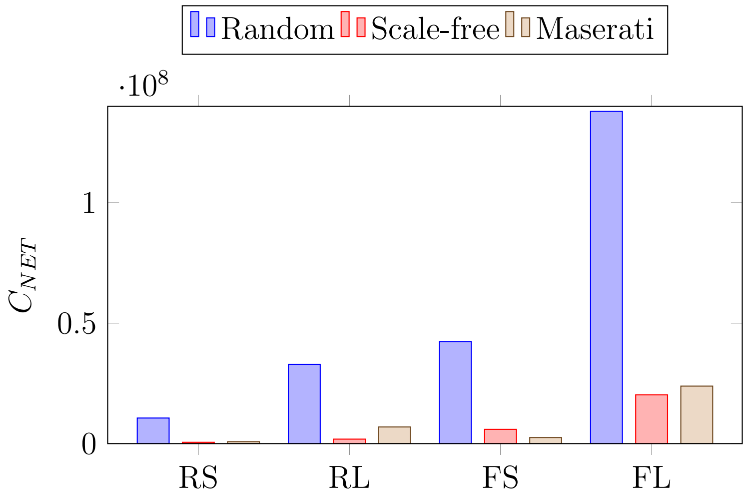
FIGURE 6.5: C_{NET} and FR_{NET} of FMCG company under disruptions compared to its theoretical equivalents. RS (rare, short); RL (rare long); FS (frequent short); FL (frequent long)



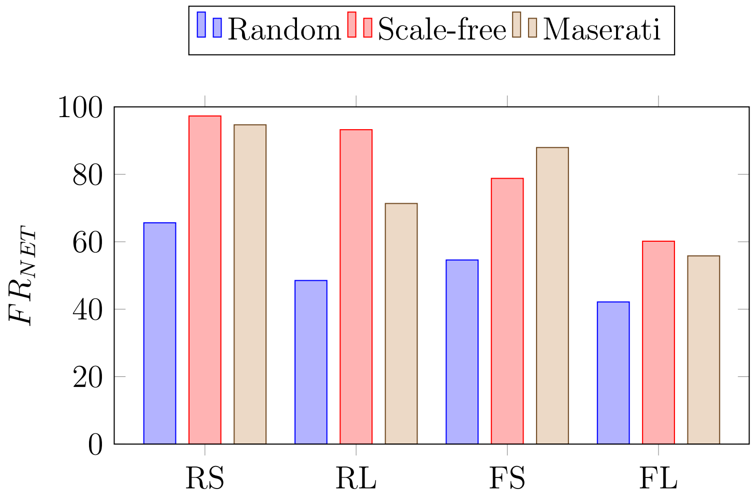
(A) C_{NET} for FMCG

(B) FR_{NET} for FMCG

FIGURE 6.6: C_{NET} and FR_{NET} of Maserati under disruptions compared to its theoretical equivalents. RS (rare, short); RL (rare long); FS (frequent short); FL (frequent long)



(A) C_{NET} for automotive



(B) FR_{NET} for automotive

TABLE 6.2: Effectiveness of supply networks exposed to disruptions. σFR_{NET} and σC_{NET} are standard deviations of fill-rates and costs respectively.

Topology (n, m)	Risk profile	FR_{NET}*	σFR_{NET}	C_{NET}*	σC_{NET}
FMCG (103,472)	rare, short	34.75%	0.78%	335,585,856.50$	6,097,455.67$
	rare, long	31.51%	2.35%	352,810,431.70$	21,845,181.67$
	frequent, short	29.78%	3.08%	315,820,857.90$	41,886,940.12$
	frequent, long	20.65%	0.56%	490,804,717.40$	27,941,853.20$
Maserati (565,652)	rare, short	94.68%	1.40%	817,891.86$	244,862.63$
	rare, long	71.35%	0.96%	6,908,904.30$	189,694.28$
	frequent, short	87.94%	2.12%	2,525,580.33$	656,619.82$
	frequent, long	55.81%	0.97%	23,860,195.52$	431,143.45$

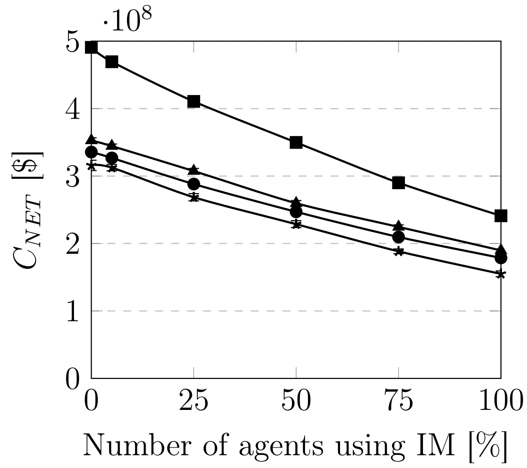
* average over 5 topologies and 30 trials

6.3 Effectiveness of inventory mitigation in empirical networks

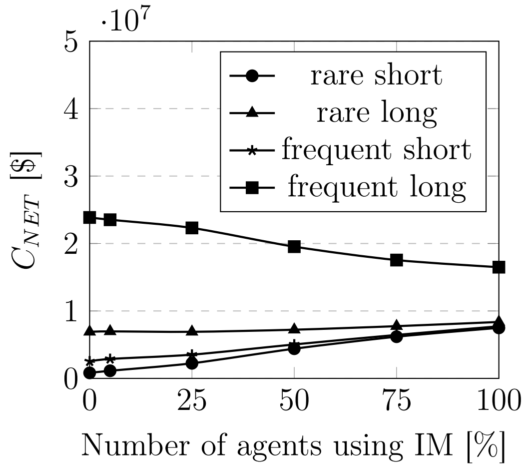
In the FMCG company, any amount of inventory reduced costs and increased fill-rates for the whole network and the manufacturer. For all risk profiles C_{NET} has decreased by 46.22% to 50.92% when all agents applied inventory mitigation. For all risk profiles FR_{NET} has been increased by 22.88% to 33.35%. Inventory mitigation is so effective in FMCG network because the network is unstable, which proves how effective inventory mitigation is in shock absorption. Nonetheless, FMCG still does not reach the effectiveness levels of its theoretical equivalents.

The Maserati network is similar to scale-free automotive networks in its resilience to disruptions, and does not need as much additional inventory as random automotive networks. The Maserati network needs less inventory for frequent disruptions than for rare disruptions because costs are increased by "only" 21.14% for rare and short disruptions, and increased by 205.77% for frequent and short disruptions. Higher cost increase indicates that the inventory threshold has been passed and adding any additional amount will result in costs' increase. Inventory mitigation has increased fill-rates for the Maserati network for all risk profiles, being the most effective for rare and long disruptions.

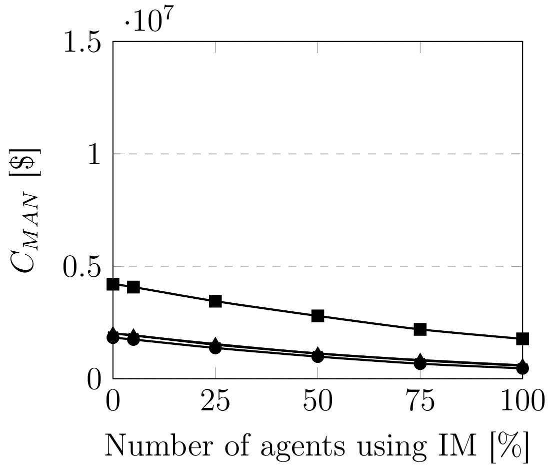
Figure 6.7: (a, b) Network and (c, d) manufacturer's costs for inventory mitigation (IM) strategy for FMCG company and Maserati.



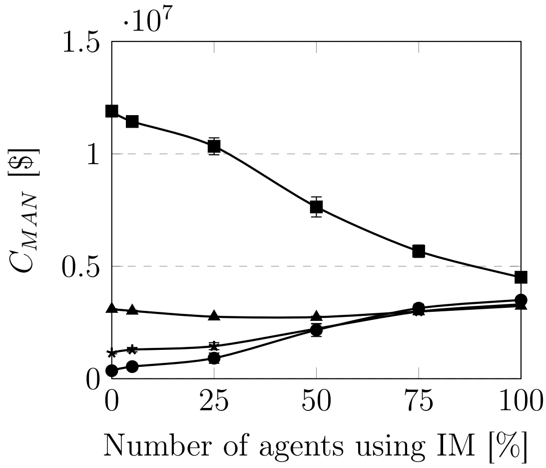
(a) C_{NET} for FMCG company



(b) C_{NET} for Maserati

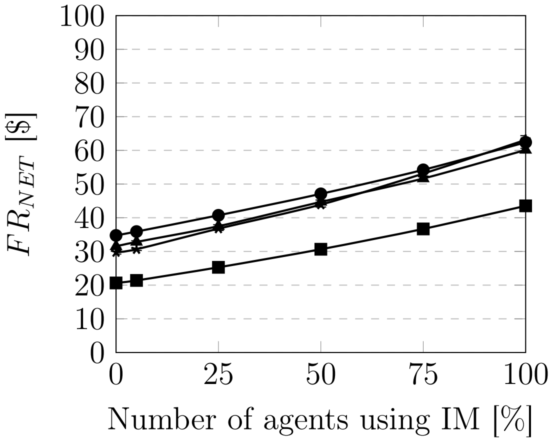


(c) C_{MAN} for FMCG company

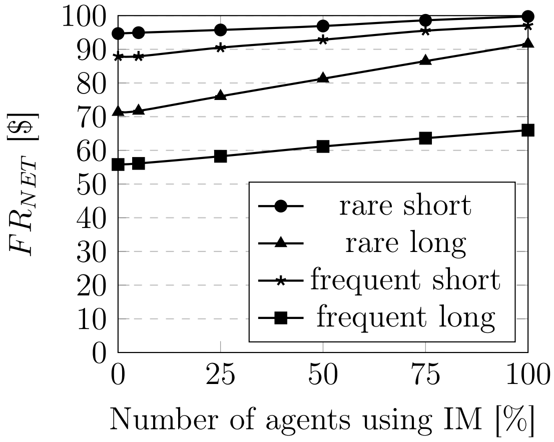


(d) C_{MAN} for Maserati

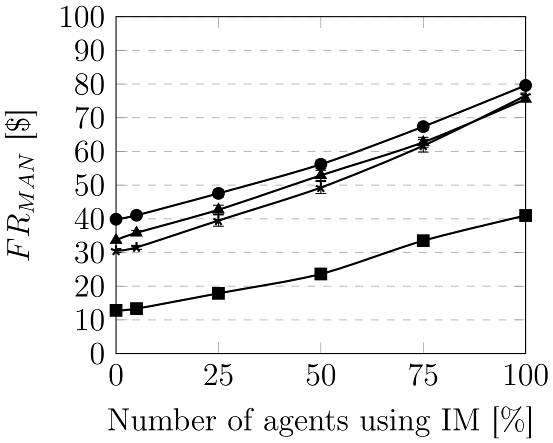
FIGURE 6.8: (a, b) Network and (c, d) manufacturer's fill-rates for inventory mitigation (IM) strategy for FMCG company and Maserati.



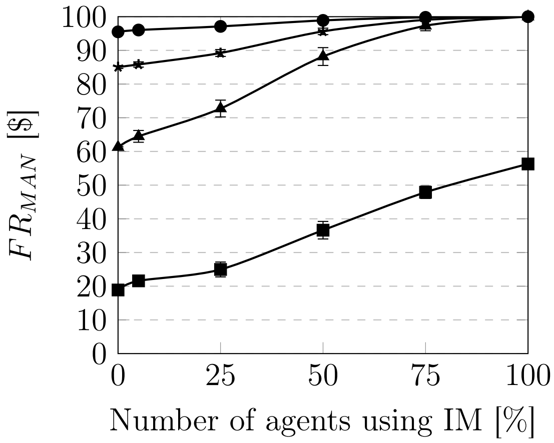
(A) FR_{NET} for FMCG company



(B) FR_{NET} for Maserati

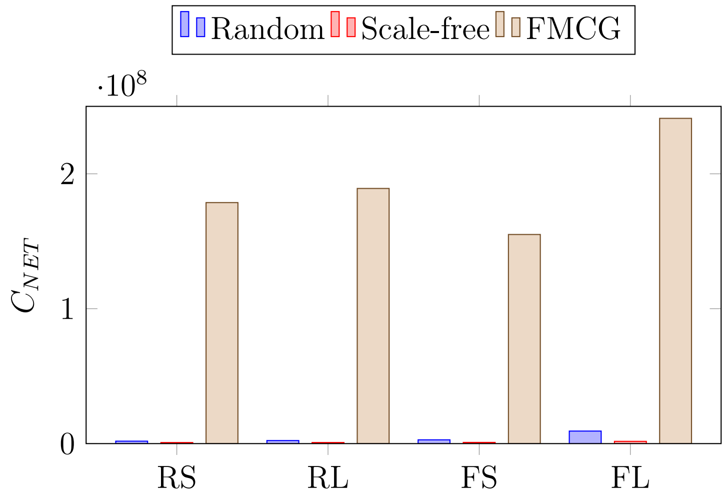


(C) FR_{MAN} for FMCG company

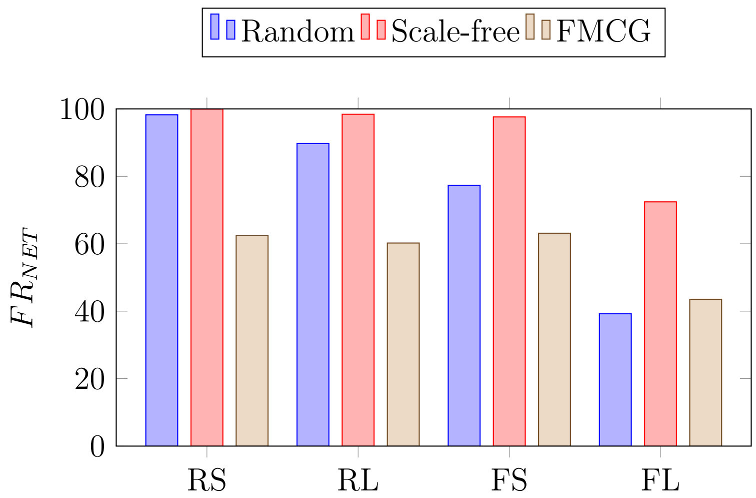


(D) FR_{MAN} for Maserati

Figure 6.9: C_{NET} and FR_{NET} of FMCG company compared to its theoretical equivalents when all agents apply IM. RS (rare, short); RL (rare long); FS (frequent short); FL (frequent long); IM(inventory mitigation).

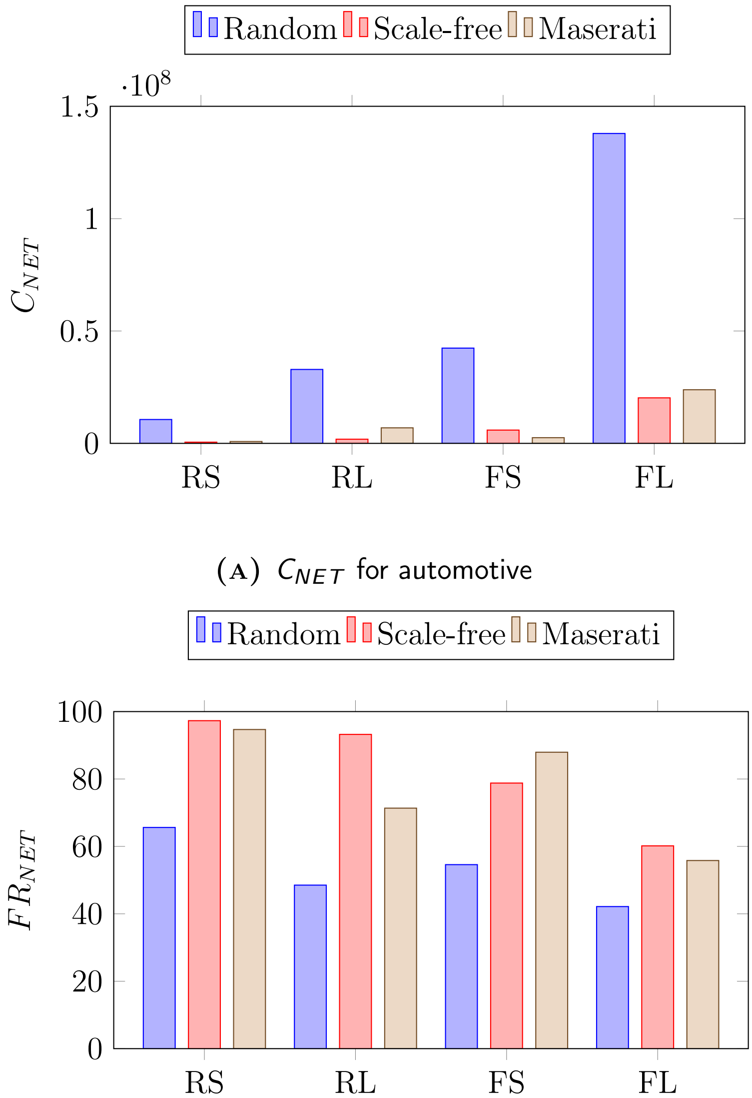


(A) C_{NET} for FMCG



(B) FR_{NET} for FMCG

FIGURE 6.10: C_{NET} and FR_{NET} of Maserati compared to its theoretical equivalents when all agents apply IM. RS (rare, short); RL (rare long); FS (frequent short); FL (frequent long); IM(inventory mitigation).



(A) C_{NET} for automotive

(B) FR_{NET} for automotive

6.4 Effectiveness of contingent rerouting in empirical networks

Contingent rerouting is effective for the majority of cases for the FMCG company, but its effectiveness is dependent on the disruption duration. When disruptions are long, the fill-rates are improved and costs reduced. When disruptions are short, both costs and fill-rates are decreased.

Contingent rerouting does not prove to be effective for Maserati. For short and long disruptions the strategy caused fill-rates to decrease by 1.37% to 9.06% and costs to increase by 8.96% to 49.64% for most of the time. The ineffectiveness of contingent rerotuing comes from its low mean degree. Maserati's mean degree is slightly higher than 1, which implies that each agent in the network has approximately only one supplier. There are no alternative suppliers to source from in case when there is a supplier disruption. Maserati responds to contingent rerouting in a very similar fashion as scale-free automotive networks. Also, as in previous cases, it is more effective in reducing disruption impact than scale-free automotive networks exposed to frequent and short disruptions.

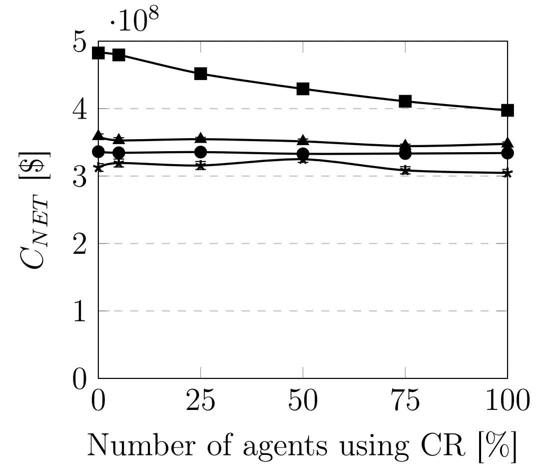
6.5 Summary

In this section, the effectiveness of empirical networks under disruptions has been evaluated. Also, it has been assessed how empirical networks reduce impact of disruptions using inventory mitigation and contingent rerouting compared to their random and scale-free equivalents. Since the empirical FMCG network is a logistics cyclic network, not an acyclic supply network, the conclusions will be drawn separately for both empirical examples.

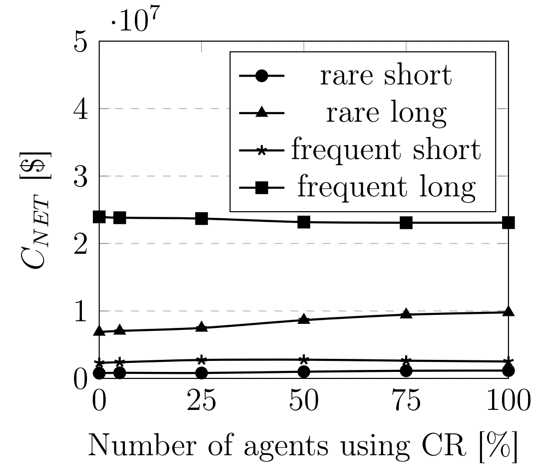
Results suggest that: (1) the Maserati network has shown high resilience to disruptions; (2) Maserati and scale-free networks show sensitivity to the type of risk. Scale-free networks are more resilient to long disruptions, whereas Maserati is resilient to frequent but short disruptions.

The following conclusions have been drawn from application of risk management strategies in empirical Maserati network: (1) inventory mitigation decreases costs

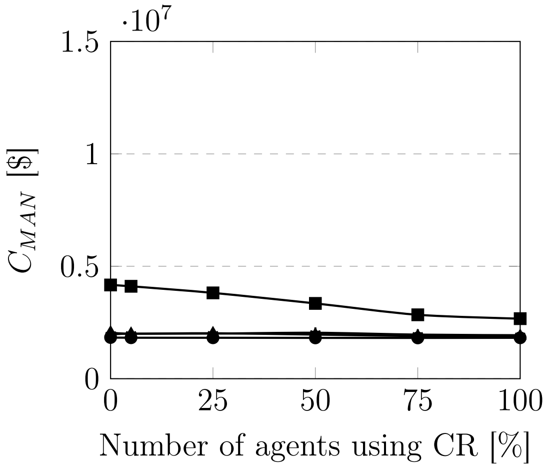
FIGURE 6.11: (a, b) Network and (c, d) manufacturer's costs for contingent rerouting (CR) strategy for FMCG company and Maserati.



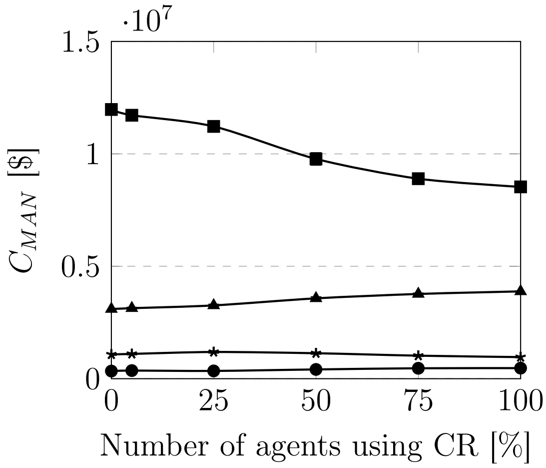
(A) C_{NET} for FMCG company



(B) C_{NET} for Maserati

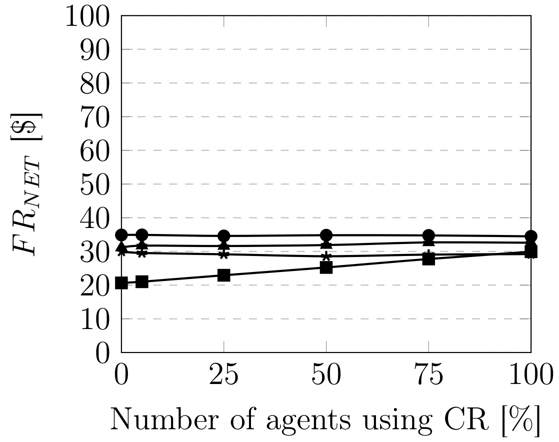


(C) C_{MAN} for FMCG company

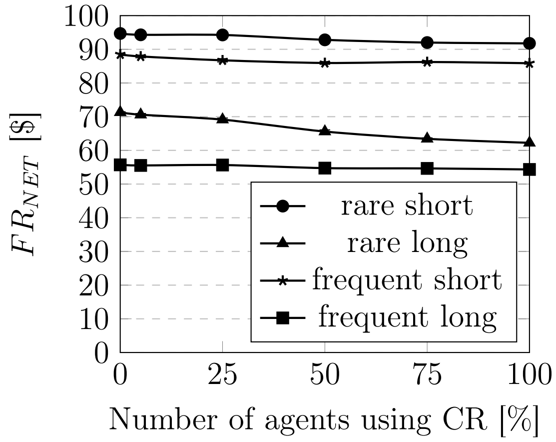


(D) C_{MAN} for Maserati

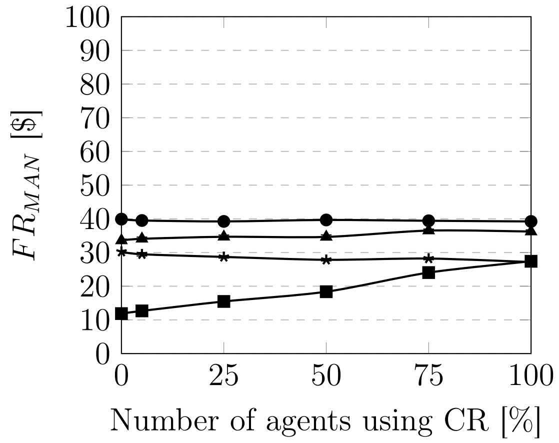
FIGURE 6.12: (a, b) Network and (c, d) manufacturer's fill-rates for contingent rerouting (CR) strategy for FMCG company and Maserati.



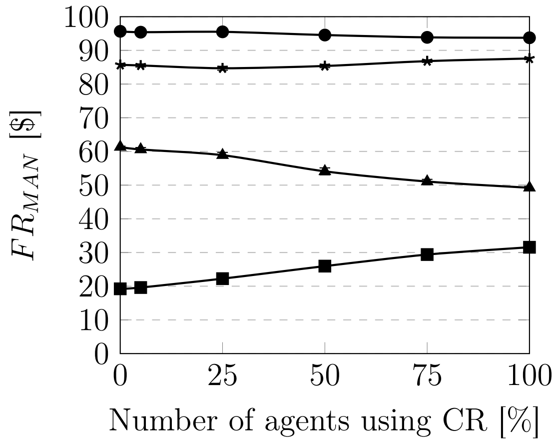
(A) FR_{NET} for FMCG company



(B) FR_{NET} for Maserati

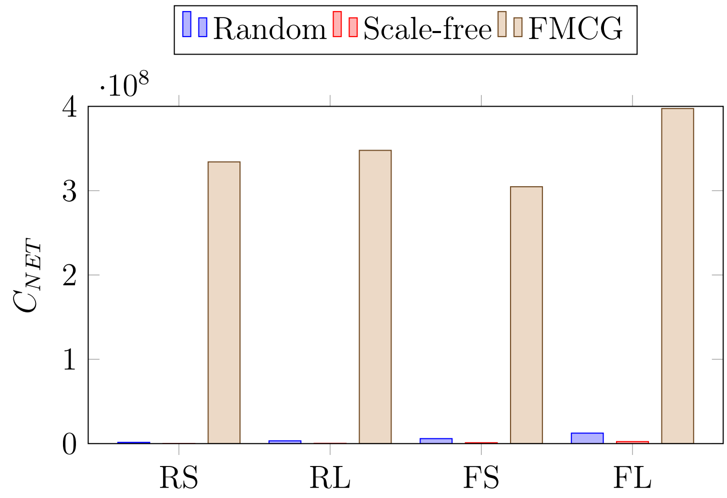


(C) FR_{MAN} for FMCG company

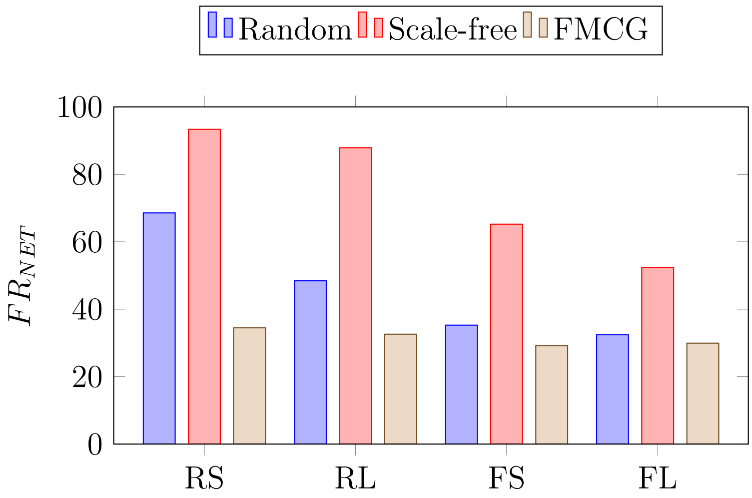


(D) FR_{MAN} for Maserati

Figure 6.13: C_{NET} and FR_{NET} of FMCG company compared to its theoretical equivalents when all agents apply CR. RS (rare, short); RL (rare long); FS (frequent short); FL (frequent long); CR(Contingent rerouting).

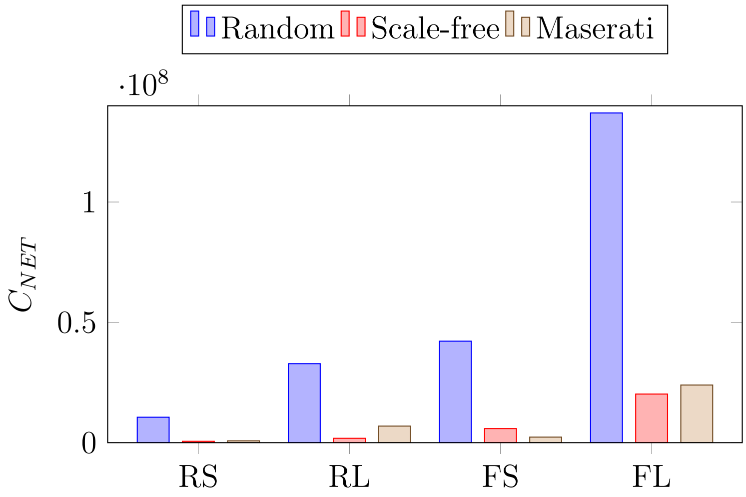


(A) C_{NET} for FMCG

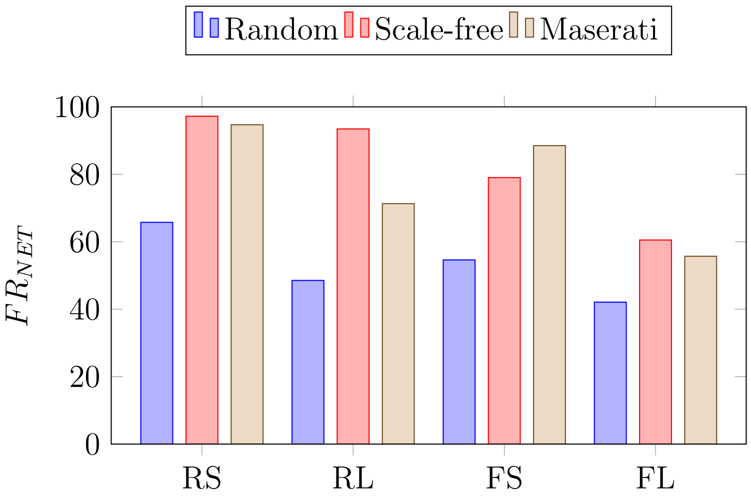


(B) FR_{NET} for FMCG

Figure 6.14: C_{NET} and FR_{NET} of Maserati compared to its theoretical equivalents when all agents apply CR. RS (rare, short); RL (rare long); FS (frequent short); FL (frequent long); CR(Contingent rerouting).



(a) C_{NET} for automotive



(b) FR_{NET} for automotive

TABLE 6.3: Effectiveness of mitigation and contingency when all agents apply IM or CR strategies. % change from when no IM/CR strategy is applied.

Topology (n, m)	Risk profile	FR_{NET} IM*	FR_{NET} CR*	C_{NET} IM*	C_{NET} CR*
FMCG (103,472)	rare, short	27.64%	-0.40%	-46.76%	-0.59%
	rare, long	28.62%	1.43%	-46.22%	-3.07%
	frequent, short	33.35%	-0.76%	-50.92%	-2.56%
	frequent, long	22.88%	9.26%	-50.87%	-17.63%
Maserati (565,652)	rare, short	5.06%	-2.94%	816.28%	49.64%
	rare, long	20.25%	-9.06%	21.14%	42.18%
	frequent, short	9.13%	-2.64%	205.77%	8.96%
	frequent, long	10.18%	-1.37%	-30.89%	-3.56%

* IM (inventory mitigation); CR (contingent rerouting)

only for high risk profiles because similarly to scale-free networks, Maserati network needs less inventory; (2) inventory mitigation always increases fill-rates; (3) contingent rerouting is not effective for short and long disruptions because of the network's low mean degree.

It has been observed that in the majority cases the Maserati network reduced disruption impact almost as well as scale-free networks. Interestingly, Maserati and scale-free networks showed resilience to different risk types. Namely, Maserati showed higher resilience to frequent and short disruptions, whereas scale-free networks showed higher resilience to rare and long disruptions. This property might indicate that supply network design with the focus on specific risk profile is possible.

Results of FMCG show that: (1) acyclic logistics network is still able to reduce disruptions impact despite having order feedback loops; (2) risk management in an unstable environment causes high effectiveness of these strategies.

Chapter 7

Targeted risk management in automotive networks

In this chapter, targeted inventory mitigation and targeted contingent rerouting are applied in empirical and theoretical automotive networks. The study on targeted risk management is motivated by the claims of Kleindorfer and Saad (2005), Schmitt and Singh (2012) who state that improving the weakest link is necessary to improve the overall network performance. In this study, improving the weakest link is interpreted as the strategic choice of companies embedded in a supply network to apply risk management. The strategic choice is informed by the topological position of the firm (e.g. centrality metrics) or its operational performance obtained without applying any strategy (e.g. highest costs). First, centrality metrics are applied in random automotive, scale-free automotive and Maserati networks to identify topologically critical suppliers. Then, inventory mitigation and contingent rerouting strategies are applied targeting firms with the highest centrality metrics, highest costs and lowest fill-rates. The effectiveness of targeted risk management is then compared with random choice of agents applying the management strategy. Later in this chapter, random automotive networks are referred to as random, and scale-free automotive as scale-free.

7.1 Node-level characteristics of automotive networks

The following centrality metrics have been applied for random, scale-free and Maserati networks: degree k, Katz centrality C_k, authority centrality C_A, hub centrality C_H, closeness centrality C_C, radiality centrality C_R and betweenness centrality C_{BT}. The higher the centrality value, the higher the criticality of a specific firm.

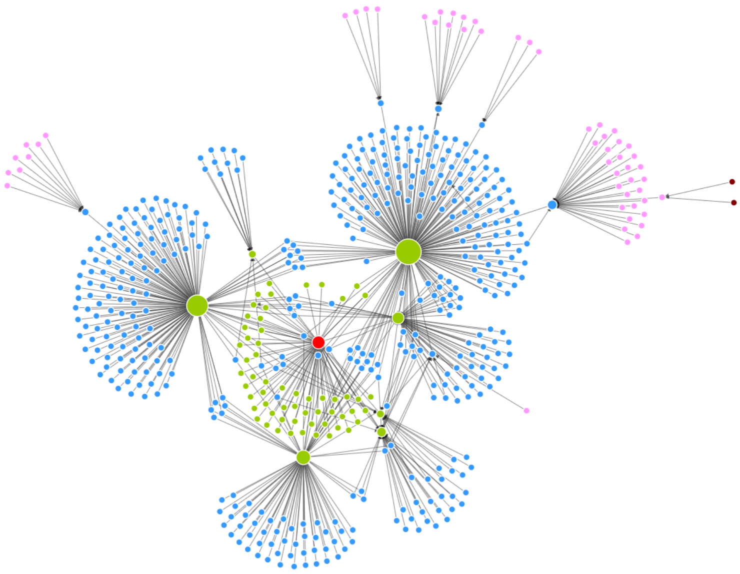
Degree k and Katz C_K centralities of automotive networks are presented in Figures 7.1, 7.2 and 7.3. The higher the centrality metric, the bigger node size in the figure. Each metric is normalised using feature scaling, which means that a relationship between respective centrality values is captured rather than their exact magnitudes. One random and one scale-free network are chosen to visualise centrality metrics for demonstration purposes.

Degree is the highest for nodes with the highest number of immediate suppliers, as observed for 1^{st} tier suppliers in the Maserati network, OEM in scale-free networks, and multiple other nodes in random networks. The degree centrality distribution of a random network is uniform because the connections between nodes were chosen at random. In Maserati and scale-free networks there are only few suppliers with high degree because in these networks there are many small suppliers selling their products to a few hubs.

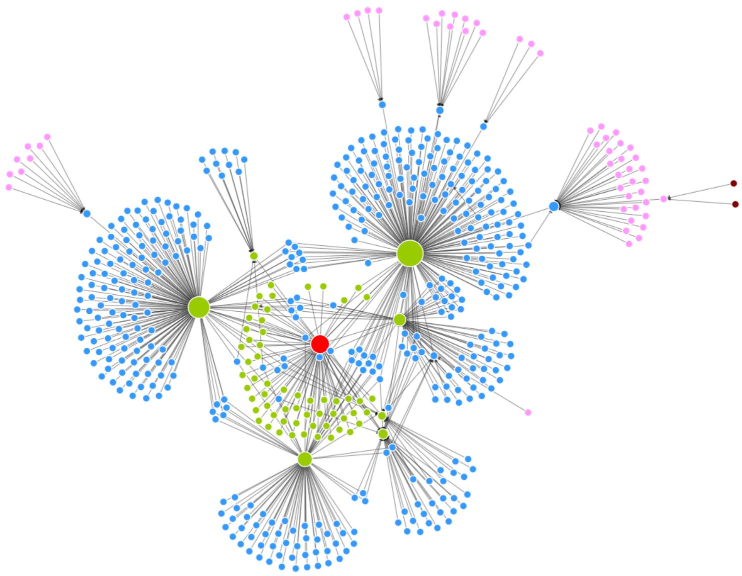
Katz centrality shows similar patterns for all network types, with higher Katz values closer to the OEM. Katz centrality denotes high undirected risk spread (Ledwoch et al., 2016). This is because Katz centrality is updated taking into account not only the immediate number of suppliers, but also the whole structure of the network. The supply "stress" is propagated downstream, therefore the highest Katz centrality can be observed in OEMs and their highly connected direct suppliers. One might observe that nodes sized by Katz centrality in random networks are similar in size, which implies that values are quite high compared with the biggest value and have relatively small differences between each other.

Authority and hub centralities for Maserati, random and scale-free networks are presented in Figures 7.4 A, 7.4 B, 7.5 A,7.5 B, 7.6 A and 7.6 B. For all the networks, authorities are nodes with the highest number of hubs and hubs are nodes supplying to authorities. Authority centrality denotes supply pressure and hub centrality

FIGURE 7.1: Visualisation of the degree and Katz centralities for Maserati supply network. Nodes are coloured according to the tier, and sized according to their centrality.

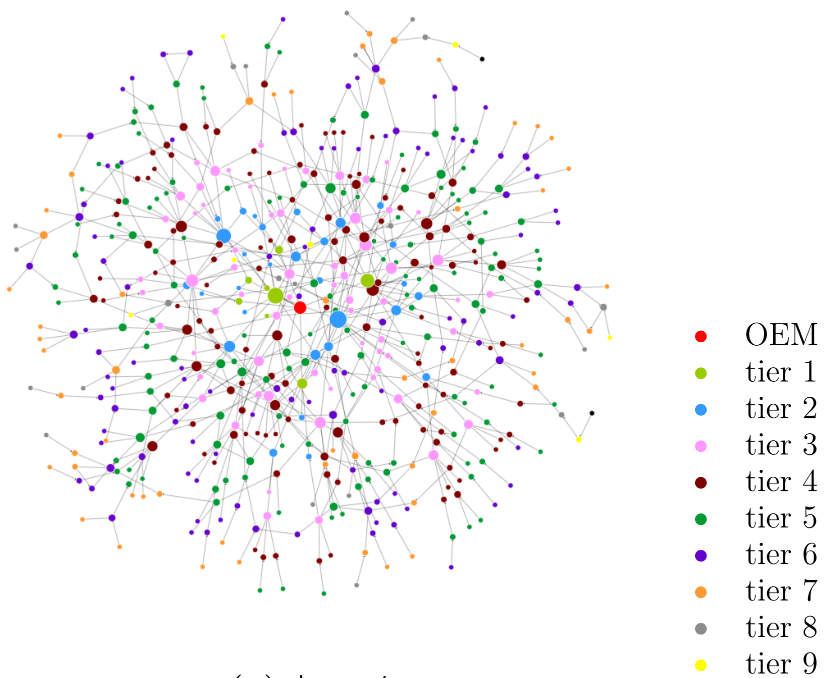


(A) degree k

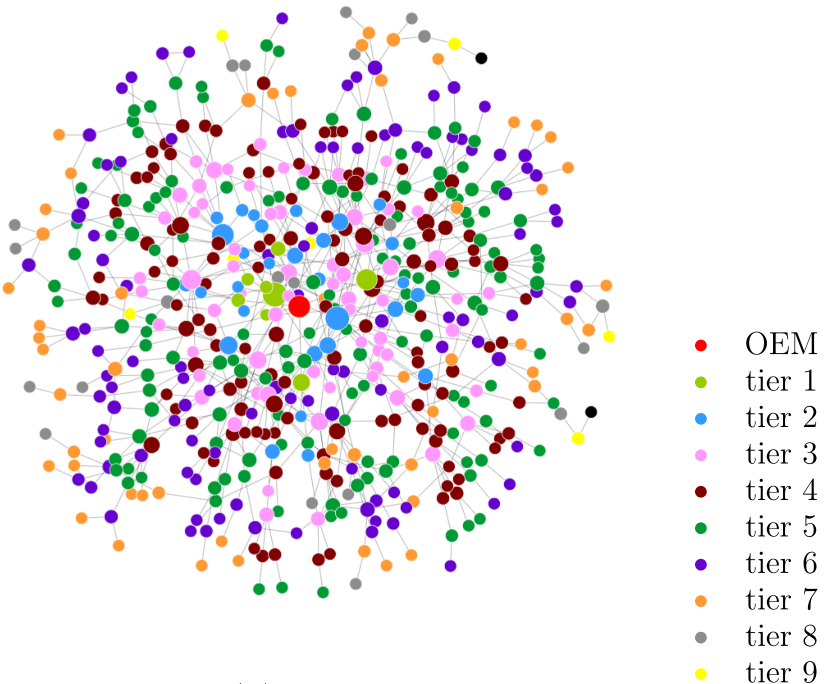


(B) Katz C_K

FIGURE 7.2: Visualisation of the degree and Katz centralities for random automotive supply network. Nodes are coloured according to the tier, and sized according to their centrality.

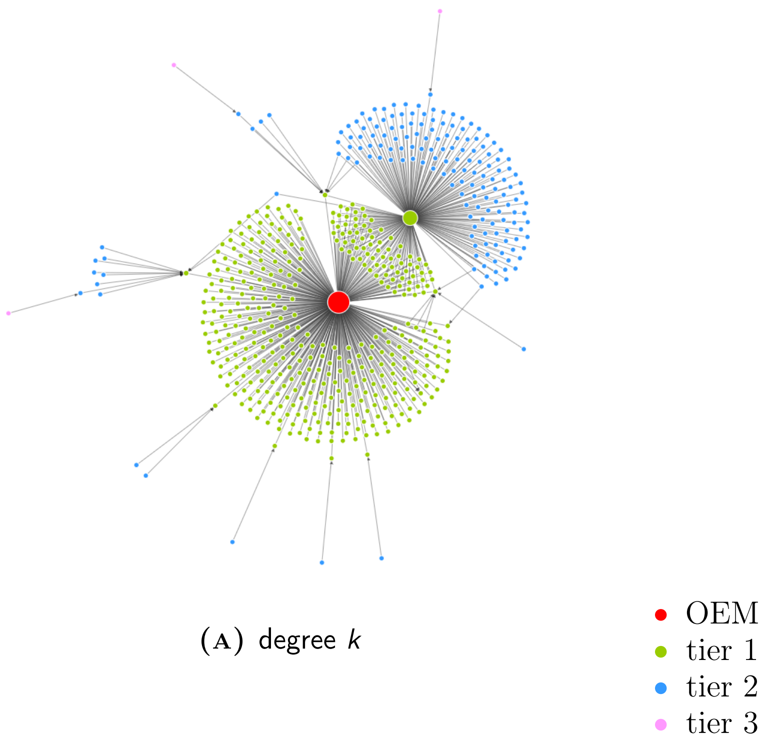


(A) degree k

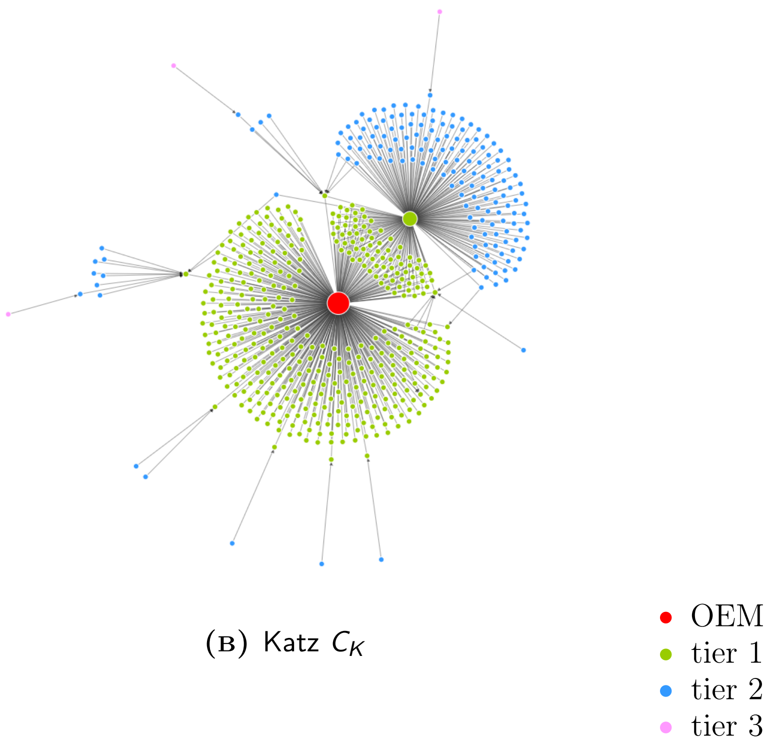


(B) Katz C_K

FIGURE 7.3: Visualisation of the degree and Katz centralities for scale-free automotive supply network. Nodes are coloured according to the tier, and sized according to their centrality.



(A) degree k



(B) Katz C_K

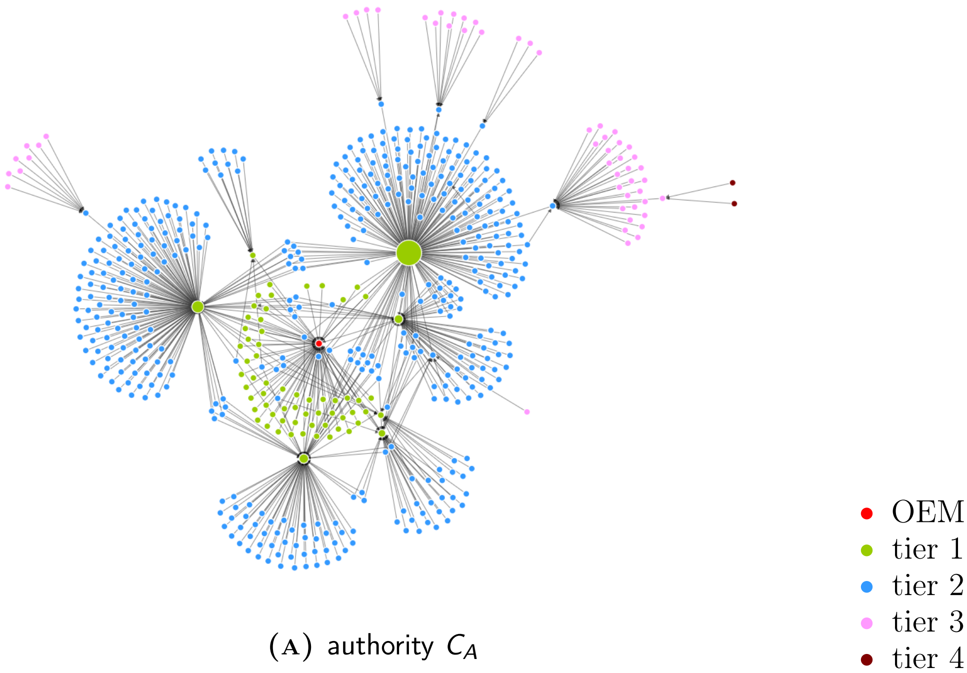
denotes customer-side pressure (Ledwoch et al., 2016). Both, in Maserati and scale-free networks, only few authorities have been identified. In Maserati, an authority is a single 1^{st} tier supplier, in scale-free network it is a single 1st tier supplier and an OEM, and in random network these are two suppliers: one in 1^{st} and one i 2^{nd} tiers. Nodes with high hub centralities are nodes, which are directly supplying to authorities. In the Maserati network, these are 2nd tier suppliers delivering to a single authority, in the scale-free network these are mostly 1st tier suppliers, and in the random network these are few suppliers in 2^{nd} and 3^{rd} tiers.

Closeness and radiality centrality are presented in Figures 7.7, 7.8 and 7.9. They are associated with the speed of cascading failures (Ledwoch et al., 2016). For all network types, closeness and radiality are high for all nodes. This implies that the differences in values between nodes in the same network are small. The closer to the OEM, the higher closeness and radiality centralities for all networks. The difference in closeness and radiality centralities between the central and peripheral nodes is higher for random networks than for scale-free and Maserati. This is because there are more tiers in random network, therefore the distances and time needed for goods to travel from the raw-material supplier to the OEM is higher than for the other topologies.

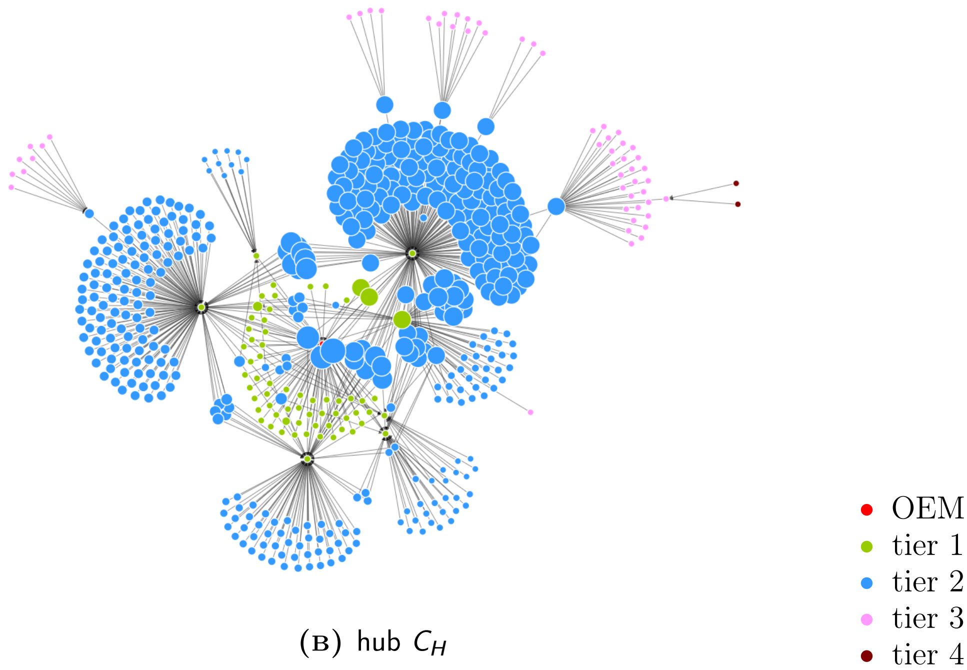
Betweenness centrality is presented in Figures 7.10 and 7.11. It is associated with firms being an intermediary and having high risk (Ledwoch et al., 2016). For Maserati the nodes with high betweenness are also nodes with highest degrees, for scale-free networks only one node in the network has high betweenness. This implies that for these networks there are only few critical paths leading from raw-material suppliers to OEM, and that the network relies heavily on these nodes. If these nodes suffer from disruption, the operations of that network would be highly disrupted. Random network has numerous nodes with high betweenness, what would imply that there are numerous alternative paths from raw-material supplier to the OEM. This might sound like random networks are more robust, but in fact if disruptions are random, there is higher chance that a critical supplier will be affected. In scale-free and Maserati networks, there are only few such path-critical suppliers, therefore there is very low probability that these suppliers will be affected.

Critical suppliers identified by different centrality metrics often overlap, meaning that some metrics might perform similarly when applying targeted risk management.

Figure 7.4: Visualisation of the authority and hub centralities for Maserati supply network. Nodes are coloured according to the tier, and sized according to their centrality.

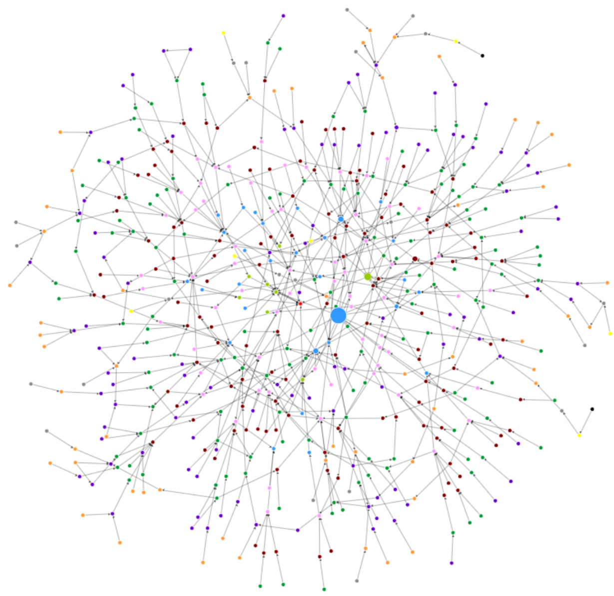


(A) authority C_A

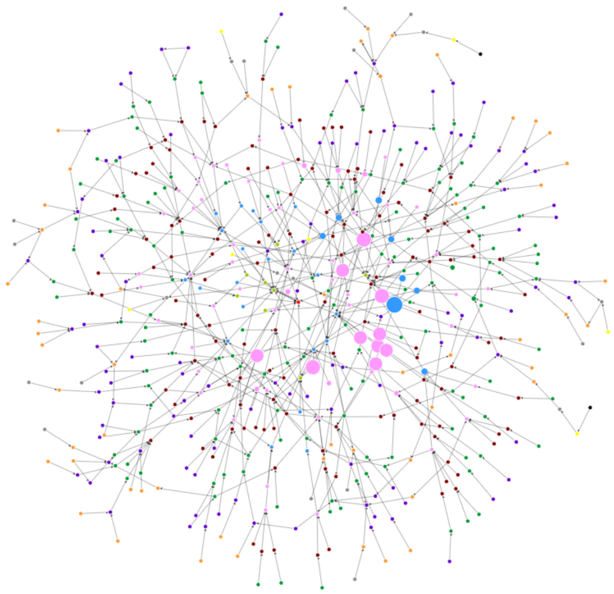


(B) hub C_H

FIGURE 7.5: Visualisation of the authority and hub centralities for random automotive supply network. Nodes are coloured according to the tier, and sized according to their centrality.

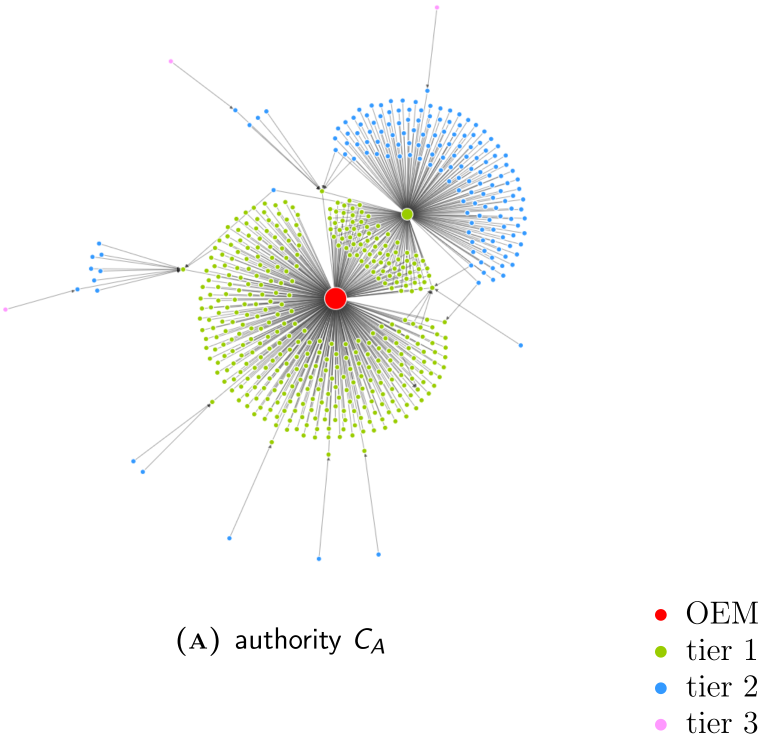


(A) authority C_A

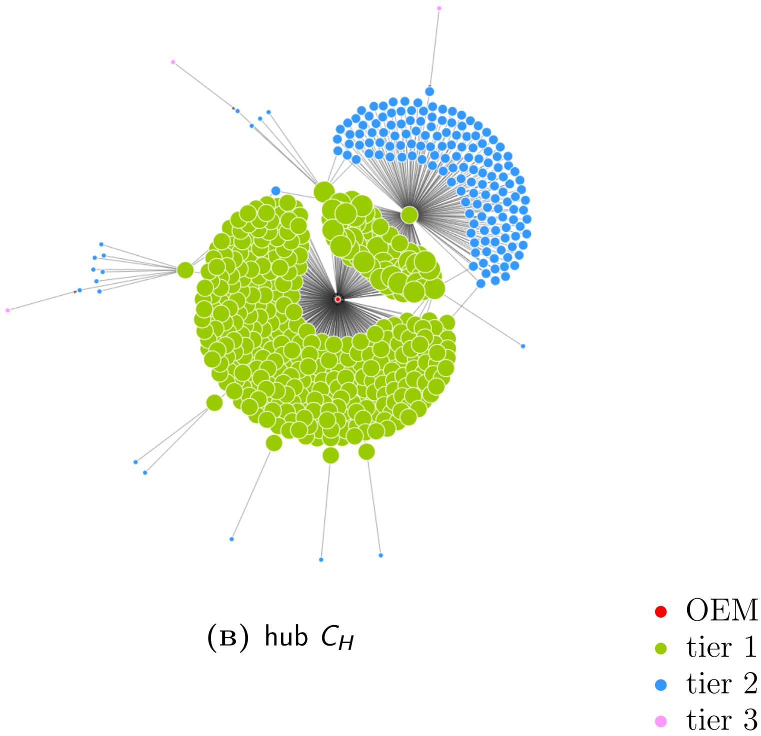


(B) hub C_H

Figure 7.6: Visualisation of the authority and hub centralities for scale-free automotive supply network. Nodes are coloured according to the tier, and sized according to their centrality.

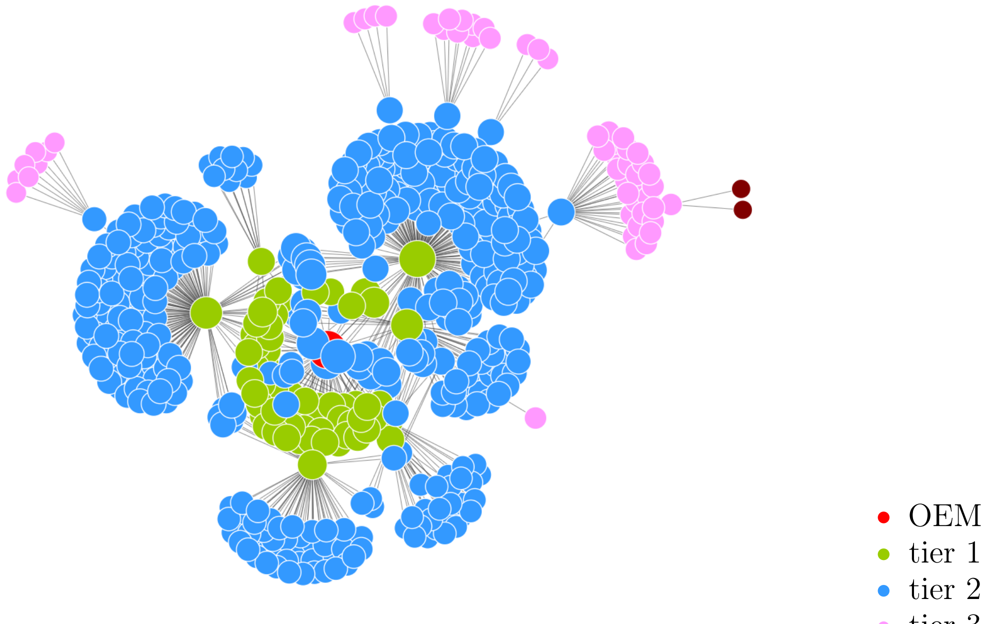


(A) authority C_A

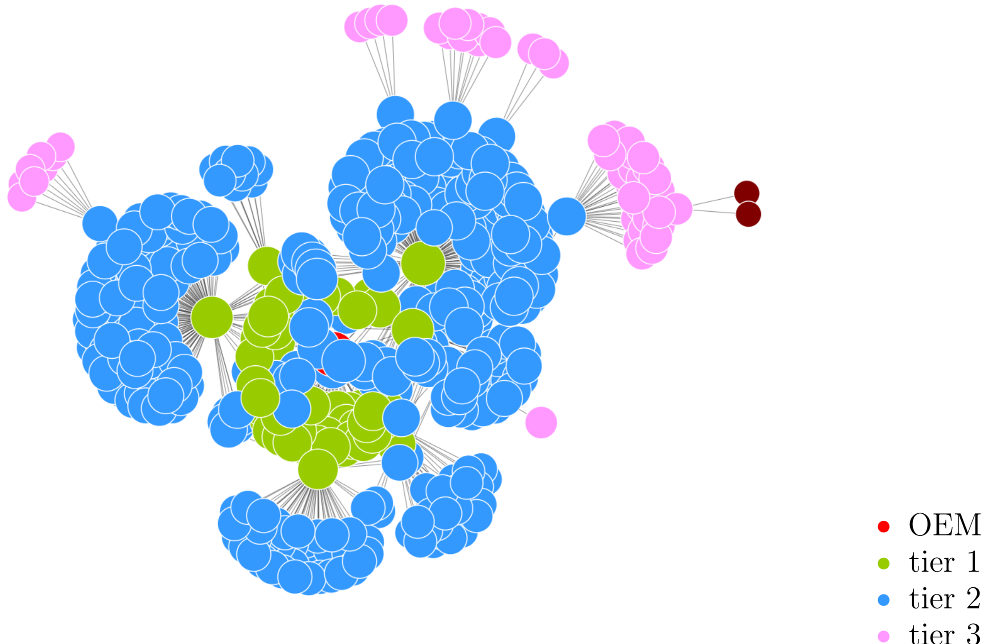


(B) hub C_H

Figure 7.7: Visualisation of closeness, radiality and betweenness centralities for Maserati supply network. Nodes are coloured according to the tier, and sized according to their centrality value.

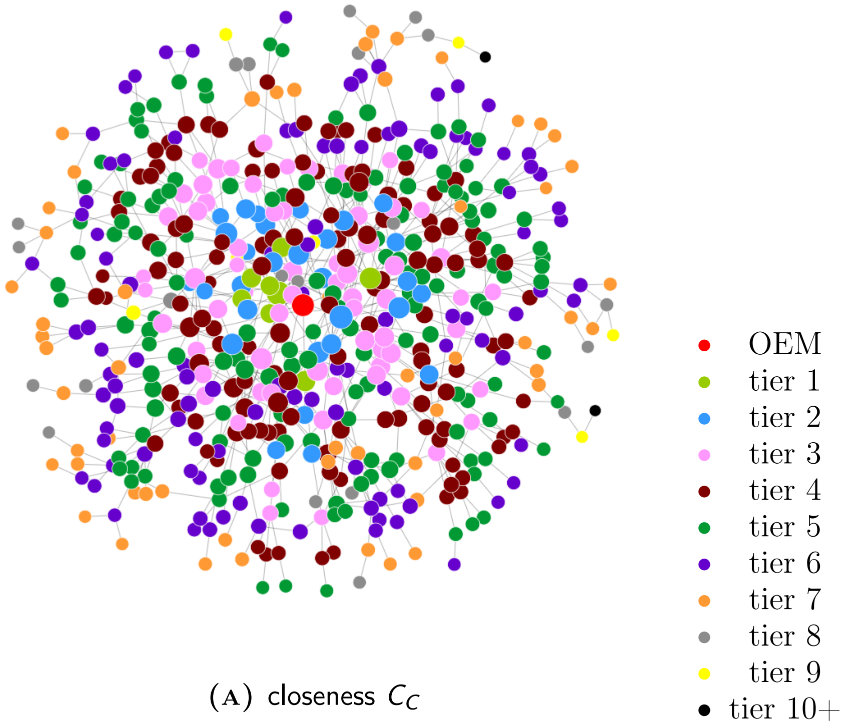


(A) closeness C_C

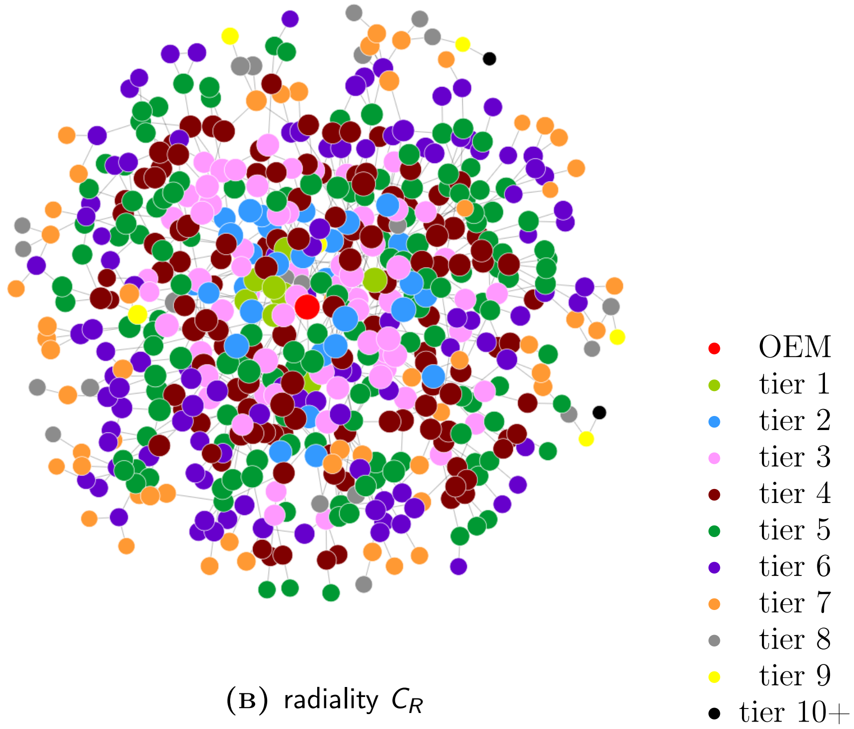


(B) radiality C_R

Figure 7.8: Visualisation of closeness and radiality centralities for random automotive supply network. Nodes are coloured according to the tier, and sized according to their centrality.

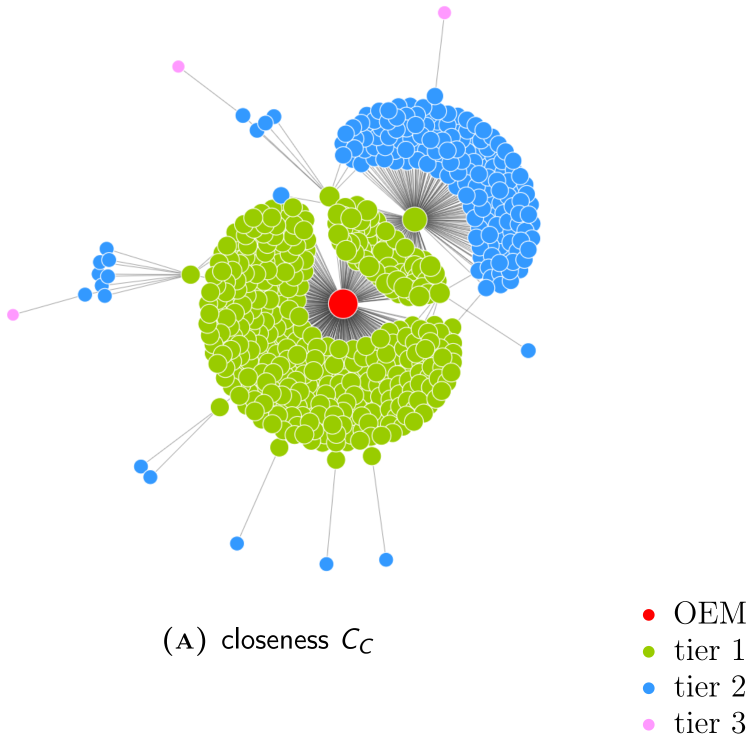


(a) closeness C_C

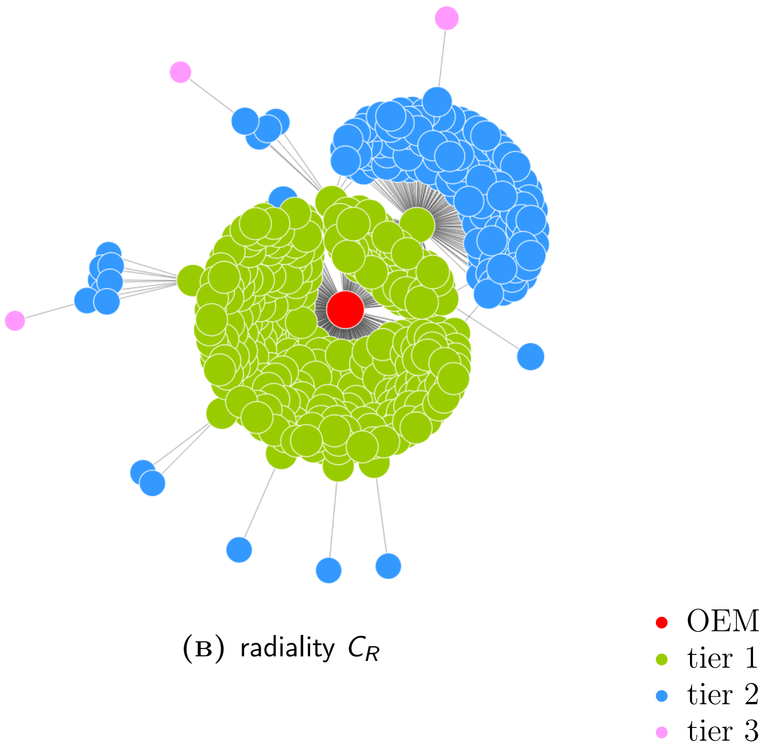


(b) radiality C_R

Figure 7.9: Visualisation of closeness and radiality centralities for scale-free automotive supply network. Nodes are coloured according to the tier, and sized according to their centrality.



(A) closeness C_C



(B) radiality C_R

Figure 7.10: Visualisation of betweenness centrality for Maserati supply network. Nodes are coloured according to the tier, and sized according to their centrality value.

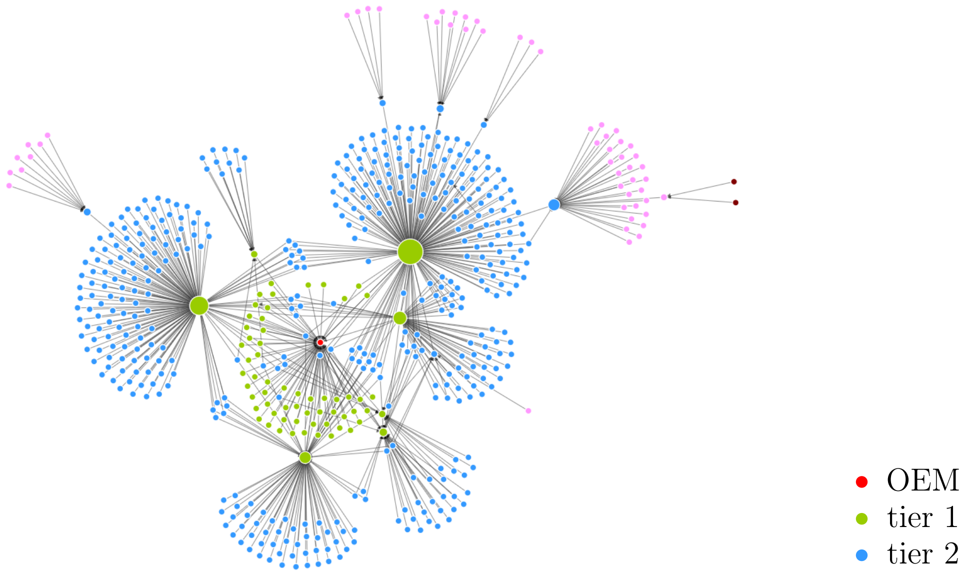
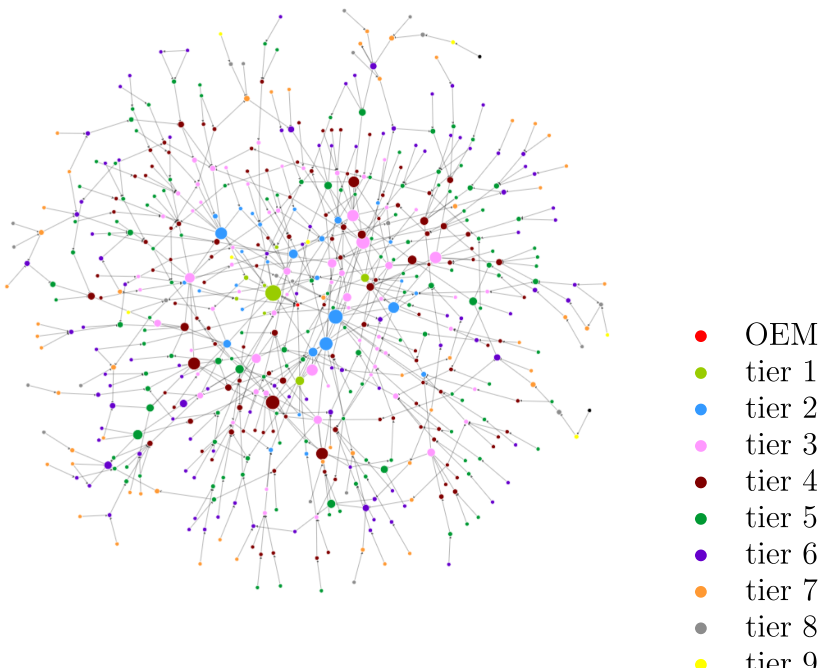
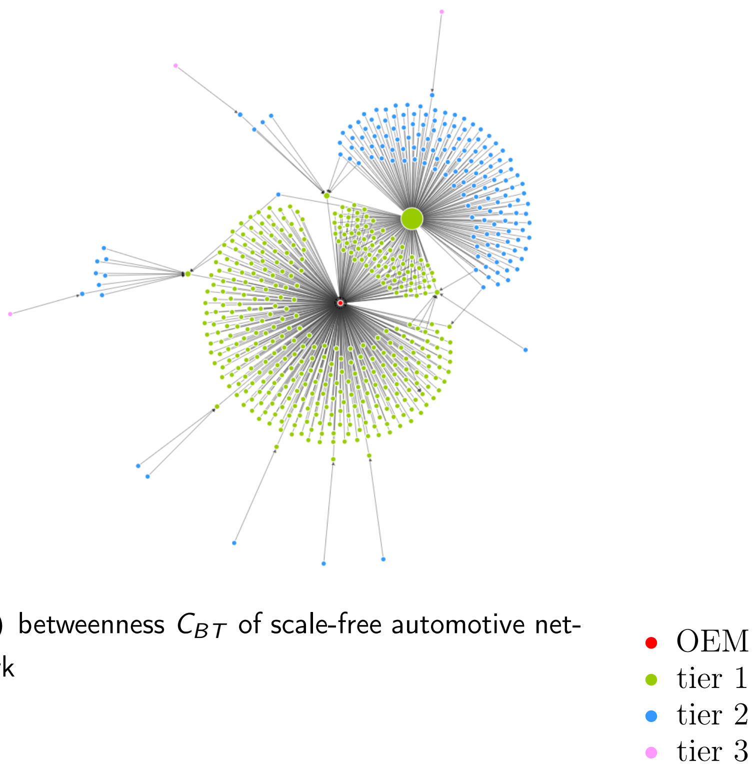


FIGURE 7.11: Visualisation of betweenness centrality for random and scale-free automotive supply network. Nodes are coloured according to the tier, and sized according to their centrality.



(A) betweenness C_{BT} of random automotive network



(B) betweenness C_{BT} of scale-free automotive network

7.2 Targeted inventory mitigation for automotive networks

In this section, results on targeted inventory mitigation will be discussed. The firms identified to apply risk mitigation are chosen using the following criteria: The highest degree centrality k_i, the highest Katz centrality C_{K_i}, the highest authority centrality C_{A_i}, the highest hub centrality C_{H_i}, the highest closeness centrality C_{C_i}, the highest radiality centrality C_{R_i}, the highest betweenness centrality C_{BT_i}, the highest costs C_i and the lowest fill-rate FR_i. For each network instance, 5% of nodes with the metrics presented are chosen. Results of targeting these nodes to apply mitigation strategy is compared with random mitigation to identify how the choice of agents can improve performance. For all networks, targeted nodes were chosen for each risk profile and topology separately, giving in total 44 different results. Then, for theoretical networks these results were averaged over 5 topologies of the same type.

The effectiveness of the targeted inventory mitigation is dependent on the topology, risk profile and targeting strategy applied. For the majority of cases, targeted inventory mitigation does not seem to be an effective strategy for low risk profiles for Maserati and scale-free networks because costs can be increased by around 400% - 600% for some targeting strategies. Targeted inventory mitigation performs in these cases even worse than if inventory mitigation was applied for firms chosen at random. This is because Maserati and scale-free networks need much less inventory than random networks, therefore when risk is low, the amount of inventory kept by agents is higher than needed, generating high inventory holding costs. Usually nodes which have high centrality have critical positions in the network. The central location of such nodes implies that these nodes must have high number of suppliers and that the volume flowing through this node must be significant. If the volume is significant, the amount of additional inventory kept by that agent also will be very high, generating high cost. Not all centrality metrics applied in Maserati and scale-free networks resulted in performance worse than random mitigation. For example, targeting C_{H_i} in Maserati for rare and short disruptions resulted in increase by 7%, which is lower than increase by 38.53% when using random mitigation. The effectiveness of inventory mitigation for low risk profile in random networks depends on the targeting strategy applied. For example, costs were decreased by 15.49%, 8.25% and 7.18% when targeting C_{BT_i}, C_{H_i} and FR_i, respectively, compared to decrease by 3.31% when random mitigation was applied. Using other metrics, such as C_{K_i} or C_{R_i} resulted in cost increase by 17.32% and 19.94%, respectively.

Targeted inventory mitigation is effective for high risk profile in all the networks, decreasing costs and increasing fill-rates, when a certain targeting strategy is applied. For example, when C_{A_i} is targeted for Maserati for frequent and long disruptions, there is a decrease in costs by 26.37% and in increase in fill-rates by 2.00%, which is better than random mitigation. Although, when C_{H_i} is targeted for the same topology and risk profile, costs are increased by 3.43% and fill-rates decrease by 0.18%.

Targeting the same metric can result in different effects for various risk profiles. For example, targeting C_{K_i} for rare and short disruptions in Maserati results in cost increase by 402.16% and fill-rate decrease by 1.65%. Targeting the same metric in frequent and long disruptions results in cost decrease by 25.73% and fill-rates increase by 0.70%. Certain metrics, when used as a targeting criteria, can lead to similar performance outcomes. For example, for rare and short disruptions in scale-free networks targeting highest k_i, C_{K_i}, C_{A_i}, C_{C_i}, C_{R_i}, and C_i results in an increase in costs by about 621.68% to 650.12%, whereas for frequent and long disruptions cost decrease by 25.15% to 27.22%. For these centrality metrics, increase and decrease in costs were within similar ranges for different risk profiles. Targeting using different centrality metrics results in various responses within the same risk profiles. For example, k_i, C_{K_i}, C_{A_i}, C_{C_i}, C_{R_i}, and C_i decreases costs for Maserati for frequent and long disruptions, whereas C_{A_i} increases costs for the same conditions.

Similar patterns can be observed for fill-rates. For example metrics FR_i, k, C_H and C_C increased fill-rates for Maserati for rare and short disruptions, whereas other metrics have decreased it. For frequent and long disruptions FR_i, C_H and C_C decreased fill-rates, whereas the other metrics have increased it.

The effect that targeted inventory mitigation has on different topologies can easily highlight their strengths and weaknesses. For example, costs are increased for Maserati when targeting nodes for frequent and short disruptions with the range from 140.31% to 175.20%. For scale-free networks for the same risk profile costs are usually decreased with the ranges from 1.59% to 2.94%. Such difference means that the Maserati network needs much less inventory for this risk profile than the scale-free network. A similar effect is seen for scale-free networks for rare and long disruptions, where scale-free networks need less inventory than the Maserati network. These effects suggest that the Maserati network is resilient to frequent and short disruptions, whereas scale-free networks are resilient to rare and long disruptions, which confirms results obtained in Chapter 6.

7.3 Targeted contingent rerouting for automotive networks

The changes in C_{NET} and FR_{NET} using targeted contingent rerouting are presented in Figures 7.3 and 7.4. As in the case of inventory mitigation, for contingent rerouting centrality metrics can be divided into clusters of metrics that have similar impact on the costs for different risk profiles. For example, k, C_K, C_A, C_C, C_R and C_i increase costs of random networks for rare and short disruptions by around 35.38% to 65%. C_H and C_BT increase these costs only by around 4, 5%, whereas FR_i decrease costs by 6.60%. For frequent and long disruptions, C_H and C_BT increase costs by 7.91% and 13.02% respectively. The rest of centrality metrics increase costs in the range from 20.65% to 55.08%. In this particular case, $C_H$and C_{BT} increase the costs less than the rest of centrality metrics.

Centrality metrics prove to be very effective in the Maserati network for rare and long disruptions, where all of the metrics decrease costs by up to 70% and increase fill-rates by up to 17%. This is much higher than a random strategy because when applying targeted contingent rerouting focused on centrality metrics, the suppliers with high number of business partners are chosen to apply the strategy. Therefore these "hubs" have numerous suppliers, despite the rest of the network having rather small number, resulting in high effectiveness of contingent rerouting. Targeted contingent rerouting is not as effective in scale-free networks because they have less "hubs" than Maserati. Scale-free networks have usually one or two "super-hubs", whereas Maserati has around 8.

In general, targeted contingency rerouting is not effective for short disruptions, increasing costs and decreasing fill-rates. For example, targeting highest C_C in Maserati network for frequent and short disruptions results in C_{NET} increase by 325.24% and FR_{NET} decrease by 26.30%, compared to increase in costs by 4.57%

TABLE 7.1: The change in C_{NET} for inventory mitigation. The comparison is done for the case with disruptions between no mitigation and 5% mitigation.

Topology	Selection strategy		C_{NET} RS*	RL*	FS*	FL*
Maserati	Random		38.53%	0.90%	14.25%	-1.43%
	Targeted	Highest k_i	402.16%	-36.09%	157.98%	-26.97%
		Highest C_{K_i}	442.56%	-36.62%	140.31%	-25.73%
		Highest C_{A_i}	432.42%	-18.19%	162.19%	-26.37%
		Highest C_{H_i}	7.71%	-57.94%	164.03%	3.43%
		Highest C_{C_i}	413.28%	-36.91%	160.75%	-20.61%
		Highest C_{R_i}	427.77%	-21.09%	163.76%	-26.45%
		Highest C_{BT_i}	32.02%	-45.94%	164.12%	-2.02%
		Highest C_i	533.50%	-17.21%	175.20%	-26.67%
		Lowest FR_i	3.65%	-37.79%	154.87%	-23.44%
Random	Random		-3.31%	-3.83%	-2.18%	-0.92%
	Targeted	Highest k_i	11.41%	-20.53%	-13.81%	-9.65%
		Highest C_{K_i}	17.32%	-22.96%	-17.96%	-9.96%
		Highest C_{A_i}	2.61%	-8.18%	-15.68%	-10.72%
		Highest C_{H_i}	-8.25%	-8.03%	-6.52%	-4.40%
		Highest C_{C_i}	10.41%	-15.92%	-19.08%	-14.20%
		Highest C_{R_i}	19.94%	-12.19%	-19.42%	-9.00%
		Highest C_{BT_i}	-15.49%	-8.90%	-10.82%	-3.89%
		Highest C_i	33.92%	-20.97%	-24.28%	-13.21%
		Lowest FR_i	-7.18%	-15.58%	-22.02%	-8.08%
Scale-free	Random		56.84%	8.01%	-0.08%	-1.70%
	Targeted	Highest k_i	635.22%	133.90%	-2.61%	-27.22%
		Highest C_{K_i}	621.68%	117.74%	-2.53%	-26.31%
		Highest C_{A_i}	623.48%	135.01%	-0.14%	-25.12%
		Highest C_{H_i}	73.80%	26.42%	-1.59%	1.04%
		Highest C_{C_i}	632.34%	128.09%	-2.94%	-25.23%
		Highest C_{R_i}	650.12%	133.89%	0.22%	-25.58%
		Highest C_{BT_i}	25.92%	-20.79%	-2.68%	-3.29%
		Highest C_i	626.28%	125.43%	0.18%	-26.39%
		Lowest FR_i	27.69%	19.93%	1.20%	-26.88%

* R (rare disruptions); F (frequent); S (short); L (long)

Table 7.2: The change in FR_{NET} for inventory mitigation. The comparison is done for the case with disruptions between no mitigation and 5% mitigation.

Topology	Selection strategy		FR_{NET}			
			RS*	RL*	FS*	FL*
Maserati	Random		0.26%	0.36%	-0.02%	0.32%
	Targeted	Highest k_i	1.97%	19.52%	-16.92%	0.11%
		Highest C_{K_i}	-1.65%	19.62%	-14.11%	0.70%
		Highest C_{A_i}	-1.02%	12.02%	-16.66%	2.00%
		Highest C_{H_i}	0.19%	15.77%	-15.04%	-0.18%
		Highest C_{C_i}	0.53%	16.91%	-15.93%	-0.05%
		Highest C_{R_i}	-0.92%	14.06%	-16.30%	1.69%
		Highest C_{BT_i}	0.09%	12.75%	-16.50%	0.00%
		Highest C_i	-0.49%	17.20%	-15.57%	2.47%
		Lowest FR_i	0.66%	19.01%	-16.08%	-0.07%
Random	Random		1.63%	1.07%	0.50%	0.12%
	Targeted	Highest k_i	1.49%	1.76%	0.88%	0.41%
		Highest C_{K_i}	1.50%	1.93%	0.94%	1.06%
		Highest C_{A_i}	1.88%	1.32%	1.27%	0.34%
		Highest C_{H_i}	1.35%	1.69%	0.74%	-0.16%
		Highest C_{C_i}	2.16%	1.50%	1.25%	1.20%
		Highest C_{R_i}	1.25%	1.84%	1.51%	0.82%
		Highest C_{BT_i}	2.21%	1.36%	1.06%	0.31%
		Highest C_i	0.99%	1.15%	1.74%	0.97%
		Lowest FR_i	1.89%	1.50%	1.25%	-0.03%
Scale-free	Random		0.07%	0.59%	1.03%	0.95%
	Targeted	Highest k_i	0.12%	0.44%	1.59%	1.58%
		Highest C_{K_i}	0.44%	1.94%	1.98%	1.66%
		Highest C_{A_i}	0.53%	-0.45%	0.95%	0.83%
		Highest C_{H_i}	-0.69%	-1.12%	1.63%	0.77%
		Highest C_{C_i}	0.30%	0.85%	1.48%	1.57%
		Highest C_{R_i}	-0.66%	0.00%	0.85%	0.96%
		Highest C_{BT_i}	0.33%	2.29%	1.64%	2.68%
		Highest C_i	0.63%	1.17%	1.05%	1.25%
		Lowest FR_i	0.05%	1.03%	-0.19%	1.32%

* R (rare disruptions); F (frequent); S (short); L (long)

and decrease in fill-rates by -0.63% when random contingency is applied. The decrease in performance for short disruptions is caused by mailing delay time, which disables an agent to react in time when its supplier is disrupted. When the most critical suppliers are targeted, the losses are more severe, since these critical suppliers carry higher volumes than the rest of the network, thus higher potential costs.

Contingent rerouting mostly works for long disruptions, but its effectiveness is dependent on the network structure and targeting strategy. When nodes are chosen at random for mitigation, the strategy is not effective because Maserati, random and scale-free networks have low mean degree, meaning that there is low average number of alternative suppliers. The strategy starts to be effective for targeted contingent rerouting for scale-free and Maserati networks because nodes with high number of suppliers are chosen, therefore they have numerous possibilities of rerouting the disrupted volume to other operational suppliers.

7.4 Summary

In this chapter, targeted risk management strategies have been applied in automotive networks: random, scale-free and Maserati, where 5% of selected firms were applying the specific strategy. Different firm targeting criteria have been chosen with the following conclusions: (1) targeted risk management is dependent of risk profile, topology and targeting strategy; (2) targeting the weakest company does not always result in an increased performance; on the contrary, the effectiveness of such a strategy can be even worse than if management was performed in firms chosen at random.

The following conclusions have been drawn from targeted risk mitigation: (1) targeted inventory mitigation usually performs worse than random mitigation for low risk profiles in scale-free and empirical networks because these networks need less safety stock; (2) targeted inventory mitigation performs better than random for high risk profile because critical suppliers absorb disruptions better; (3) some targeting strategies are better for specific risk profiles than others. For example, in Maserati costs are increased by C_A in frequent and long disruptions, but decreased by C_{C_i}; (4) some metrics have similar effects across different risk profiles. For example, targeting k_i, C_{K_i}, C_{A_i}, C_{C_i}, C_{R_i}, and C_i in Maserati increases costs by similar amount

TABLE 7.3: The change in C_{NET} for contingent rerouting. The comparison is done for the case with disruptions between no rerouting and 5% rerouting.

Topology	Selection strategy		C_{NET} RS*	RL*	FS*	FL*
Maserati	Random		6.94%	2.29%	4.57%	-0.52%
	Targeted	Highest k_i	71.75%	-44.07%	327.14%	0.81%
		Highest C_{K_i}	39.04%	-46.69%	325.87%	-2.69%
		Highest C_{A_i}	27.87%	-73.76%	319.79%	-8.08%
		Highest C_{H_i}	-10.24%	-43.66%	189.72%	5.60%
		Highest C_{C_i}	34.91%	-64.26%	325.24%	-5.47%
		Highest C_{R_i}	48.56%	-70.14%	320.90%	-11.26%
		Highest C_{BT_i}	33.77%	-52.44%	207.04%	1.69%
		Highest C_i	46.96%	-64.14%	322.15%	-6.85%
		Lowest FR_i	10.32%	-65.16%	194.97%	-2.05%
Random	Random		0.71%	1.13%	3.24%	2.84%
	Targeted	Highest k_i	46.29%	15.67%	39.44%	26.65%
		Highest C_{K_i}	47.02%	4.18%	40.67%	30.79%
		Highest C_{A_i}	35.38%	14.48%	25.81%	20.65%
		Highest C_{H_i}	5.51%	5.68%	5.37%	7.91%
		Highest C_{C_i}	52.23%	6.37%	47.46%	39.03%
		Highest C_{R_i}	60.26%	8.59%	44.87%	27.00%
		Highest C_{BT_i}	4.61%	8.69%	11.55%	13.02%
		Highest C_i	65.11%	7.05%	44.91%	44.80%
		Lowest FR_i	-6.60%	7.38%	52.04%	55.08%
Scale-free	Random		-7.24%	2.93%	2.11%	0.25%
	Targeted	Highest k_i	28.25%	-8.95%	42.63%	-4.41%
		Highest C_{K_i}	51.12%	-4.53%	42.86%	-2.81%
		Highest C_{A_i}	80.44%	22.15%	45.99%	-4.50%
		Highest C_{H_i}	2.60%	-8.11%	1.30%	0.13%
		Highest C_{C_i}	64.24%	-12.77%	42.04%	-4.69%
		Highest C_{R_i}	29.03%	22.63%	43.48%	-6.48%
		Highest C_{BT_i}	3.05%	-6.77%	1.47%	0.00%
		Highest C_i	52.78%	13.14%	41.84%	-3.81%
		Lowest FR_i	-3.66%	-8.12%	41.99%	-4.72%

* R (rare disruptions); F (frequent); S (short); L (long)

Table 7.4: The change in FR_{NET} for contingent rerouting. The comparison is done for the case with disruptions between no rerouting and 5% rerouting.

Topology	Selection strategy		FR_{NET} RS*	RL*	FS*	FL*
Maserati	Random		-0.40%	-0.72%	-0.63%	-0.18%
	Targeted	Highest k_i	-4.98%	10.67%	-26.11%	-2.14%
		Highest C_{K_i}	-2.42%	12.35%	-26.22%	-0.52%
		Highest C_{A_i}	-1.28%	17.33%	-26.37%	-0.45%
		Highest C_{H_i}	0.72%	11.97%	-16.68%	-0.95%
		Highest C_{C_i}	-2.82%	14.70%	-26.30%	-1.66%
		Highest C_{R_i}	-2.03%	16.00%	-26.51%	-0.58%
		Highest C_{BT_i}	-1.83%	12.27%	-20.83%	-0.49%
		Highest C_i	-2.90%	13.74%	-25.95%	-0.31%
		Lowest FR_i	-1.31%	15.30%	-20.59%	-2.21%
Random	Random		-0.41%	0.02%	-0.31%	-0.19%
	Targeted	Highest k_i	-7.30%	-1.07%	-2.99%	-5.96%
		Highest C_{K_i}	-7.46%	0.24%	-3.26%	-6.15%
		Highest C_{A_i}	-5.94%	0.16%	-2.22%	-2.79%
		Highest C_{H_i}	-1.72%	-0.05%	-0.47%	-1.46%
		Highest C_{C_i}	-8.01%	-0.14%	-3.48%	-7.97%
		Highest C_{R_i}	-8.02%	0.35%	-3.39%	-6.24%
		Highest C_{BT_i}	-3.30%	-0.53%	-2.55%	-4.56%
		Highest C_i	-7.82%	-0.15%	-2.91%	-4.34%
		Lowest FR_i	0.35%	-0.57%	-3.51%	-6.83%
Scale-free	Random		0.16%	-0.38%	-0.56%	-0.28%
	Targeted	Highest k_i	-1.20%	-0.73%	-10.55%	-3.82%
		Highest C_{K_i}	-1.80%	-1.10%	-9.98%	-4.22%
		Highest C_{A_i}	-2.61%	-2.91%	-10.70%	-3.72%
		Highest C_{H_i}	-0.03%	0.61%	-0.37%	0.02%
		Highest C_{C_i}	-2.28%	-0.74%	-10.44%	-3.50%
		Highest C_{R_i}	-1.20%	-2.86%	-10.45%	-2.71%
		Highest C_{BT_i}	-0.44%	-0.33%	-1.22%	-0.63%
		Highest C_i	-1.95%	-2.13%	-10.36%	-3.95%
		Lowest FR_i	-0.20%	0.35%	-9.96%	-3.39%

* R (rare disruptions); F (frequent); S (short); L (long)

for rare and short disruptions, and decreases costs by similar amount for frequent and long disruptions.

The following conclusions have been drawn from targeted risk contingency: 1) targeted rerouting is not effective for short disruptions for all cases. Targeting gives even worse effect than random rerouting; 2) targeted contingent rerouting can be more effective than random for networks with low mean degree if targeting is applied on "hubs", nodes with high number of alternative supplier. The effect was observed only for Maserati and scale-free networks.

In this work it has been proven that risk in complex supply networks can be effectively treated with relatively small cost, if appropriately applied. The effectiveness of mitigation strategies is dependent on many factors including risk profile, topology and targeting strategy. Targeting appropriate nodes, having known the risk profile and topology can result in a decrease in costs and improvements in customer service. When targeted risk management is ill-performed without prior knowledge of risk profile, topology, or suitable targeting strategy it can do more harm than random risk management, causing an increase in costs and decrease in fill-rates.

Chapter 8

Targeted risk management in FMCG networks

This chapter presents an empirically informed topology, intended as validation for the artificially generated networks in Chapter 7. The results are similar. It has been shown that there is not a single selection criteria that would increase the performance of one risk management strategy for all networks and under all risk profiles, which highlights the need for topology informed decision-making.

In this chapter, targeted inventory mitigation and targeted contingent rerouting are applied to theoretical FMCG networks. First, random and scale-free FMCG topologies and the centrality values of supply chain members are visualised and discussed. Next, targeted risk management strategies are applied to selected supply chain members. The selection is guided by two criteria: (a) the suppliers who suffered the most in experiments from Chapter 5, and (b) the suppliers based on their topological positions in the network.

Selection of suppliers who suffered the most is guided by highest costs generated by this supplier and lowest fill-rate achieved during the simulation runs. Selection of suppliers based on their topological position is guided by suppliers who have the highest centrality metrics: degree, Katz, authority, hub, closeness, radiality and betweenness.

Then, selected suppliers, while being exposed to disruptions, apply inventory mitigation and contingent rerouting. The effectiveness of targeted risk management strategies in supply networks is discussed. Here, random FMCG network are referred to as random, and scale-free FMCG as scale-free.

8.1 Node-level characteristics of FMCG networks

The following centrality metrics have been applied for random and scale-free networks: degree k, Katz centrality C_k, authority centrality C_A, hub centrality C_H, closeness centrality C_C, radiality centrality C_R, and betweenness centrality C_{BT}. Visualisations of networks and corresponding centrality metrics are presented in Figures 8.1, 8.2, 8.3, 8.4, 8.5, 8.6, and 8.7. The higher the centrality metric, the bigger the node size in the figure. Each metric is normalised using feature scaling, which means that a relationship between respective centrality values is captured rather than their exact magnitudes. One random and one scale-free network are chosen to visualise centrality metrics for demonstration purposes.

Degree k is presented in Figures 8.1 A and 8.2 A, which represents the supply chain members who have the highest number of immediate suppliers. For both random and scale-free networks these are the OEM, and some of its first tier suppliers. For scale-free networks there are only few first tier suppliers with high degrees, to which the majority of the network connects. Katz centrality values are similar to these of the degree, as noted in Chapter 7.

Authority and hub centralities are presented in Figures 8.3 and 8.4. Similarly to Chapter 7, hub centralities are high for companies who supply to companies with high authority centrality. Authority centrality is high for companies who are customers of companies who have high hub centrality. Authorities usually have high number of incoming links; whereas hubs have high number of outgoing links. In both random and scale-free networks companies with high authority are the OEM and some first tier suppliers. Companies with high hub centrality are mostly second tier suppliers for random networks; and majority of 1st tier suppliers in scale-free networks.

Closeness and radiality centralities are presented in Figures 8.5 and 8.6. Values of closeness and radiality centralities are similarly distributed across the network; suppliers with higher values are closer to the OEM, and lower are further away from the OEM, for both random and scale-free networks. This is because the average path length is quite small for both networks, as indicated in Chapter 5, which means that there is relatively low distance between all the nodes.

Betweenness centrality for random and scale-free networks is presented in Figure 8.7. Companies that have high betweenness in random networks are located mainly in the first and second tiers. Companies that have high betweenness in scale-free networks are located in the first tier. There are more nodes with high betweenness in random networks than in the scale-free network, and this is because the material flow is more distributed in random networks, which means that there are many intermediary suppliers and more independent paths from the raw material suppliers to the OEM. In the scale-free network, the supply is mostly dependent on a few nodes with high material flow, which means that there are fewer independent supply paths from raw material suppliers to the OEM. These observations agree with Chapter 7.

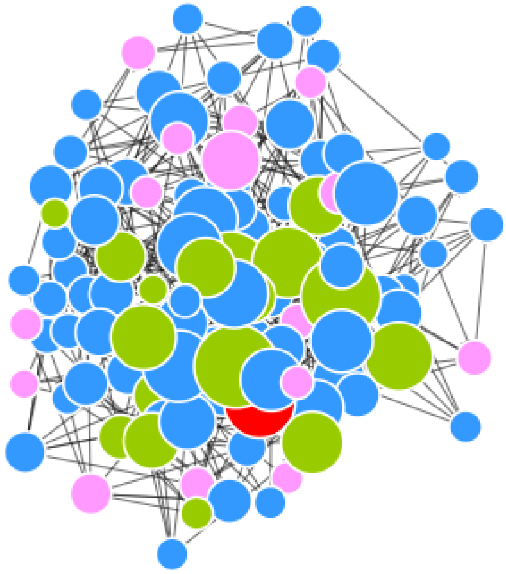
8.2 Targeted inventory mitigation for FMCG networks

In this section, results of targeted inventory mitigation are discussed. The companies that apply inventory mitigation are selected according to their performance from experiments in Chapter 5, and according to their centrality metrics. 5% of companies with 1) the highest degree centrality k, 2) the highest Katz centrality C_K, 3) the highest authority centrality C_A, 4) the highest hub centrality C_H, 5) the highest closeness centrality C_C, 6) the highest radiality centrality C_R, 7) the highest betweenness centrality C_{BT}, 8) the highest costs C_i and 9) the lowest fill-rates FR_i were chosen.

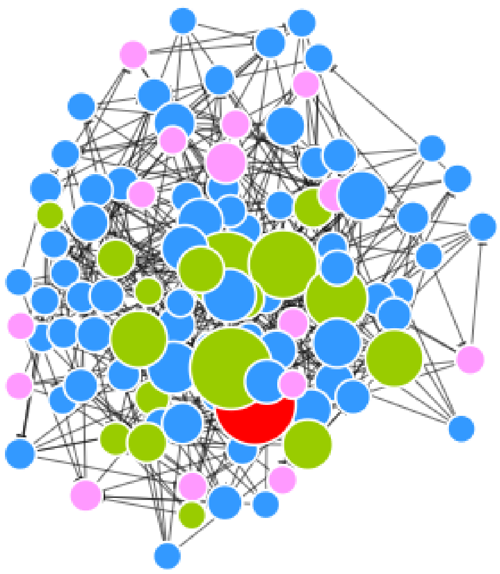
Nodes applying inventory mitigation are chosen based on their performance. Results from each simulation were averaged. The changes with respect to costs and fill-rates achieved by applying targeted strategy are presented in Tables 8.1 and 8.2. Changes are presented as a percentage increase or decrease with comparison to the base scenario where no risk management strategy was applied. These results are then compared with the effectiveness of risk management when companies that appplied the strategy were chosen at random.

The results show that the effectiveness of targeted inventory mitigation depends on the following factors: network topology, risk profile, and targeting criteria. The same targeting criteria for two different network topologies yield different results. For example, when additional inventory is kept by companies with high C_H in random

FIGURE 8.1: Visualisation of the degree and Katz centralities for random FMCG supply network. Nodes are coloured according to the tier, and sized according to their centrality.

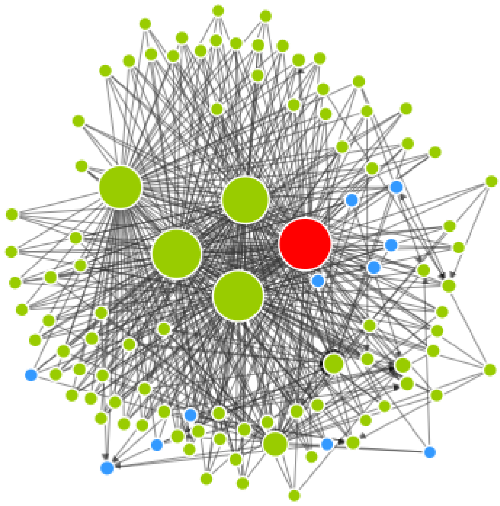


(A) degree k

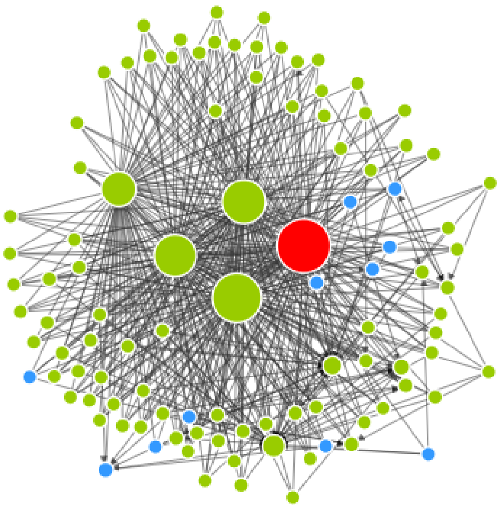


(B) Katz C_K

FIGURE 8.2: Visualisation of the degree and Katz centralities for scale-free FMCG supply network. Nodes are coloured according to the tier, and sized according to their centrality.

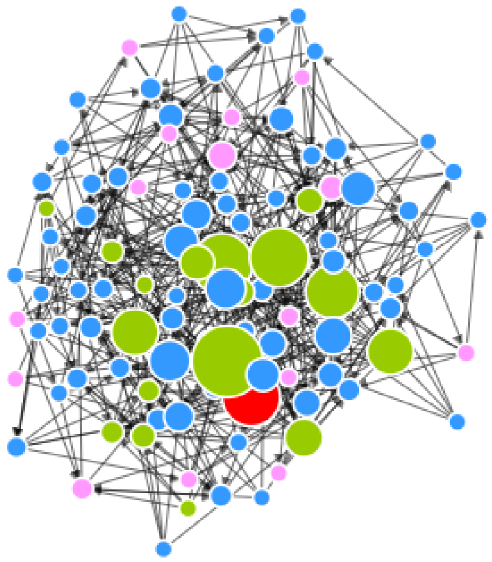


(A) degree k

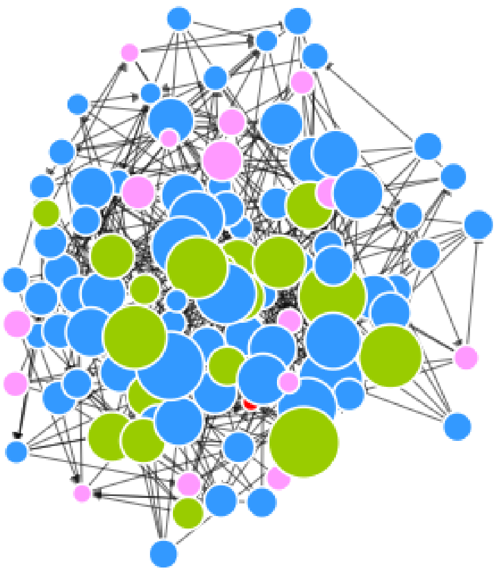


(B) Katz C_K

Figure 8.3: Visualisation of the FMCG and hub centralities for random automotive supply network. Nodes are coloured according to the tier, and sized according to their centrality.

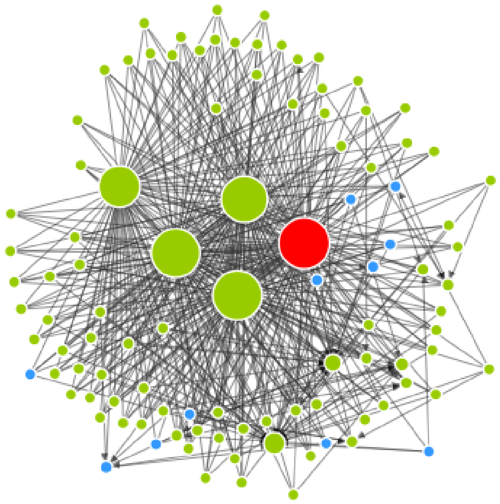


(A) authority C_A

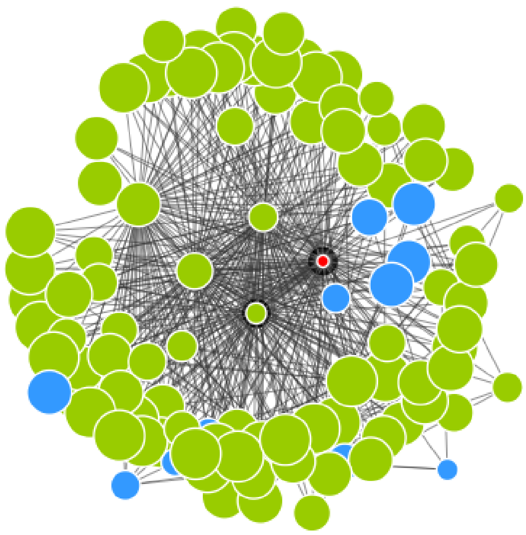


(B) hub C_H

FIGURE 8.4: Visualisation of the authority and hub centralities for scale-free FMCG supply network. Nodes are coloured according to the tier, and sized according to their centrality.

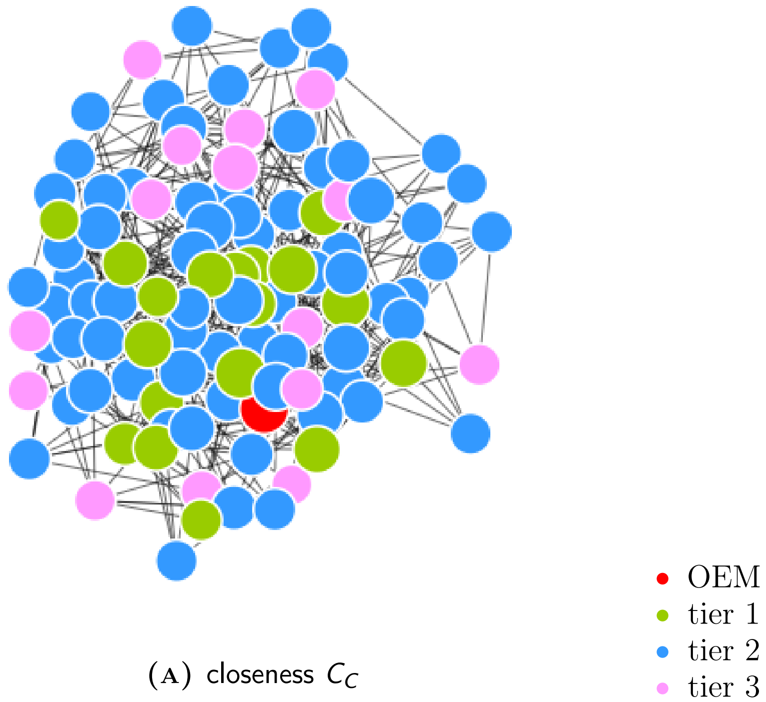


(A) authority C_A

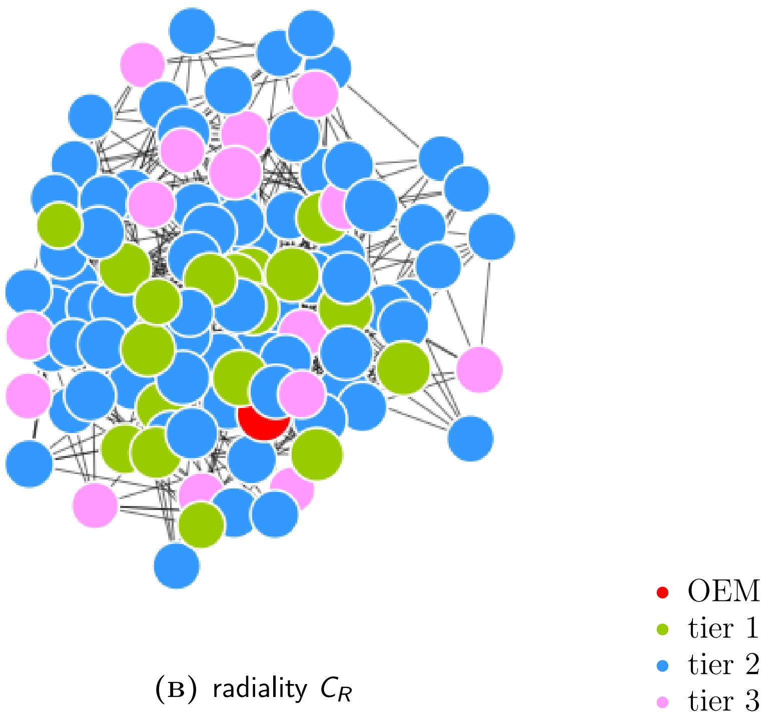


(B) hub C_H

FIGURE 8.5: Visualisation of closeness and radiality centralities for random FMCG supply network. Nodes are coloured according to the tier, and sized according to their centrality.

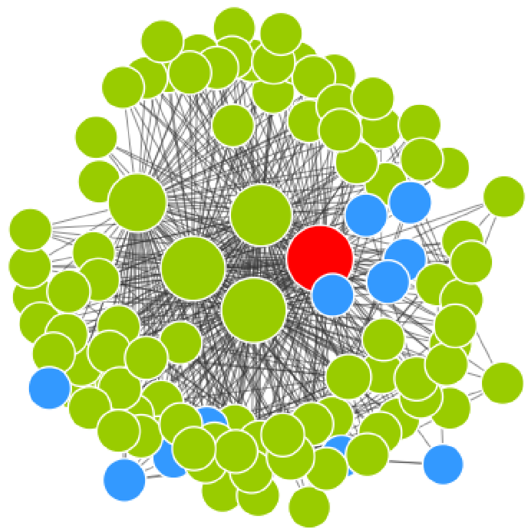


(A) closeness C_C

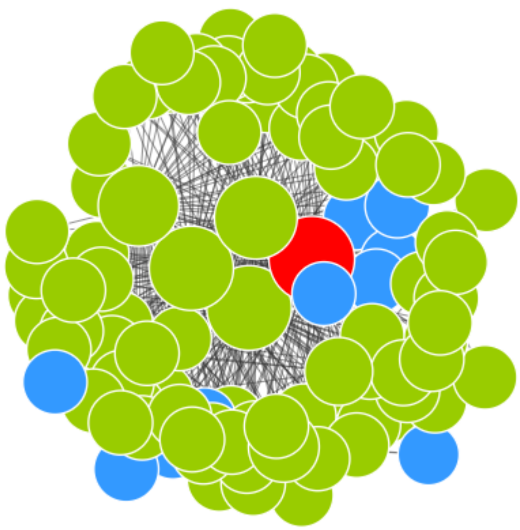


(B) radiality C_R

Figure 8.6: Visualisation of closeness and radiality centralities for scale-free FMCG supply network. Nodes are coloured according to the tier, and sized according to their centrality.

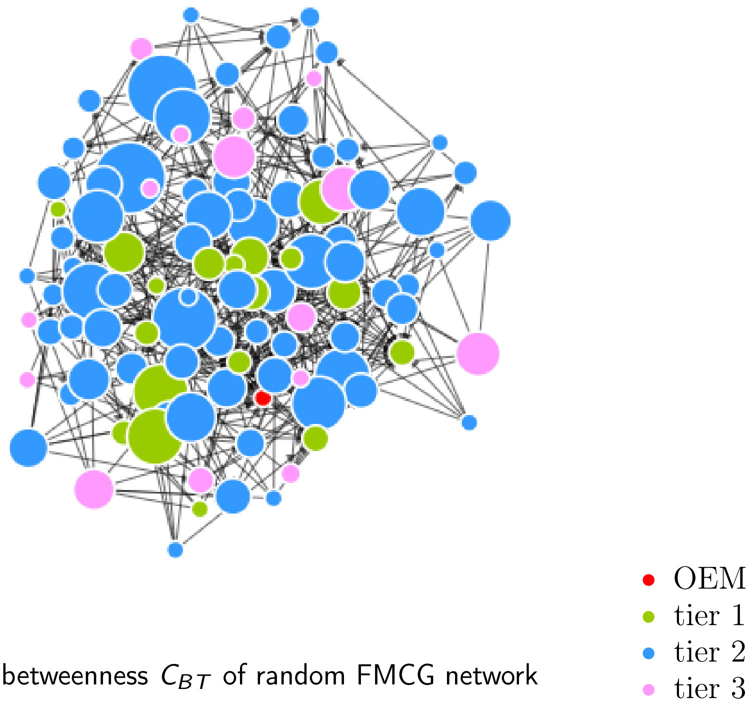


(A) closeness C_C

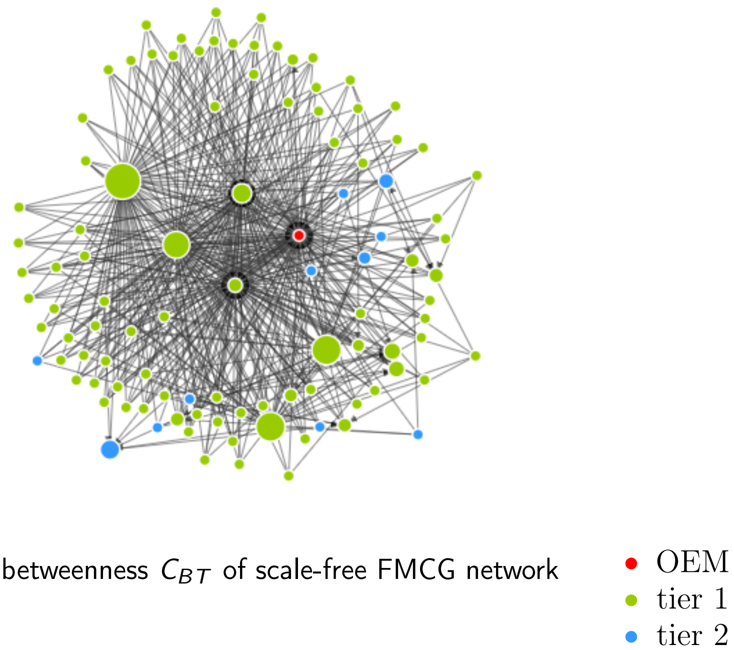


(B) radiality C_R

Figure 8.7: Visualisation of betweenness centrality for random and scale-free FMCG supply networks. Nodes are coloured according to the tier, and sized according to their centrality.



(A) betweenness C_{BT} of random FMCG network



(B) betweenness C_{BT} of scale-free FMCG network networks for rare and long disruptions, the costs are decreased by 13.51% and fill-rates are increased by 9.17%, which is a better result than when random companies keep additional inventory. On the contrary, when additional inventory is kept by companies with high C_H in scale-free networks for rare and long disruptions, costs are increased by 39.13% and fill-rates are decreased by 2.66%, and for both cases the result is worse than if random companies kept additional inventory. This shows that in order to achieve higher resilience, the selection of companies that keep safety stock should be informed not only by the topological position, but also the degree distribution of the supply network.

Furthermore the effectiveness of targeted inventory mitigation for the same selection criteria might differ for different risk profiles. For example, when companies with high betweenness centrality apply inventory mitigation in random topology under rare and short disruptions, the costs are decreased by 10.99% and fill-rates are increased by 3.78%. A result which yields better results than randomly selected companies applying the strategy. On the other hand, when the same companies with high betweenness centrality apply inventory mitigation in random network under frequent and long disruptions, the costs are increased by 1.55% and fill-rates are decreased by 1.60%, which is worse than if randomly selected companies applied the strategy. This means that the effectiveness of targeted inventory mitigation depend not only on selection criteria of companies applying the strategy, but also the frequency and duration of disruptions the network is exposed to. For some risk profiles, regardless of selection criteria for targeted inventory mitigation, costs were increased. For example, for random networks under frequent and long disruptions, degree k, C_K, C_A, C_H, C_C, C_R, C_i, and FR_i decreased costs better than when companies were selected at random. For scale-free networks under frequent and long disruptions the effect was the same. This means that the risk profile moderates the extent to which selection criteria influences costs and fill-rates.

The selection criteria for companies that apply inventory mitigation affects how the strategy improves network fill-rates and decreases the costs. Targeting by different centrality metrics might yield completely different results for the same network topology, under the same risk profile. For example, by selecting companies with high degree k in random networks the costs were decreased by 20.71%, but when companies with high Katz centrality were selected, costs were increased by 14.55%.

Selecting companies with high degree k in random networks exposed to rare and short disruptions increased fill-rates by 4.56%, whereas selecting companies with high Katz centrality C_K under the same conditions decreases fill-rates by 1.06%. This shows that the topological position of the company applying risk management strategy moderates supply network resiliency.

8.3 Targeted contingent rerouting for FMCG networks

In this section, the effect of targeted contingent rerouting are compared for random and scale-free networks. The costs and fill-rates are presented in Figures 8.3 and 8.4, respectively. Similarly for the case of inventory mitigation, the effectiveness of the strategy depends on the risk profile, the topology in which it has been applied, and the selection strategy itself.

The results show that certain groups of metrics affect costs and fill-rates similarly within different network topologies, and risk profiles. For example, degree k, Katz centrality C_K, authority centrality C_A, closeness centrality C_C, radiality centrality C_R, and costs C increase C_{NET} by 36 - 41% for scale-free networks exposed to frequent and short disruptions. The same group of metrics increase C_{NET} by 31-58% in scale-free networks exposed to rare and short disruptions.

Some metrics are effective in decreasing costs for both random and scale-free networks, regardless of the risk profile. An example of such a metric is betweenness centrality C_{BT}, which decreases costs in random networks by 11.79%, 13.12%, 5.28%, and 2.47% for rare and short, rare and long, frequent and short, and frequent and long disruptions respectively. Targeting agents by betweenness centrality C_{BT} decreases costs also for scale-free networks by 5.64%, 2.82%, and 2.34% for i) rare and long, ii) frequent and short, and iii) frequent and long disruptions, respectively.

Other metrics show to be effective in increasing fill-rates for one topology but not the other. For example, closeness centrality C_C increased fill-rates by 1.90%, 2.57%, 0.55%, 3.28% in random networks exposed to rare and short, rare and long, frequent and short, and frequent and long disruptions, respectively. Targeting suppliers by closeness centrality decreases fill-rates for scale-free networks in majority of risk profiles by 1.48%, 12.93%, and 5.55% for i) rare and short, ii) frequent and short, and

Table 8.1: The change in C_{NET} for inventory mitigation. The comparison is done for the case with disruptions between no mitigation and 5% mitigation.

Topology	Selection strategy		C_{NET}			
			RS*	RL*	FS*	FL*
Random	Random		-4.27%	-3.82%	-3.27%	-1.29%
	Targeted	Highest k_i	-20.71%	-10.05%	-5.73%	-2.23%
		Highest C_{K_i}	14.55%	-15.37%	-9.09%	-10.03%
		Highest C_{A_i}	-1.43%	-15.95%	-13.62%	-8.74%
		Highest C_{H_i}	1.62%	-13.51%	-5.03%	-4.40%
		Highest C_{C_i}	3.63%	-13.33%	-8.28%	-6.58%
		Highest C_{R_i}	-11.60%	-5.67%	-10.82%	-3.93%
		Highest C_{BT_i}	-10.99%	2.98%	-4.36%	1.55%
		Highest C_i	0.60%	-21.21%	-14.75%	-9.25%
		Lowest FR_i	-26.44%	-10.13%	-8.36%	-1.76%
Scale-free	Random		41.31%	10.27%	-0.33%	-1.72%
	Targeted	Highest k_i	379.79%	54.65%	-6.70%	-21.82%
		Highest C_{K_i}	393.51%	77.46%	-4.51%	-22.85%
		Highest C_{A_i}	381.09%	62.78%	-6.35%	-24.39%
		Highest C_{H_i}	6.10%	39.13%	-1.62%	-4.33%
		Highest C_{C_i}	373.34%	77.14%	-9.50%	-23.96%
		Highest C_{R_i}	384.80%	63.70%	-5.90%	-24.88%
		Highest C_{BT_i}	15.27%	-18.42%	-8.28%	-1.36%
		Highest C_i	382.36%	72.74%	-5.09%	-22.68%
		Lowest FR_i	30.99%	-15.60%	-2.17%	-23.43%

* R (rare disruptions); F (frequent); S (short); L (long)

Table 8.2: The change in FR_{NET} for inventory mitigation. The comparison is done for the case with disruptions between no mitigation and 5% mitigation.

Topology	Selection strategy		FR_{NET} RS*	RL*	FS*	FL*
Random	Random		2.86%	5.65%	3.80%	2.16%
	Targeted	Highest k_i	4.56%	6.58%	5.75%	1.82%
		Highest C_{K_i}	-1.06%	6.34%	2.58%	3.64%
		Highest C_{A_i}	3.24%	3.72%	6.83%	2.84%
		Highest C_{H_i}	-0.77%	9.17%	3.85%	2.89%
		Highest C_{C_i}	0.13%	9.38%	5.77%	3.96%
		Highest C_{R_i}	2.79%	4.81%	8.40%	3.73%
		Highest C_{BT_i}	3.78%	4.92%	5.50%	1.60%
		Highest C_i	4.90%	9.90%	5.20%	2.89%
		Lowest FR_i	6.46%	11.18%	5.38%	0.56%
Scale-free	Random		0.25%	0.24%	1.20%	1.35%
	Targeted	Highest k_i	0.86%	3.52%	3.32%	0.89%
		Highest C_{K_i}	-0.15%	-0.03%	2.66%	-0.29%
		Highest C_{A_i}	0.80%	2.52%	2.84%	1.75%
		Highest C_{H_i}	1.05%	-2.66%	2.16%	1.52%
		Highest C_{C_i}	1.34%	0.37%	4.38%	1.81%
		Highest C_{R_i}	0.43%	2.19%	2.86%	2.09%
		Highest C_{BT_i}	0.63%	3.08%	4.52%	0.25%
		Highest C_i	1.28%	1.53%	2.99%	1.17%
		Lowest FR_i	0.21%	3.14%	2.00%	1.33%

* R (rare disruptions); F (frequent); S (short); L (long)

iii) frequent and long disruptions, respectively. Targeting with closeness centrality C_C is better than random supplier selection in random networks, but is worse than random supplier selection in scale-free networks.

In general, targeted contingent rerouting is not effective for short disruptions in agreement with conclusions in Chapter 5, 6, and 7. This is due to the mailing delay time which slows down time of agent's reaction to the supplier's disruption. When the disruption is short, the disrupted supplier is already back in business when the agent applies contingent rerouting, leading to unnecessarily increased demand in other operational suppliers, therefore increased oscillations in the network. This has been shown in Appendix A, where the customer demand fluctuations caused by contingent rerouting strategy misinformed the operational supplier about the possible increase in general demand pattern, rather than the temporary oscillation caused by a disruption.

Using targeted contingent rerouting seems to be more effective in random networks than in scale-free networks. Similar conclusions have been drawn in Chapter 5, although in Chapter 5 the strategy was applied in randomly chosen suppliers. When suppliers are chosen at random in random FMCG network, there is a higher probability that an agent with multiple suppliers are chosen, whereas in scale-free FMCG networks there is a higher probability that an agent with a few or single suppliers is selected. This makes contingent rerouting more effective in random networks because there is a higher probability of high-degree suppliers to be chosen. Although, in targeted contingent rerouting, suppliers chosen are usually suppliers with high topological position, such as the OEM, first tier suppliers etc. These agents usually have high number of connections, therefore high potential to have many alternative suppliers when it comes to applying contingent rerouting. For example, a decrease in fill-rates by 5.41% and 6.07% in scale-free networks exposed to long disruptions when targeting by degree k is surprising. The low effectiveness of targeted contingent rerouting in Chapter 8, but not in Chapter 7, might have been caused by high density of networks under experimentation. High density would imply that inventory oscillations caused by contingent rerouting are more likely to affect more companies, resulting in higher backlogs and therefore higher costs and lower fill-rates.

Table 8.3: The change in C_{NET} for contingent rerouting. The comparison is done for the case with disruptions between no rerouting and 5% rerouting.

Topology	Selection strategy		C_{NET} RS*	C_{NET} RL*	C_{NET} FS*	C_{NET} FL*
Random	Random		-2.01%	-3.25%	2.25%	-0.76%
	Targeted	Highest k_i	-2.52%	6.24%	-8.40%	-8.45%
		Highest C_{K_i}	16.70%	-6.54%	2.72%	-12.43%
		Highest C_{A_i}	7.51%	-7.64%	1.45%	-4.37%
		Highest C_{H_i}	-16.25%	-10.73%	-1.30%	-3.59%
		Highest C_{C_i}	-19.12%	2.03%	-5.00%	-7.07%
		Highest C_{R_i}	1.65%	8.35%	-3.52%	-5.95%
		Highest C_{BT_i}	-11.79%	-13.12%	-5.28%	-2.47%
		Highest C_i	25.39%	-9.26%	8.28%	-3.76%
		Lowest FR_i	-0.76%	-0.69%	3.48%	-0.01%
Scale-free	Random		2.88%	-2.93%	3.56%	-0.66%
	Targeted	Highest k_i	58.45%	43.27%	36.77%	-4.42%
		Highest C_{K_i}	23.07%	-8.16%	36.95%	-3.99%
		Highest C_{A_i}	57.83%	6.98%	38.01%	-5.16%
		Highest C_{H_i}	6.12%	22.57%	-7.97%	0.63%
		Highest C_{C_i}	38.70%	-12.23%	39.47%	-6.32%
		Highest C_{R_i}	31.71%	19.98%	37.60%	-6.13%
		Highest C_{BT_i}	13.48%	-5.64%	-2.82%	-2.34%
		Highest C_i	47.25%	-15.27%	40.84%	-4.97%
		Lowest FR_i	34.08%	-0.94%	2.38%	-2.73%

* R (rare disruptions); F (frequent); S (short); L (long)

TABLE 8.4: The change in FR_{NET} for contingent rerouting. The comparison is done for the case with disruptions between no rerouting and 5% rerouting.

Topology	Selection strategy		FR_{NET}			
			RS*	RL*	FS*	FL*
Random	Random		0.05%	0.97%	-1.07%	1.12%
	Targeted	Highest k_i	-0.98%	-0.87%	3.93%	4.53%
		Highest C_{K_i}	-5.76%	2.69%	-0.44%	6.49%
		Highest C_{A_i}	-4.18%	2.29%	-0.94%	2.80%
		Highest C_{H_i}	1.93%	2.95%	-0.32%	3.81%
		Highest C_{C_i}	1.90%	2.57%	0.55%	3.28%
		Highest C_{R_i}	-1.14%	-2.43%	1.02%	3.59%
		Highest C_{BT_i}	0.49%	5.00%	1.20%	2.68%
		Highest C_i	-5.59%	5.53%	-3.01%	3.65%
		Lowest FR_i	0.06%	3.14%	-0.86%	3.10%
Scale-free	Random		-0.16%	0.20%	-1.03%	-0.31%
	Targeted	Highest k_i	-2.29%	-5.41%	-13.01%	-6.07%
		Highest C_{K_i}	-0.93%	-0.13%	-12.60%	-7.28%
		Highest C_{A_i}	-2.21%	-1.73%	-12.84%	-5.45%
		Highest C_{H_i}	-0.01%	-1.64%	2.97%	-1.45%
		Highest C_{C_i}	-1.48%	0.19%	-12.93%	-5.55%
		Highest C_{R_i}	-1.20%	-3.13%	-12.86%	-5.01%
		Highest C_{BT_i}	-0.35%	0.89%	0.54%	0.27%
		Highest C_i	-1.71%	0.79%	-12.10%	-5.37%
		Lowest FR_i	-0.71%	1.01%	0.26%	-6.74%

* R (rare disruptions); F (frequent); S (short); L (long)

8.4 Summary

In this chapter, targeted risk management strategies have been applied in random and scale-free FMCG networks. The inventory mitigation and contingent rerouting strategies were applied in 5% companies which had certain characteristics: (a) suffered the most from disruptions, as expressed by experiments in Chapter 5, and (b) have specific topological position as informed by centrality metrics. In conjunction with Chapter 7, this chapter yields similar lessons, mainly:

1. targeted risk management is dependent on the risk profile, topology and targeting strategy. Targeting by certain selection criteria might prove to be effective in one scenario but not the other;
2. targeting the weakest company does not always result in increased effectiveness of the system and sometimes it might decrease it;
3. targeted inventory mitigation performs better than random in high risk profiles;
4. targeted inventory mitigation performs worse than random in low risk profiles because of excessive inventory carried over a long period of time;
5. targeted contingent rerouting performs worse than random when networks are exposed to short disruptions;
6. targeted contingent rerouting does not always work for long disruptions. This is because of inventory oscillations that are likely to propagate more in dense networks.

Chapter 9

Discussion and Conclusions

9.1 Overall discussion and conclusions

Supply chain risk management involve practices that are well understood on the local scale. However, the effectiveness of these strategies in different supply network topologies has thus far not been investigated.

Following a literature review which identified widely practiced risk management strategies, two strategies were chosen to represent flexibility and redundancy based approaches, namely inventory mitigation and contingent rerouting. Network topologies include 11 automotive supply network topologies and 11 topologies informed by a real case in the fast-moving consumer goods industry. Automotive topologies consist of 1 empirical Maserati supply network, 5 random and 5 scale-free topologies which were generated based on the empirical example. Fast-moving consumer goods topologies consisted of 1 empirical logistics network, 5 random supply networks and 5 scale-free supply networks which were generated based on the empirical example. Due to the ongoing debate as to the nature of supply network topology, empirical networks were treated separately. Theoretical random and scale-free topologies were chosen because of a lack of consensus on complex supply network topology in the extant empirical literature; and, thus, reflect the extreme ends of the possible topological continuum.

A simulation approach was developed to test which strategy, at what level, in which topology results in a better performance for the manufacturer and for the overall network. Performance criteria included both network and the manufacturer's fill-rate and associated costs. Next, the study was extended to targeted inventory mitigation and targeted contingent rerouting, where the weakest firms embedded in the automotive supply networks were selected to apply risk management strategy. The experiments were performed to conclude how firm's position can influence the effectiveness of a risk management strategy.

The results are discussed to conclude on the influence of network topology on supply chain resilience. Resilience is expressed as the ability of a network to fulfil customer demand regardless of its part being perturbed.

The work on how network topology influences disruption impact is concluded as follows, thus answering 1^{st} research objective:

1. Different topologies absorb disruptions differently. Maserati and scale-free automotive networks under disruptions generate lower costs and higher fill-rates than random networks. Scale-free FMCG networks generate lower costs and higher fill-rates than random networks. The FMCG empirical network generate the highest costs and lowest fill-rates than other networks because it contains cycles;

2. Topology of a supply network impacts resilience to different risk types. The Maserati network is more resilient to frequent and short disruptions, whereas scale-free networks are more resilient to rare but long disruptions. Both networks generate similar costs and fill-rates in other risk profiles.

The above conclusions show that different supply network topologies moderate the impact of disruptions differently. Scale-free supply networks suffer less from random disruptions than random supply networks, which has also been observed in network science literature with regard to other network types (Barabasi and Albert, 1999, Nair and Vidal, 2011, Thadakamalla et al., 2004, Zhao et al., 2011). This is because when a network is exposed to random disruptions, there is higher probability of a peripheral node being disrupted in scale-free networks. These peripheral nodes, while disrupted, tend to affect smaller numbers of nodes resulting in reduced impact of disruptions on network performance. The Maserati network respond to disruptions similarly as scale-free networks due to existence of hubs. The Maserati network and scale-free networks are able to satisfy customer demand better while being perturbed, therefore they show increased resilience to random disruptions.

The results on inventory mitigation in theoretical and empirical networks are as follows, answering the 2^{nd} research objective:

1. Additional inventory always increases fill-rate;

2. Additional inventory might decrease or increase costs depending on risk profile and network topology. Application of inventory mitigation for rare and long disruptions decreased costs in random automotive, random FMCG and FMCG networks and increased costs in scale-free automotive, scale-free FMCG and Maserati networks;

3. Scale-free automotive, scale-free FMCG and Maserati networks have higher disruption tolerance and need less inventory than random automotive and random FMCG topologies for the same risk profiles.

4. Maserati needs less inventory in frequent and short disruptions, scale-free automotive networks need less inventory in rare and long disruptions.

5. Inventory mitigation has proven to be very effective in networks prone to instabilities, such as FMCG empirical network, regardless of the risk profile applied.

It has been shown that when additional inventory is kept in the supply network, the impact of the disruption is usually smaller than if this inventory is not present. This is evidenced by high fill-rates. When a network is resilient while companies apply inventory mitigation, it does not have to necessarily imply that this network generates low costs. This is because when companies keep additional inventory they incur additional inventory holding costs. If the disruption impact on the companies embedded in a network is lower, or if companies return to their desired inventory quicker, they will carry more inventory. This has been shown in Appendix B, where inventory mitigation indeed increases resilience of the network by reducing the impact of the disruption on companies, however also significantly increases costs. Similar observations were made by Colicchia et al. (2010), Tomlin (2006), who mention that inventory mitigation is not effective in some risk profiles because excessive inventory is carried for long periods of time resulting in high inventory holding costs. Similar observations are reported in Chapters 5 and 6 for some scenarios, however it has been shown that inventory mitigation can be also cost effective.

When the amount of additional inventory is just right, it not only improves fill-rates, but also decreases costs because additional inventory has a reduction effect on the disruptions (Kamalahmadi and Parast, 2017, Mishra et al., 2016). The amount of inventory needed is moderated by risk profile, as reported by (Kurano et al., 2014), but also by network topology. The amount of inventory that is "just right" for a specific topology and a specific risk profile can be defined as the *inventory threshold*. When additional inventory exceeds this threshold, higher fill-rates can be achieved but also costs incurred are higher due to excessive inventory carried out for long periods of time. When additional inventory is below the threshold, lower fill-rates are achieved, but also higher costs are incurred because of backlog costs generated when there is not enough inventory. The threshold therefore represents a good balance between inventory holding costs and backlog costs.

Interestingly, network topology also affects the inventory threshold value. The threshold value is lower for scale-free networks and empirical Maserati network, and higher for random networks. This implies that scale-free networks need less additional inventory to achieve the same fill-rates as random networks. Moreover they generate higher inventory holding costs with the same amount of additional inventory as random networks. Network topology affects the threshold because it affects the resilience to random disruptions (Barabasi and Albert, 1999, Mari et al., 2015). There is higher probability that a peripheral company will be disrupted in networks with scale-free property; and when a peripheral company is disrupted it affects less firms embedded in the supply network, resulting in higher fill-rates. When less firms are affected by the disruption, less additional inventory is needed.

In summary, inventory mitigation proves to be a good shock absorption mechanism, ensuring the production continuity and decreasing the impact of disruptions on the overall network, therefore increasing resilience of the complex supply network.

The conclusions on contingent rerouting, answering 3^{rd} research objective, are as follows:

1. The effectiveness of contingent rerouting depends on the risk profile of the network. Contingent rerouting is not effective for short disruptions because of mailing delay time, where it increases costs and decreases fill-rates. The strategy might be effective for long disruptions, but its effectiveness depends on the topology in which it has been applied.

2. The effectiveness of contingent rerouting depends on topology. The strategy is not effective in networks where majority of nodes have small number of alternative suppliers, such as scale-free FMCG networks;

3. Contingent rerouting is not effective in networks with a low mean degree, such as scale-free automotive, random automotive and Maserati because majority of firms have small number of alternative suppliers.

Literature highlights the dominance of flexibility-based approaches over redundancy-based approaches (Carvalho et al., 2012, Dong and Tomlin, 2012, Talluri et al., 2013). In contrast, this thesis results show that contingent rerouting does not always increase the resilience of the supply network.

As shown in Chapters 5 and 6, contingent rerouting was effective only when the network was exposed to long disruptions. It did not work for short disruptions because of the mailing delay time. The mailing delay is the time it takes the order to reach the supplier. This implies a lag in executing contingent rerouting, therefore a long reaction time to a supplier's disruption. Before the company realises that its supplier is disrupted, the supplier becomes operational again. The company still reroutes the order volumes, affecting operational suppliers. Appendix B shows the inventory dynamics in such a situation, and proves that an agent redirecting the volume to operational supplier actually causes more disruption for this supplier. This is because the operational supplier does not realise that the network experiences a disruption, therefore it counts an unexpected increase in demand as a valid customer demand pattern, therefore orders more to accommodate for future demand. Later, this excessive inventory is not really needed and creates additional inventory holding costs. Contingent rerouting in scale-free networks might be beneficial for the OEM, but not necessarily for the rest of the network.

The reason why literature claims the dominance of the strategy over inventory mitigation might come from the fact that it has not been explored how the strategy affects companies that do not apply the contingency strategy.

In this thesis, it has been shown that most of the time, contingent rerouting negatively impacts the majority of supply chain members in short disruptions and therefore do not increase resilience of the network. Contingent rerouting might increase resilience of the network by increasing fill-rates when certain criteria are met: (a) companies applying the strategy must have multiple suppliers available; (b) the time needed to implement the strategy (the response time) must be shorter than the duration of the disruption.

The conclusions on targeted inventory mitigation, answering the 4^{th} research objective, are as follows:

1. Targeted inventory mitigation might increase performance of the overall network if applied appropriately. The targeting strategy was mostly effective in high risk profiles.

2. Targeting the weakest firms does not always increase performance of the overall network. For example, for low risk profiles costs were higher than when random inventory mitigation was applied.

3. Different targeting strategies perform better in various risk profiles. For example, C_H and C_{BT} perform better than others in rare and short disruptions, but perform worse for frequent and long disruptions.

4. Maserati reduces disruption impact better better in rare and long disruptions using different targeting strategies than scale-free networks. Scale-free networks reduce disruption impact more effective than Maserati for frequent and short disruptions.

The conclusions on targeted contingent rerouting, answering 5^{th} research objective, are as follows:

1. Targeting the weakest firms does not always increase performance of the overall network. For example, targeting firms in short disruptions resulted in higher costs and lower fill-rates than if random contingency was applied because this strategy is not effective when disruption duration is short;

2. Certain targeting strategies are more effective in specific risk profiles than others. For example, targeting C_{H_i} decreased costs and increased fill-rates for Maserati in rare and short disruptions, whereas targeting k_i increased costs and decreased fill-rates;

3. Targeted contingent rerouting is more effective in Maserati in rare and long disruptions than in random and scale-free because: (a) targeted nodes usually have high number of alternative suppliers; (b) Maserati network is vulnerable to rare and long disruptions, therefore it reduces disruption impact better using the strategy.

4. Targeted contingent rerouting showed to be less effective in scale-free FMCG networks than in scale-free automotive networks. This is because scale-free FMCG networks are more dense, hence inventory oscillations affect more suppliers and imply higher backlogs and lower fill-rates.

Literature mentions that in order to improve the performance of the whole system, the weakest company needs to be strengthened (Kleindorfer and Saad, 2005, Schmitt and Singh, 2012). However, in this work it has been shown that this is not always the case. This is because supply chains often have been treated as hierarchical structures, whereas they are complex systems with multiple inter-firm dependencies and non-trivial dynamics. In a complex system a small change might invoke a significant response; therefore strengthening the weakest firm does not necessarily result in increased performance.

Targeted inventory mitigation in the majority of experiments did not decrease costs, nor improved fill-rates when the network was exposed to low risk profiles; and did not perform better than randomly selecting companies that apply the strategy.

This is because: (1) excessive amount of inventory was kept for long periods of time, and (2) the companies that were chosen to carry the additional inventory had a strategic position implying that in general they dealt with higher inventories. Dealing with high inventories implied high inventory carrying costs. Low effectiveness of targeted inventory mitigation in low risk profiles implies that additional inventory might not be needed in firms occupying central topological positions, but rather on the peripheries. Peripheral companies keeping additional inventory would prevent the disruption from affecting companies further downstream.

On the other hand, targeted inventory mitigation proven to be effective for high risk profiles, by decreasing costs and increasing fill-rates. This implies that when risk is high, the inventory might be needed more in the centrally-located companies rather than on the peripheries.

In most cases, targeted contingent rerouting worked better in random automotive networks for longer disruptions than when companies were selected at random, because mostly hubs were targeted. However, the strategy did not work well in FMCG scale-free networks because of high density of the network as discussed in Chapter 8. High density implied that more companies were affected by inventory oscillations.

Targeted risk management experiments have shown that applying risk management strategies in supply chain members guided by centrality metrics, or how much the companies have suffered from disruptions needs to be applied with extra care because the supplier selection strategy will greatly affect the resilience of the supply network. The effectiveness of the targeting strategy depends not only on the selection criteria, but also on the risk profile and topology in which firms are embedded. This implies that what works for one supply network, might not work for another.

This work, thus, shows that network topology plays a crucial role in reducing impact of disruptions, which motivates for topology-informed decision-making. The results show that inventory mitigation outperforms contingent rerouting for the majority of cases, implying that additional inventory serves as a useful shock absorption mechanism. Moreover, it is shown that different topologies exhibit different responses to risk duration and frequency. This observation suggests the need for topology-informed supply network design, which enables resilience to certain risk types. Experiments on targeted risk management suggest that targeting nodes is a powerful tool in cost reduction, although when applied inadequately it might cause severe damages in costs and customer service.

One needs to bear in mind that strategies considered are not a one-fits-all solution and they might increase other types of risks e.g. inventory risks (Chopra and Sodhi, 2004). Also, the network-focused approach discussed in this thesis is only applicable if the companies have at least a rough idea of the topological and operational characteristics of their supply network.

This research is the foundation for the following managerial implications:

1. The literature often had underestimated inventory mitigation as the risk management strategy; this research shows that it serves well in the majority of cases as an effective disruption absorption mechanism.
2. Some supply networks need less inventory than others, therefore it is important to identify the level at which the inventory starts to be excessive for a specific topology and risk profile.
3. Contingent rerouting has proven to be the less effective and harder to implement than inventory mitigation in a complex supply network setting; In order for contingent rerouting to work well, specific conditions need to be met: (1) the majority of supply chain members need to have multiple alternative suppliers, which might turn out not to be practical in real-world scenarios; (2) the response time has to be less than the disruption duration, otherwise it results in increased inventory oscillations and drop in effectiveness of this strategy.
4. Since supply network topologies showed resilience to different risk types, it is possible to design a supply network in a way that it is resilient to specific risk e.g. frequent disruptions.
5. Targeted risk management can be a very effective tool to remedy impact of disruptions. However it is necessary to understand the role each firm plays in the supply network. If misaligned, the strategy that initially was aimed at decreasing risk might significantly hurt the performance of the overall system.

In order to understand how to remedy effects of disruptions in the extended supply network, it is necessary to have a visibility beyond one's direct suppliers and customers. With the current advances in the information technology, it is a matter of time when partial, or even complete, supply network information will be available to all stakeholders. This research showed that topology is a crucial variable when considering supply chain resilience, and in the future supply networks might be designed in a way to absorb disruptions and reduce disruption impact more effectively.

9.2 Novelty and contribution to knowledge

Although resilience of supply networks has already been a topic broadly discussed in the literature, for the first time the influence of supply network topology on its ability to reduce disruption impact using risk management strategies has been tackled in a fully dynamic environment, where each supplier is an independent decision-maker. For the first time, costs and fill-rates of different supply network topologies have been compared to conclude on the effectiveness of broadly used risk management strategies, namely inventory mitigation and contingent rerouting. Moreover, to the best of the author's knowledge, supply network members have not been targeted to apply certain risk management strategies to conclude how strengthening the weakest firm in the network will affect the overall network performance.

9.3 Research limitations and future work

In this section, limitations of this study are reviewed to provide direction for the future research.

Firstly, the agent-based model that has been built, assumes perfect substitutability of goods. This has implications on the results of simulations. If companies were sourcing multiple products, they would need to carry more stock for each product/-component. More stock implies more costs, which in turn might show that inventory mitigation is less cost effective. However, inventory mitigation might be shown to still increase resilience of the supply network because it would enable production continuity. For example, when products A and B are used to manufacture a product C, if product A is stocked-out, the company might halt orders of product B as well because product C will not be able to be manufactured without product

A anyway. Additional inventory would create a buffer against disruptions of other supply chain members and therefore increase fill-rates.

Product substitutability would also affect effectiveness of contingent rerouting. A company which has multiple suppliers might not be able to apply contingent rerouting strategy if these suppliers deliver different products. For example, if a company has two suppliers where one supplier delivers product A and the other product B, if the supplier delivering product A is disrupted, the company will not be able to reroute the order volumes to the other operational supplier because it supplies a different product. This would create a situation where many companies are not able to apply contingent rerouting strategy due to lack of multiple suppliers of the same product. Further study is needed to investigate the effect of imperfect substitutability.

Multi-product considerations give rise to a discussion on product criticality. Some goods might not be equally important. For example, if the product A is a critical component to manufacture product C; and product B can be substituted, then a disruption of supplier delivering product A would cause the customer to halt production. Moreover, a company sourcing the critical part/component might want to have more than just one supplier for this part, or seek for an alternative source when the critical component supplier is disrupted.

Another limitation is that the agent-based model developed in this thesis does not allow the possibility to reorganise network structure, whereas in reality supply networks continuously evolve and change over time (Pathak et al., 2007). This would imply that if a supplier fails often, the company might seek a more reliable supplier, and destroy or form new supplier-customer connections with agents. The impact of this kind of behaviour might improve network resilience because it would ensure production continuity, but could also increase inventory oscillations in the network since it would change the companies customer demand patterns.

Thirdly, only two strategies as an example of redundancy and flexibility approaches has been used. In the future, more mitigation and contingency strategies could be explored.

This research considers only disruption risk, but more risk types could be incorporated, such as fluctuating demand risk, or economic or political risks.

It has also to be noted here that all companies within an agent-based model had the same probability of being disrupted. In the real world, this might not be the case. Some suppliers might be more reliable than others.

Degree, Katz, hub, authority, closeness, betweenness and radiality centralities, costs and fill-rate have been chosen as a criteria to target the suppliers to apply chosen risk management strategy, but other metrics could be used.

Finally, other empirical supply networks could be considered.

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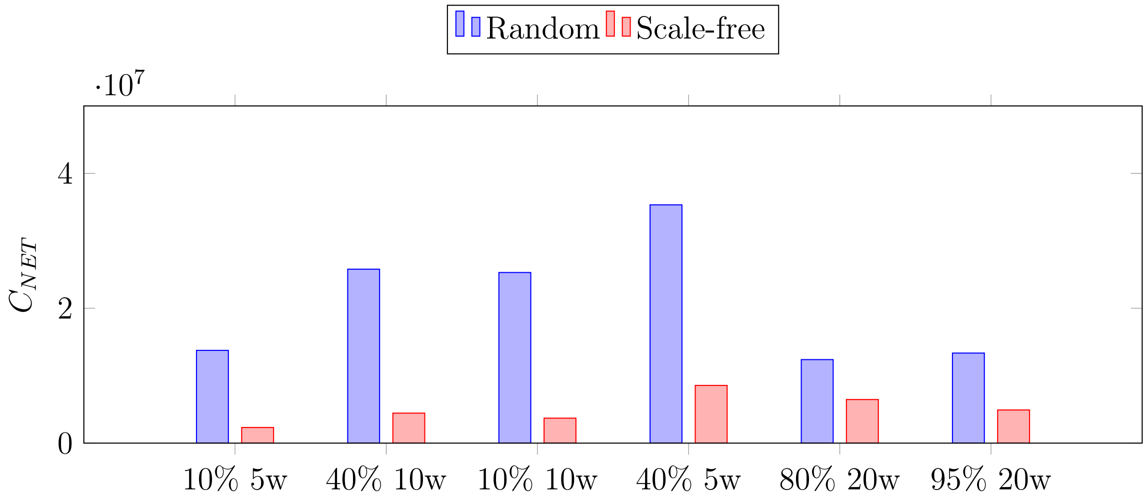
Appendix A

Rationale of choice for simulation parameters

A.1 Trial and error experiments

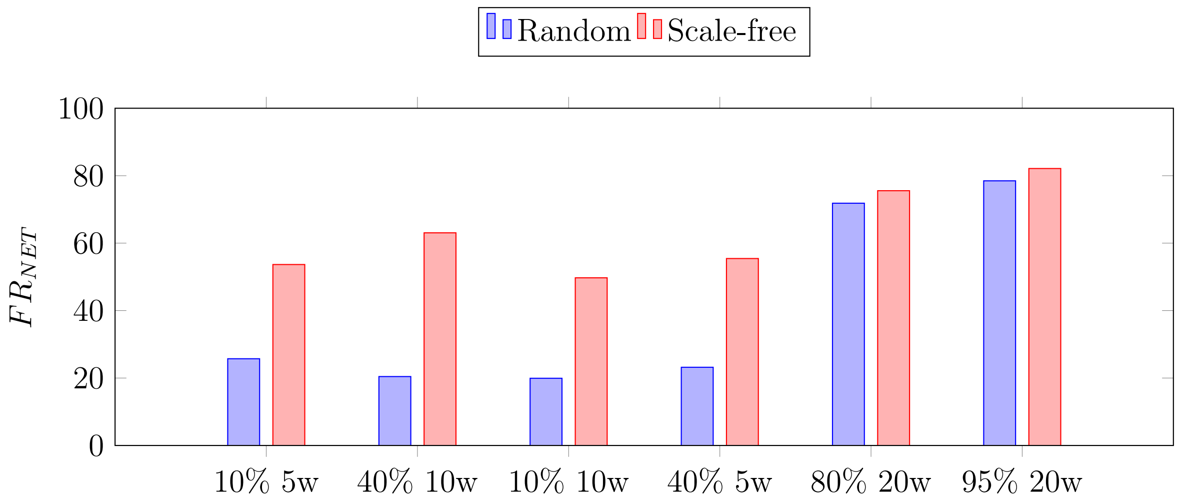
This appendix presents the trial and error experiments performed on supply network topologies to understand how disruption duration and disruption frequency affect the overall network performance. It has been observed that with an increase in disruption frequency and duration, network performance decreases i.e. costs increase and fill-rates decrease for all network types. Although this behaviour is observed up to some point. If the disruption frequency and duration are unnaturally high (i.e. suppliers are always disrupted) the performance starts to increase i.e. costs decrease and fill-rates increase. This phenomenon occurs because when all suppliers are disrupted at all times, there is a material flow freeze, where no one sells nor buys from each other. When there are no transactions, the inventories stay at the same level and there is no unmet demand because there is no demand at all. This is observed in Figures A.1, A.2, A.3 and A.4, where costs C_{NET} increase approximately to the middle of the diagram and FR_{NET} decrease up to the middle of the diagram. After mid-point, costs start to decrease and fill-rates increase. Unnaturally high risk should not be considered in the model because even if non-zero probability these are situations that do not happen in the real-life and moreover distort the simulation results.

FIGURE A.1: C_{NET} of FMCG random 1 and scale-free 1 networks under different disruption frequency and duration. Frequency and duration are expressed on x-axis by numbers with % and w, respectively.



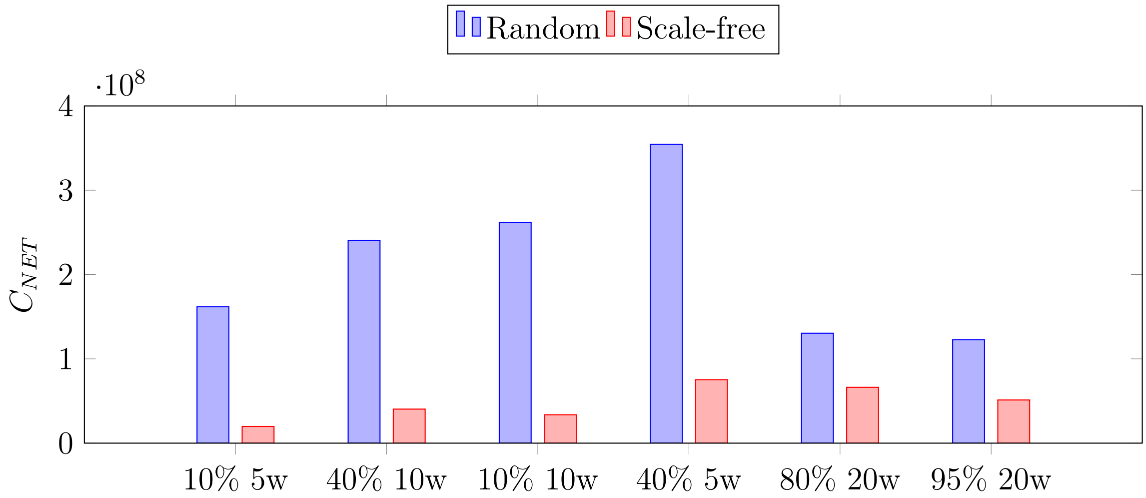
(A) C_{NET}

FIGURE A.2: FR_{NET} of FMCG random 1 and scale-free 1 networks under different disruption frequency and duration. Frequency and duration are expressed on x-axis by numbers with % and w, respectively.



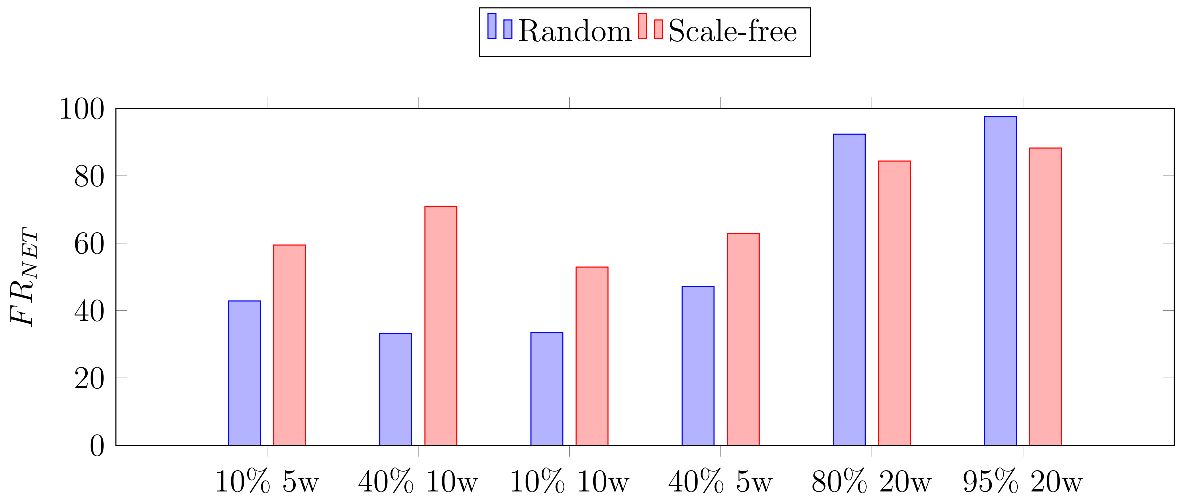
(A) FR_{NET}

Figure A.3: C_{NET} of Maserati random 1 and scale-free 1 networks under different disruption frequency and duration. Frequency and duration are expressed on x-axis by numbers with % and w, respectively.



(A) C_{NET}

Figure A.4: FR_{NET} of Maserati random 1 and scale-free 1 networks under different disruption frequency and duration. Frequency and duration are expressed on x-axis by numbers with % and w, respectively.

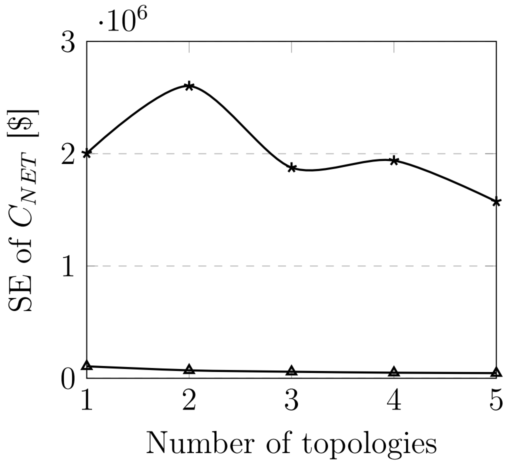


(A) FR_{NET}

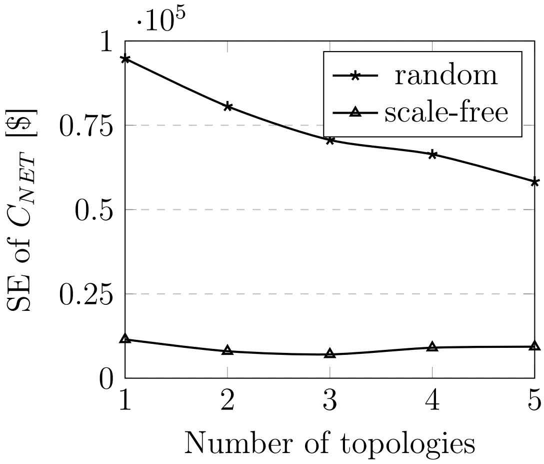
A.2 Choice of topologies

5 scale-free and 5 random topologies were generated for each empirical topology, giving 5 random automotive, 5 scale-free automotive, 5 random FMCG, and 5 scale-free FMCG topologies. The choice of number of generated topologies was guided by the decrease of the standard error for both costs and fill-rates; 5 topologies were enough to decrease the standard error and adding more topologies would not significantly increase the accuracy of the results. The standard error for networks under frequent and long disruptions was plotted in Figures A.5 and A.6 for 100% agents applying inventory mitigation; and in Figures A.7 and A.8 for 100% agents applying contingent rerouting. Frequent and long disruptions were chosen for presentation because these form the highest risk profile considered in this thesis, therefore will result in the highest standard error. It is possible to observe that the more topologies considered in the experimentation, the lower the standard error for fill-rates. Standard error of costs increases slightly when two topologies are considered because a new supply network topology is added which increases variability of the results. Then, adding even more topologies results in a decrease in standard errors to the point when it is not significantly improved beyond five topologies. Additionally, to show the proximity of results obtained and replication of patterns across the same family of topologies, extended plots are presented in Figures A.9, A.10, A.11, A.12, A.13, A.14, A.15, A.16.

Figure A.5: C_{NET} standard error decrease in scale-free and random networks while adding more topologies for frequent and long disruptions for inventory mitigation (IM).

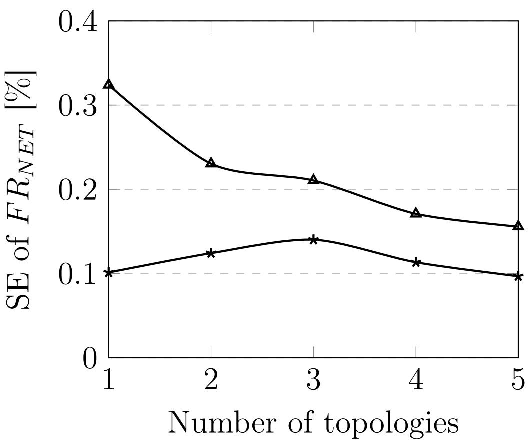


(A) automotive networks

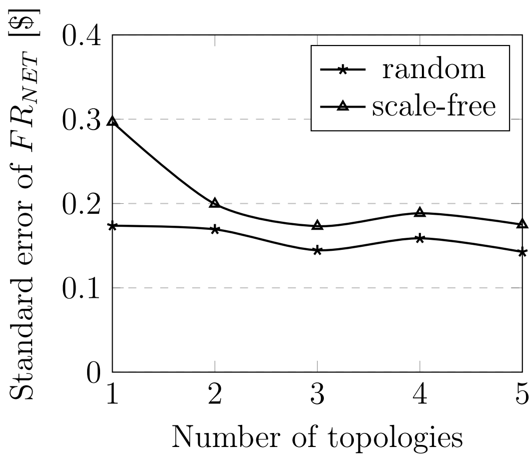


(B) FMCG networks

Figure A.6: FR_{NET} standard error decrease in scale-free and random networks while adding more topologies for frequent and long disruptions for inventory mitigation (IM).

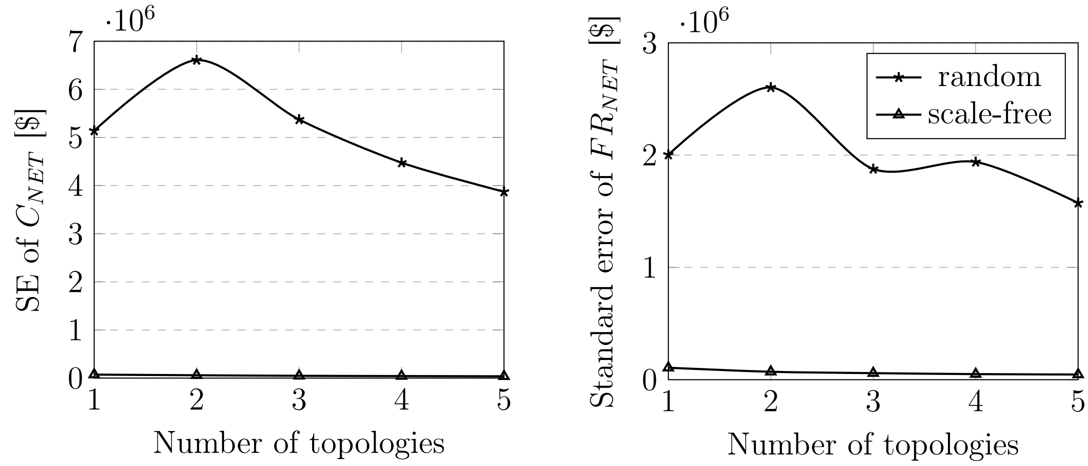


(A) automotive networks



(B) FMCG networks

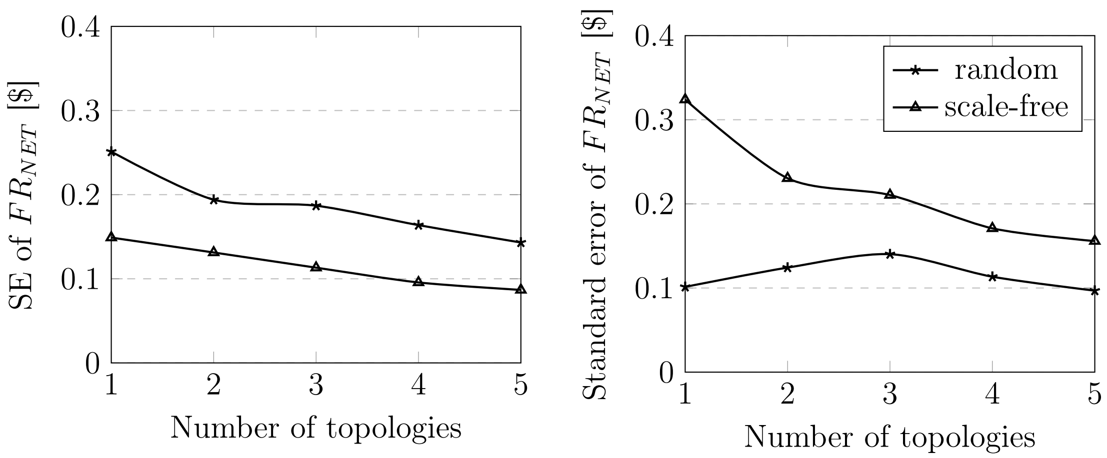
Figure A.7: C_{NET} standard error decrease in scale-free and random networks while adding more topologies for frequent and long disruptions for contingent rerouting (CR).



(A) automotive networks

(B) FMCG networks

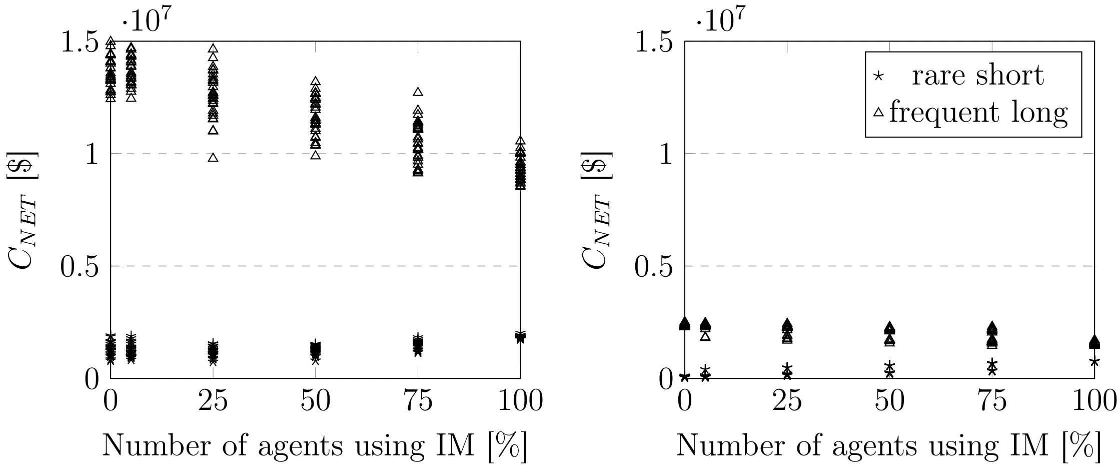
Figure A.8: FR_{NET} standard error decrease in scale-free and random networks while adding more topologies for frequent and long disruptions for contingent rerouting (CR).



(A) automotive networks

(B) FMCG networks

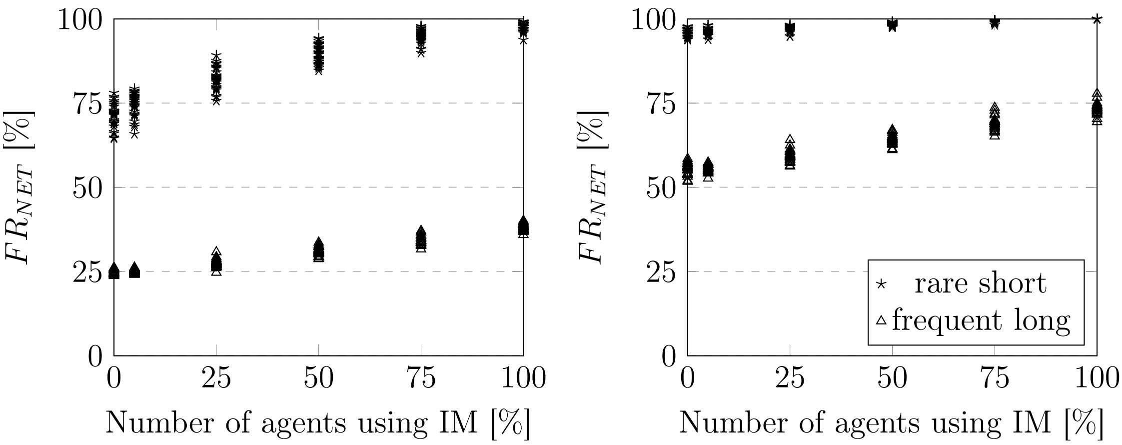
Figure A.9: Inventory mitigation random 1 FMCG and scale-free FMCG 1 (n=103, m=472), 0.5% 1 week (star) and 10% 5 weeks, C_{NET}



(A) C_{NET} for random networks

(B) C_{NET} for scale-free networks

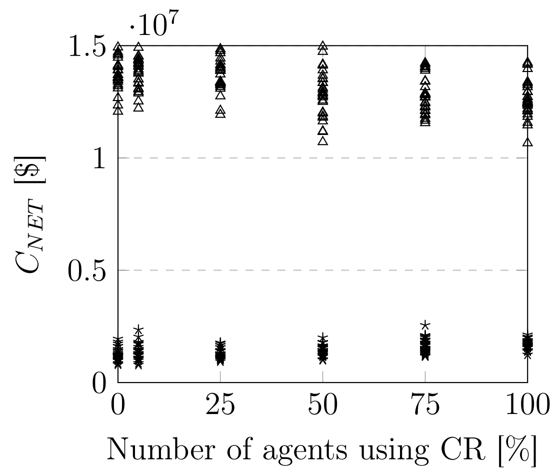
Figure A.10: Inventory mitigation random FMCG 1 and scale-free FMCG 1 (n=103, m=472), 0.5% 1 week (star) and 10% 5 weeks, FR_{NET}



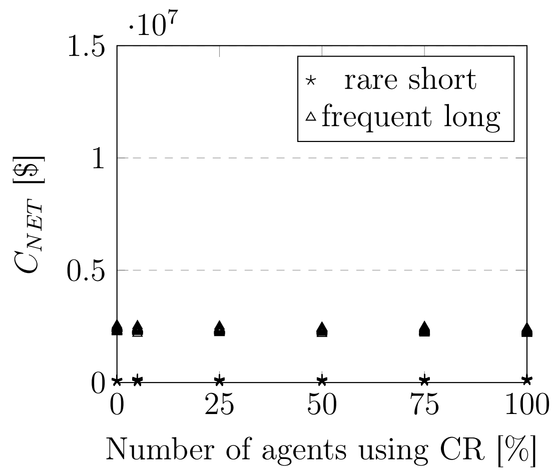
(A) FR_{NET} for random networks

(B) FR_{NET} for scale-free networks

Figure A.11: Contingent rerouting random FMCG 1 and scale-free FMCG 1 (n=103, m=472), 0.5% 1 week and 10% 5 weeks, C_{NET}

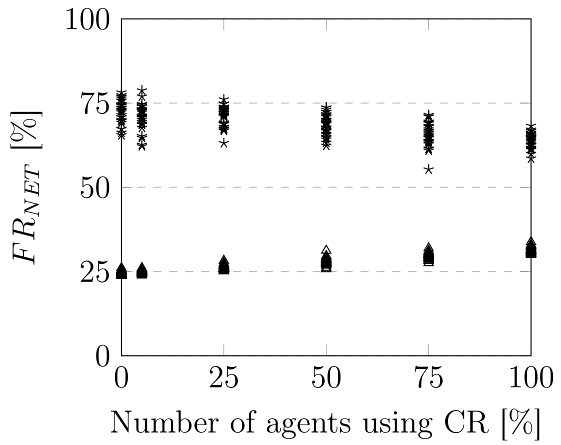


(A) C_{NET} for random networks

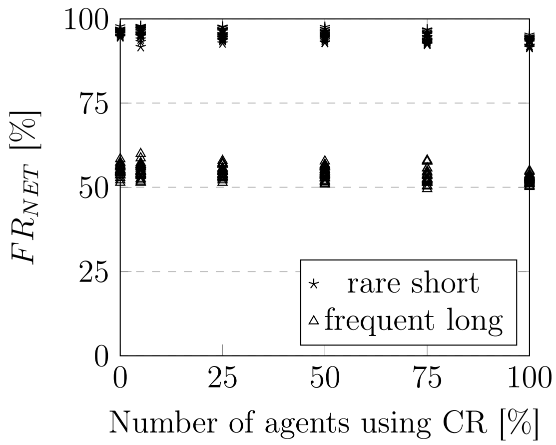


(B) C_{NET} for scale-free networks

Figure A.12: Contingent rerouting random FMCG 1 and scale-free FMCG 1 (n=103, m=472), 0.5% 1 week and 10% 5 weeks, FR_{NET}

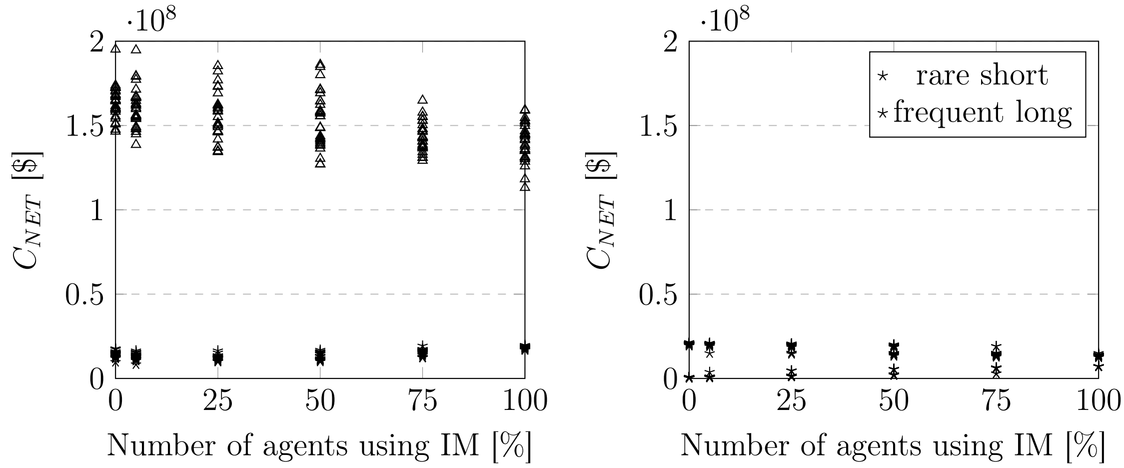


(A) FR_{NET} for random networks



(B) FR_{NET} for scale-free networks

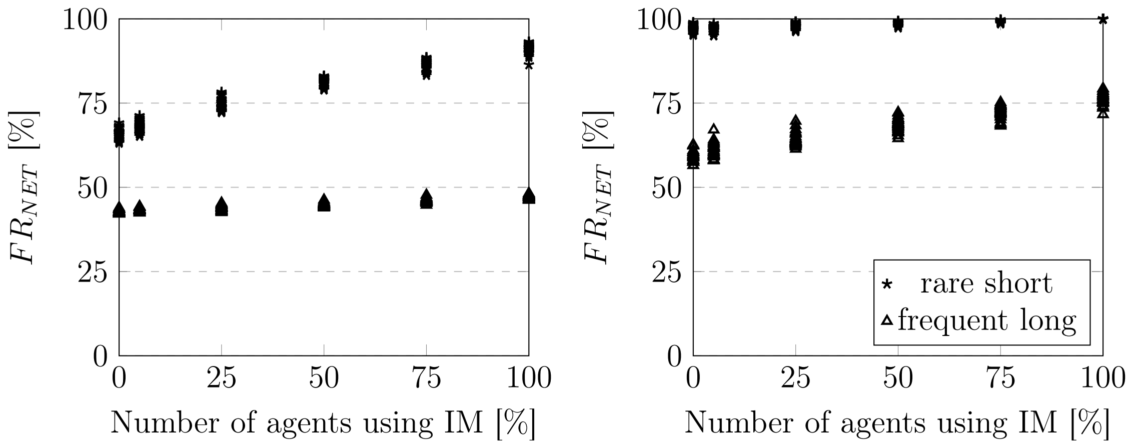
FIGURE A.13: Inventory mitigation random 1 and scale-free 1 automotive, 0.5% 1 week (star) and 10% 5 weeks, C_{NET}



(A) C_{NET} for random networks

(B) C_{NET} for scale-free networks

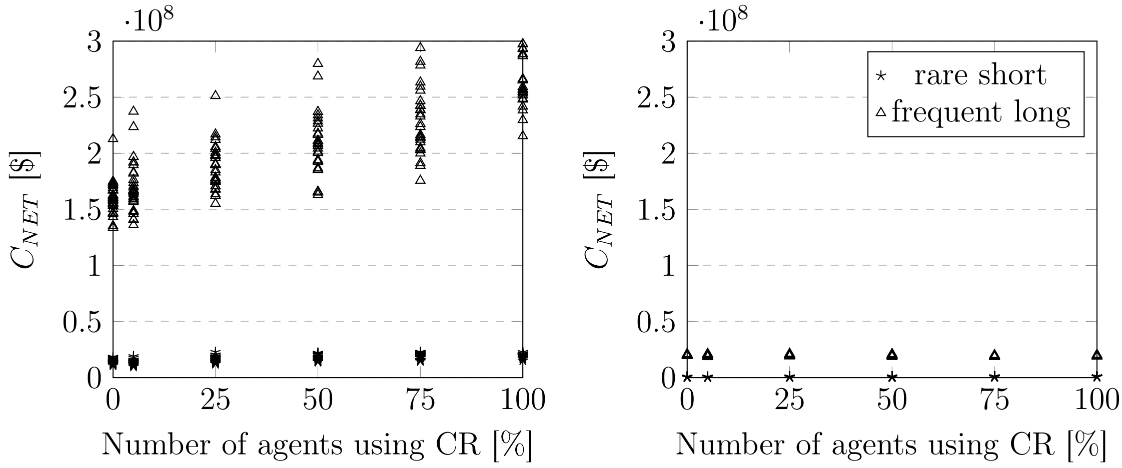
FIGURE A.14: Inventory mitigation random 1 and scale-free 1 automotive, 0.5% 1 week (star) and 10% 5 weeks, FR_{NET}



(A) FR_{NET} for random networks

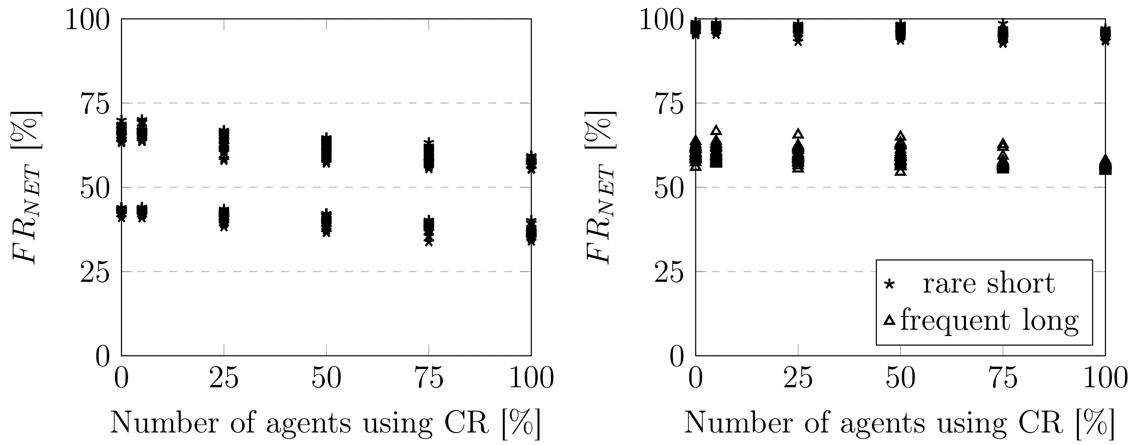
(B) FR_{NET} for scale-free networks

FIGURE A.15: Contingent rerouting random 1 and scale-free 1 automotive, 0.5% 1 week and 10% 5 weeks, C_{NET}



(A) C_{NET} for random networks (B) C_{NET} for scale-free networks

FIGURE A.16: Contingent rerouting random 1 and scale-free 1 automotive, 0.5% 1 week (star) and 10% 5 weeks, FR_{NET}



(A) FR_{NET} for random networks (B) FR_{NET} for scale-free networks

Appendix B

Evidence of the model dynamics

n this appendix, the dynamics of an agent-based model, where agents are embedded in an exemplary supply network, will be explored under four scenarios: (a) without a disruption, (b) with a disruption, (c) with a disruption applying inventory mitigation, (d) and with a disruption applying contingent rerouting. The purpose of these scenarios is to show how inventory levels (S) and customer demand (D) change when agents are exposed to a disruption.

The network topology which has been used as the basis for experimentation is presented in Figure B.1. It consists of the OEM, two first tier suppliers (suppliers 1 and 2), and three second tier suppliers (suppliers 3, 4, and 5). This network will be exposed to four scenarios (a), (b), (c), and (d) summarised in Table B.1.

Table B.1: Appendix A scenarios

Scenario	**Disruption**	**Applying inventory mitigation**	**Applying contingent rerouting**
(a)	-	-	-
(b)	supplier 3 in 6^{th} week	-	-
(c)	supplier 3 in 6^{th} week	the OEM, suppliers 1, 2, 3, 4, and 5	-
(d)	supplier 3 in 6^{th} week	-	the OEM, suppliers 1, 2, 3, 4, and 5

All agents follow anchor-and-adjust inventory policy as described in Chapter 4. The initial order for the OEM is 1400 units per week. As mentioned in the Chapter 4, the OEM has a single dummy agent as a customer that pulls the demand, although this dummy agent is not the part of the topology. The OEM then splits the order equally between it's suppliers, giving order of 700 units to supplier 1 and 700 units to supplier 2. Because supplier 1 has two suppliers 3 and 4, it again splits its order equally between these, giving initial order of 350 units submitted to supplier 3 and order of 350 units submitted to supplier 4. Supplier 2 has only one supplier, therefore order of 700 units is directly submitted to supplier 5. Suppliers 3, 4, and 5 get their supplies from dummy agents. Dummy agents attached to these suppliers provide infinite amount of raw materials, and as mentioned in Chapter 4, are there to only to provide continuous flow of goods and are not the part of the topology.

There is a one week order mailing delay, which means that when an agent submits an order to its supplier, it will arrive one week later. Goods need two weeks time to be delivered to the customer after they are shipped by the supplier. The simulation is run for 30 weeks only for the demonstration purposes (500 week-long simulations were performed for main thesis experiments).

The scenario (a) is the agent-based simulation run without disruptions. Each agent in each week sells exactly the same amount of goods as it receives from its suppliers, therefore it does not carry any inventory and the customer demand is constant. Inventory ($S_{i,t}$) and customer demand ($D_{i,t}$) for all agents are presented in Figure B.2. It can be observed that the inventory levels for the OEM, Suppliers 1, 2, 3, 4, and 5 are constant and are equal to zero; and that the customer demand for each agent is also constant and its value depends on the position of the agent: 1400 units/week for the OEM, 700 units/week for suppliers 1, 2, and 5, 350 units/week for suppliers 3 and 4.

Costs generated in scenario (a) are equal to 0$ for each agent, C_{NET} is equal to 0, and C_{OEM} is equal to 0. Goods which are received by an agent are immediately sold to the customer, therefore no excess inventory is hold nor backlog is generated. Fill rates are equal to 100% for each agent, FR_{NET} and FR_{OEM} are equal to 100% because the demand for each agent is constant. Here, C_{NET} and C_{OEM} are sum of costs generated by all network members and costs generated by the OEM, re-

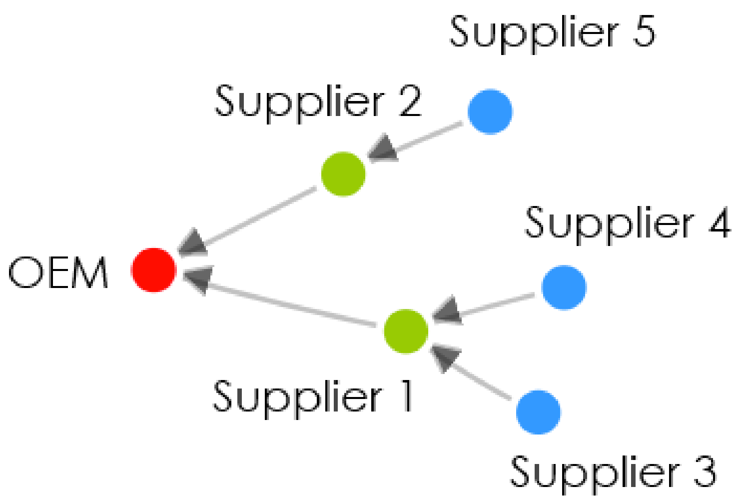


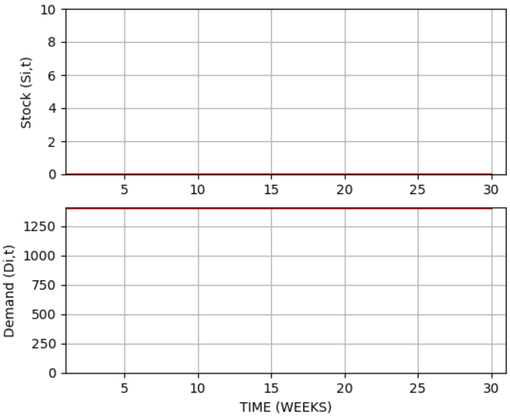
FIGURE B.1: Supply network topology under investigation

spectively. FR_{NET} and FR_{OEM} are the average fill-rates achieved by all network members and fill-rates achieved by the OEM, respectively.

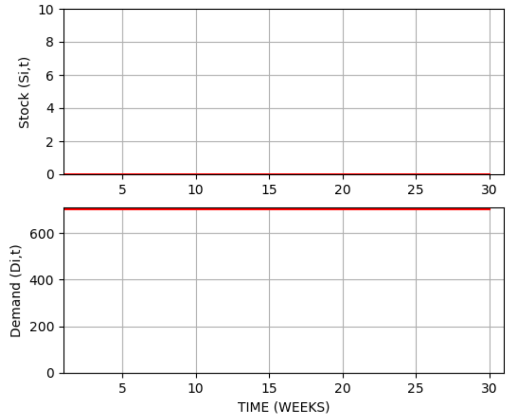
Next three scenarios focus on the effect of a single disruption on stock and demand dynamics in the presented supply network. Supplier 3 is disrupted in the 6th week of operations and the disruption lasts for one week.

The stock and demand dynamics for scenario (b) are presented in Figure B.3. From the plots it is possible to observe that the affected agents are: the OEM, suppliers 1, 3, and 4. In the week of the disruption, Supplier 3 experiences no demand from supplier 1 and no supplies from the dummy agent, therefore its stock level stays the same as in the previous week. The disruption does not affect stock of supplier 1 until week 7 because there are still goods in transit from supplier 3 that are being delivered to supplier 1. As soon as supplier 1 realises that supplier 3 will not be able to fulfil its demand due to the disruption, it increases its orders. Supplier 1 increases its order in week 7, but it is received by suppliers 3 and 4 in week 8 due to the mailing delay. This can be seen on the demand plots of supplier 3 and 4 in week 8. The unexpected demand jump experienced by supplier 4 makes it to stock

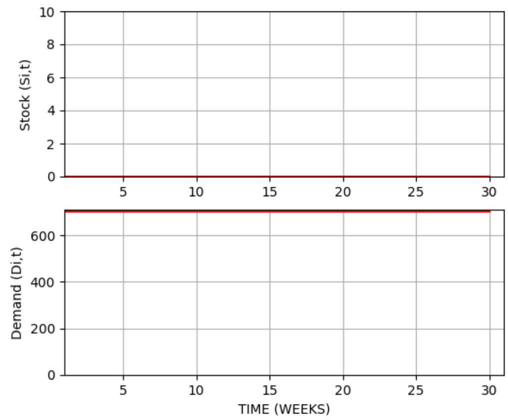
FIGURE B.2: Stock and customer demand dynamics for scenario (a): No disruptions



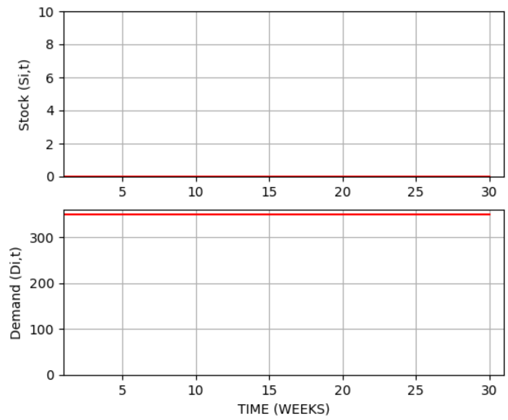
(A) OEM



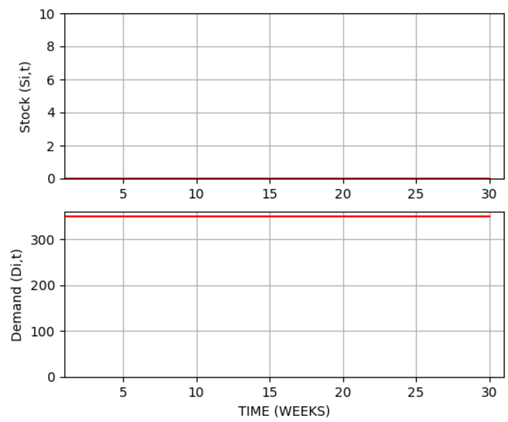
(B) Supplier 1



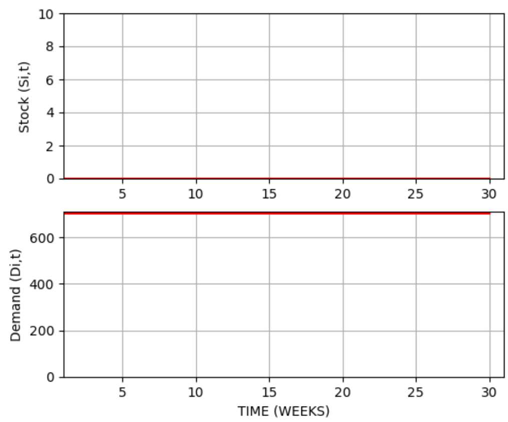
(C) Supplier 2



(D) Supplier 3



(E) Supplier 4



(F) Supplier 5

Table B.2: Scenario (a): costs and fill-rates

Agent	**Costs** (C)	**Fill-rates** (FR)
OEM	0.0$	100.00%
Supplier 1	0.0$	100.00%
Supplier 2	0.0$	100.00%
Supplier 3	0.0$	100.00%
Supplier 4	0.0$	100.00%
Supplier 5	0.0$	100.00%
Network	**0.0$**	**100.00%**

out in the same week, and therefore to experience a backlog of almost 400 units for a duration of 2 weeks.

When supplier 3 becomes operational after the disruption, it receives double amount of goods from its suppliers because goods in-transit accumulated from the previous week. It also receives an increased order from supplier 1, which causes supplier 3 to stock-out in week 11 creating a backlog of around 300 units for the period of one week. Suppliers 3 and 4 return to their initial stock levels, but interestingly supplier 3 returns faster than supplier 4. This means that the non-disrupted supplier felt the post-disruption effects for longer than the supplier that was originally disrupted. This phenomenon is caused by the way companies forecast their demand. When supplier 4 experienced an increase in the demand it has identified it as a valid demand pattern, as it did not have the knowledge that supplier 3 was disrupted. Supplier 4 forecasted that it will need more inventory in the future to accommodate higher demand, which resulted also an increase in desired supply line. Because the demand quickly returned to its original level, supplier 4 has been left with an excess inventory in the weeks following the disruption. Supplier 3 returned to desired inventory level quicker because: (1) While the supplier was disrupted it experienced demand of 0 in that week, which balanced out with the following increase in customer demand. The supplier was more accurate when predicting future demand; (2) It had higher inventory levels post-disruption because it received goods from current week and the week it was disrupted. Higher inventory levels resulted in lower backlog post-disruption.

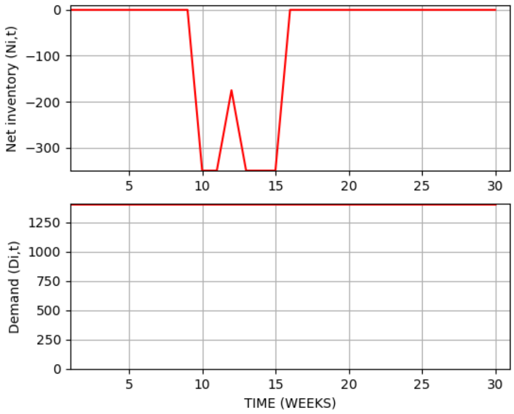
Supplier 1 and the OEM have similar responses to the disruption, but the timing of experiencing the backlog differs for both agents. Supplier 1 experiences the backlog in week 8 and it lasts for 8 weeks; the OEM experiences backlog in week 10 and it lasts for 8 weeks. The difference can be explained by the shipment delay. The OEM and supplier 1 experience backlogs because of a knock-on effect: supplier 3 did not supply goods while it was disrupted, therefore supplier 1 could not fully fulfil the order of the OEM, therefore the OEM could not fulfil the order of the dummy customer agent.

Despite the OEM and supplier 1 experiencing backlogs it is possible to observe that their customer demand is constant. This is because orders are backordered, i.e. the goods have been promised to be delivered at a later time therefore there is no need for OEM to order more from supplier 1. The backlog the OEM experiences reflects the time needed for the supplier 1 to fulfil all the backlogged orders that were promised to the OEM. As it can be observed from the plots in Figure B.3, suppliers 2 and 5 did not suffer from the disruption. This is due to steady orders submitted by the OEM to supplier 2.

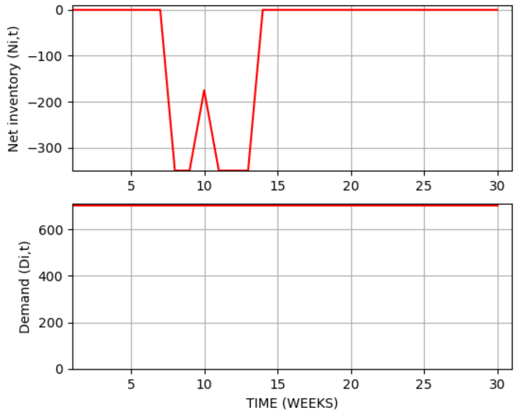
Costs and fill-rates generated by agents in scenario (b) are presented in Table B.3. As observed previously, suppliers 2 and 5 did not suffer from the disruption generating costs equal to 0$, and fill-rates equal to 100%. The OEM and supplier 1 generated the same costs of 3269.0$ because they experienced the same backlog patterns, although shifted in time. Supplier 1 experienced lower fill-rate than the OEM because in general supplier 1 deals with lower volumes than the OEM. This means that when the backlog magnitude was the same for the OEM and for the supplier 1, it hurt more the supplier 1 because it fulfilled lesser percentage of customer order volumes than the OEM. Interestingly, supplier 4 suffered more from the disruption than supplier 3 itself.

This scenario carries an important finding, as it shows that the disruption can: (a) affect not only direct business partners of the disrupted supplier, but also it can go beyond that; and (b) the connectivity patters are crucial in understanding who will be affected by a disruption and to what extend. For example, if supplier 1 had more suppliers than two, maybe the fluctuation of order volumes would affect its suppliers less.

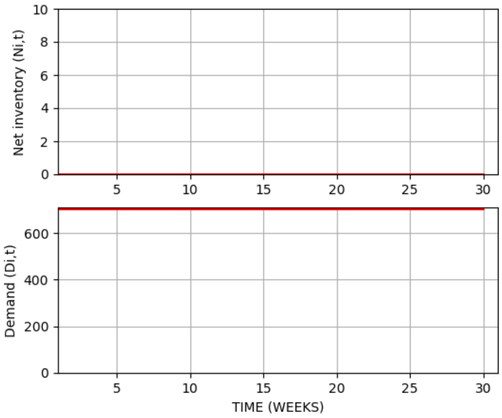
Figure B.3: Stock and customer demand dynamics for scenario (b): Disruptions



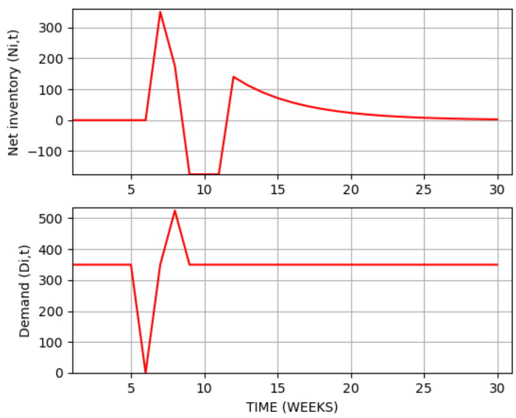
(a) OEM



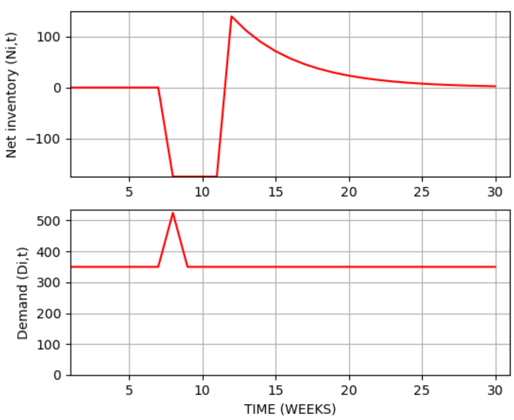
(b) Supplier 1



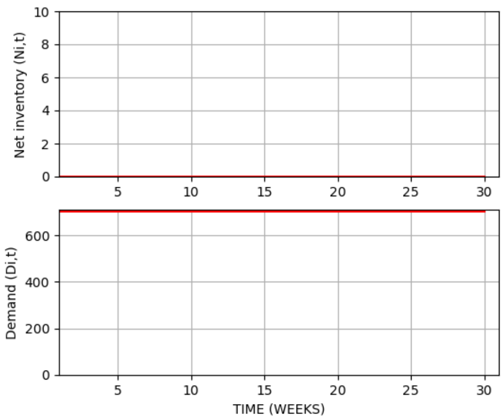
(c) Supplier 2



(d) Supplier 3



(e) Supplier 4



(f) Supplier 5

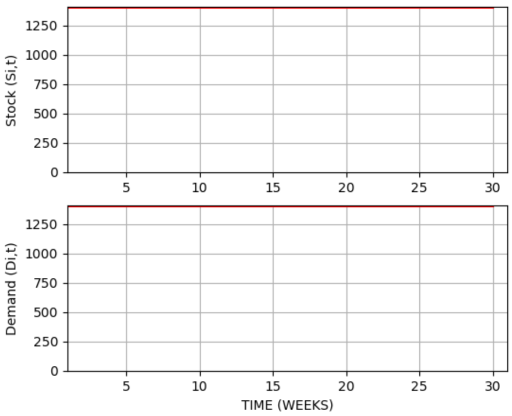
Table B.3: Scenario (b): costs and fill-rates

Agent	Costs (C)	Fill-rates (FR)
OEM	1925.0$	95.56%
Supplier 1	1925.0$	91.13%
Supplier 2	0.0$	100.00%
Supplier 3	1873.6$	95.08%
Supplier 4	1786.1$	93.65%
Supplier 5	0.0$	100.00%
Network	**7509.7$**	**95.90%**

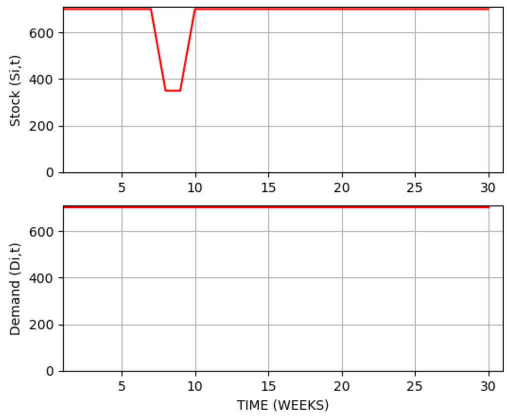
In scenario (c) the disruption of a supplier 3 in the 6^{th} week is repeated; but this time all agents keep additional inventory during the simulation run. The additional inventory of agents is equated to the initial order amount, as specified at the beginning of this appendix, and can be seen as a red line in the stock dynamics part of the plot in the Figure B.4. First observation from the plots can be that unlike in scenario (b), the OEM is not affected by the disruption. The additional stock prevented supplier 1 to experience backlog, therefore all goods ordered by the OEM were delivered on time. This shows that inventory mitigation, in this particular case, caused the network to be more resilient because agents were able to fulfil the customer demand better despite being perturbed. However, additional inventory did not prevent supplier 4 from suffering. The inventory dynamics resemble patterns seen in scenario (b), although it is shifted vertically upwards as the desired inventory is higher. Despite agents keeping additional inventory, it takes similar time for suppliers 3 and 4 to return to their original stock levels as in the scenario (b). This is because the desired inventory of these suppliers is higher than in scenario (b), therefore they need to undertake the same efforts to return to the original inventory levels. Interestingly, the time to return to desired inventory level is shorter for supplier 1 when compared with scenario (b). In scenario (c) it took supplier 1 only 3 weeks, compared to 8 weeks in scenario (b). This shows that for some suppliers the time to return to desired inventory might be improved, thus resulting in increased resilience.

When looking closer at the costs generated by each agent, one might see a significant increase when compared to scenario (b). Costs generated are almost 100 times

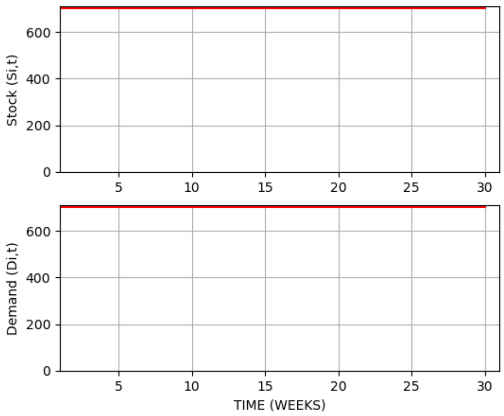
FIGURE B.4: Stock and customer demand dynamics for scenario (c): Inventory mitigation



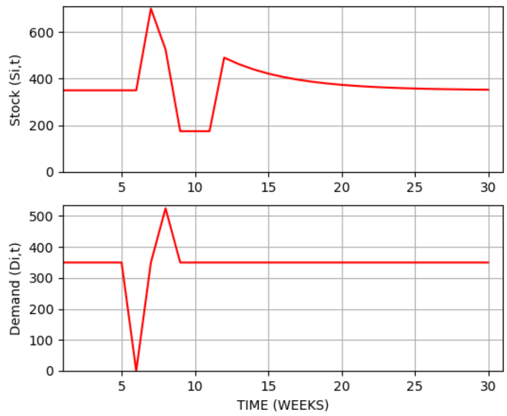
(A) OEM



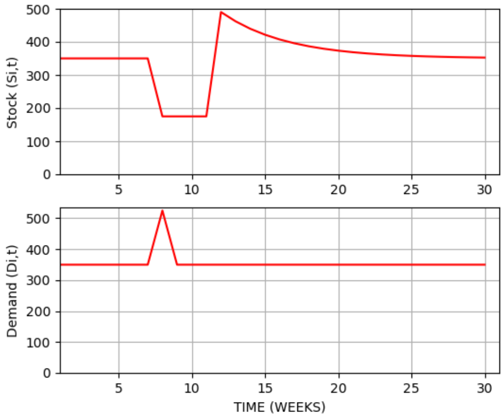
(B) Supplier 1



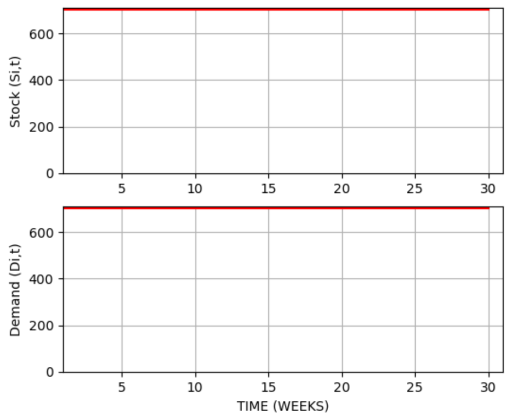
(C) Supplier 2



(D) Supplier 3



(E) Supplier 4



(F) Supplier 5

Table B.4: Scenario (c): costs and fill-rates

Agent	**Costs (C)**	**Fill-rates (FR)**
OEM	350700.0$	100.0%
Supplier 1	175000.0$	100.0%
Supplier 2	175350.0$	100.0%
Supplier 3	88761.1$	100.0%
Supplier 4	88411.1$	100.0%
Supplier 5	175350.0$	100.0%
Network	**1053572.2$**	**100.00%**

higher, and this is caused by excessive amount of inventory carried by each agent. However, this scenario is evaluating impact of only one disruption, when in reality companies are embedded in a complex supply network which might be exposed to multiple disruptions simultaneously.

Interestingly, supplier 3 incurred slightly higher costs than supplier 4. This is because in scenario (b) supplier 4 experienced higher backlog for longer period of time than supplier 3, and this was the main source of incurring high costs. On the other hand, in scenario (c) the additional stock reduced the impact of the disruption on supplier 4 which did not experience any backlog.

Inventory mitigation increased resilience of the whole network as: (1) it enabled agents to keep their fill-rates high; and (2) smaller number of agents were affected by the disruption when comparing to scenario (b). The main disadvantage of the inventory mitigation strategy is that it might be very expensive as excessive amount of inventory is carried for a long period of time. It might be necessary to adjust additional inventory to the level which suits the company and reflects the risks.

In scenario (d), agents apply contingent rerouting when exposed to a supplier's disruption. In this particular supply network only supplier 1 will be applying the strategy since it is directly affected by disruption of supplier 3. When supplier 3 is disrupted in the 6^{th} week, supplier 1 redirects the order volume to supplier 4. This can be seen in week 8, when supplier 3 does not experience any customer demand and supplier 4 experiences demand of 700 units. Supplier 4 experiences a backlog of 500 units for the duration of 3 weeks. The magnitude and duration of the backlog is

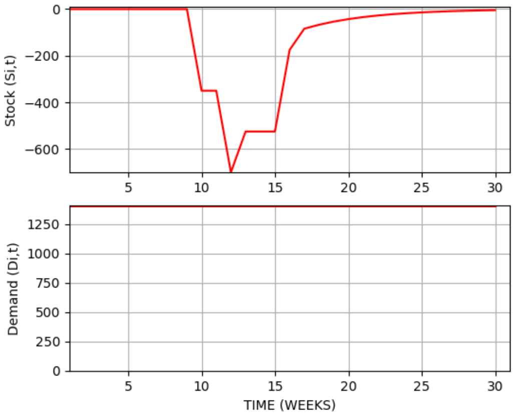
Table B.5: Scenario (d): costs and fill-rates

Agent	**Costs (C)**	**Fill-rates (FR)**
OEM	6265.7$	91.82%
Supplier 1	5295.2$	83.61%
Supplier 2	0.0$	100.00%
Supplier 3	2486.6$	94.32%
Supplier 4	5279.8$	86.15%
Supplier 5	0.0$	100.00%
Network	**19327.3$**	**92.65%**

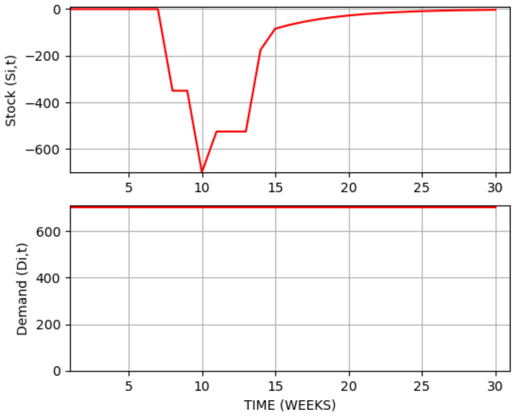
in fact higher and longer than in scenario (b). This is caused by supplier 1 increasing order submitted to supplier 4. In scenario (b) supplier 1 ordered equally from both around 500 units, whereas in scenario (d) supplier 1 ordered 700 units only from supplier 4. This made the supplier 4 to stock out quicker and therefore order more goods than in scenario (b). More goods, when arrived in week 13 turned out to be redundant because the increase in demand was a customer reaction to a disruption, not a long-term demand pattern. Applying contingent rerouting by supplier 1 turned out not only to confuse supplier 4, but also had negative effects on the rest of the network. For example, it took much longer for the OEM and supplier 1 to return to their desired inventory levels than in both scenario (b) and (c). In fact, only around week 30 the OEM and supplier 1 managed to return to their original inventories.

Costs generated for all supply network agents are higher for scenario (d) when contingent rerouting was applied by supplier 1, than in scenario (b) where risk management strategies were not applied. The resilience of the system also decrease because: (1) suppliers are not able to fulfil customer demand as well as in scenario b); and (2) suppliers return to their desired inventories slower and experience backlogs for longer period of times. The reason why contingent rerouting does not work very well here is because of mailing delay. Supplier 1 acts too slowly compared to the duration of the disruption. Supplier 1 receives the information about supplier 3 being disrupted in week 6, then orders solely from supplier 4 in week 7. The order is received by supplier 4 in week 8 due to the mailing delay. In week 8, supplier 3 is already operational and the strategy does not prove to be effective.

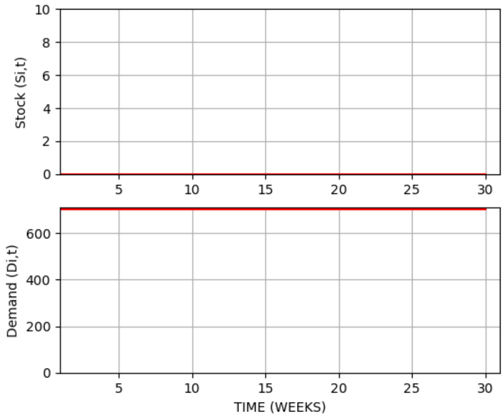
FIGURE B.5: Stock and customer demand dynamics for scenario (d): Contingent rerouting



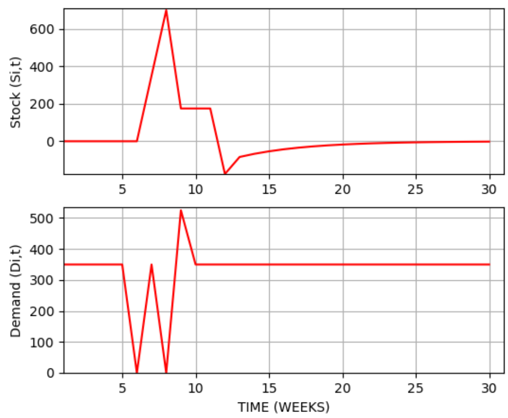
(A) OEM



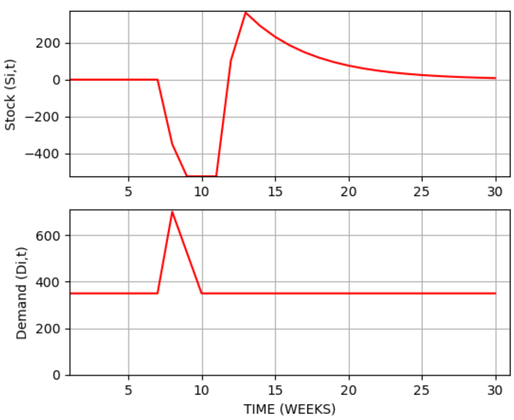
(B) Supplier 1



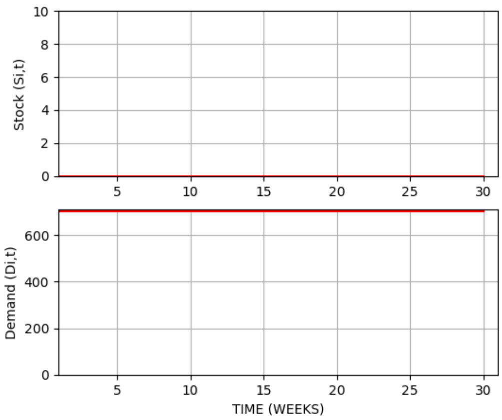
(C) Supplier 2



(D) Supplier 3



(E) Supplier 4



(F) Supplier 5

In this appendix, it has been shown that the disruption of a supplier might affect not only its direct business partners, but also might go beyond that. Scenarios (b), (c), and (d) showed that that not only the customer of disrupted supplier was affected, but most importantly its competitor and the customer's customer. It was possible to observe that the risk management strategies applied by the suppliers have an enormous effect not only on them, but also on the other companies that are connected to them. This suggests that the connectivity patters of suppliers influence supply network resilience.

Appendix C

Evidence of the model data

Results generated by Appendix'a A scenarios (a), (b), (c), and (d) are presented below. I_t is on-hand inventory in week t, S_t is stock in week t, D_t is customer demand in week t, O_t is order submitted to suppliers in week t, A_t is amount of goods that arrived in week t, EL_t is forecasted demand, $sum(O)$ is the total amount of goods ordered in previous weeks, $sum(UD)$ is the sum of unmet demands until week t.

C.1 Scenario (a)

C.1.1 OEM

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	1400.0	1400.0	1400.0	1400.0	0.0	0.0	1
0.0	0.0	1400.0	1400.0	1400.0	1400.0	1400.0	0.0	2
0.0	0.0	1400.0	1400.0	1400.0	1400.0	2800.0	0.0	3
0.0	0.0	1400.0	1400.0	1400.0	1400.0	4200.0	0.0	4
0.0	0.0	1400.0	1400.0	1400.0	1400.0	5600.0	0.0	5
0.0	0.0	1400.0	1400.0	1400.0	1400.0	7000.0	0.0	6
0.0	0.0	1400.0	1400.0	1400.0	1400.0	8400.0	0.0	7
0.0	0.0	1400.0	1400.0	1400.0	1400.0	9800.0	0.0	8
0.0	0.0	1400.0	1400.0	1400.0	1400.0	11200.0	0.0	9
0.0	0.0	1400.0	1400.0	1400.0	1400.0	12600.0	0.0	10
0.0	0.0	1400.0	1400.0	1400.0	1400.0	14000.0	0.0	11
0.0	0.0	1400.0	1400.0	1400.0	1400.0	15400.0	0.0	12

0.0	0.0	1400.0	1400.0	1400.0	1400.0	16800.0	0.0	13
0.0	0.0	1400.0	1400.0	1400.0	1400.0	18200.0	0.0	14
0.0	0.0	1400.0	1400.0	1400.0	1400.0	19600.0	0.0	15
0.0	0.0	1400.0	1400.0	1400.0	1400.0	21000.0	0.0	16
0.0	0.0	1400.0	1400.0	1400.0	1400.0	22400.0	0.0	17
0.0	0.0	1400.0	1400.0	1400.0	1400.0	23800.0	0.0	18
0.0	0.0	1400.0	1400.0	1400.0	1400.0	25200.0	0.0	19
0.0	0.0	1400.0	1400.0	1400.0	1400.0	26600.0	0.0	20
0.0	0.0	1400.0	1400.0	1400.0	1400.0	28000.0	0.0	21
0.0	0.0	1400.0	1400.0	1400.0	1400.0	29400.0	0.0	22
0.0	0.0	1400.0	1400.0	1400.0	1400.0	30800.0	0.0	23
0.0	0.0	1400.0	1400.0	1400.0	1400.0	32200.0	0.0	24
0.0	0.0	1400.0	1400.0	1400.0	1400.0	33600.0	0.0	25
0.0	0.0	1400.0	1400.0	1400.0	1400.0	35000.0	0.0	26
0.0	0.0	1400.0	1400.0	1400.0	1400.0	36400.0	0.0	27
0.0	0.0	1400.0	1400.0	1400.0	1400.0	37800.0	0.0	28
0.0	0.0	1400.0	1400.0	1400.0	1400.0	39200.0	0.0	29
0.0	0.0	1400.0	1400.0	1400.0	1400.0	40600.0	0.0	30

C.1.2 Supplier 1

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	700.0	700.0	700.0	700.0	0.0	0.0	1
0.0	0.0	700.0	700.0	700.0	700.0	700.0	0.0	2
0.0	0.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
0.0	0.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
0.0	0.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
0.0	0.0	700.0	700.0	700.0	700.0	3500.0	0.0	6
0.0	0.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
0.0	0.0	700.0	700.0	700.0	700.0	4900.0	0.0	8
0.0	0.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
0.0	0.0	700.0	700.0	700.0	700.0	6300.0	0.0	10
0.0	0.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
0.0	0.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
0.0	0.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
0.0	0.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
0.0	0.0	700.0	700.0	700.0	700.0	9800.0	0.0	15
0.0	0.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
0.0	0.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
0.0	0.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
0.0	0.0	700.0	700.0	700.0	700.0	12600.0	0.0	19

0.0	0.0	700.0	700.0	700.0	700.0	13300.0	0.0	20
0.0	0.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
0.0	0.0	700.0	700.0	700.0	700.0	14700.0	0.0	22
0.0	0.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
0.0	0.0	700.0	700.0	700.0	700.0	16100.0	0.0	24
0.0	0.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
0.0	0.0	700.0	700.0	700.0	700.0	17500.0	0.0	26
0.0	0.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
0.0	0.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
0.0	0.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
0.0	0.0	700.0	700.0	700.0	700.0	20300.0	0.0	30

C.1.3 Supplier 2

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	700.0	700.0	700.0	700.0	0.0	0.0	1
0.0	0.0	700.0	700.0	700.0	700.0	700.0	0.0	2
0.0	0.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
0.0	0.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
0.0	0.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
0.0	0.0	700.0	700.0	700.0	700.0	3500.0	0.0	6
0.0	0.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
0.0	0.0	700.0	700.0	700.0	700.0	4900.0	0.0	8
0.0	0.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
0.0	0.0	700.0	700.0	700.0	700.0	6300.0	0.0	10
0.0	0.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
0.0	0.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
0.0	0.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
0.0	0.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
0.0	0.0	700.0	700.0	700.0	700.0	9800.0	0.0	15
0.0	0.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
0.0	0.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
0.0	0.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
0.0	0.0	700.0	700.0	700.0	700.0	12600.0	0.0	19
0.0	0.0	700.0	700.0	700.0	700.0	13300.0	0.0	20
0.0	0.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
0.0	0.0	700.0	700.0	700.0	700.0	14700.0	0.0	22
0.0	0.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
0.0	0.0	700.0	700.0	700.0	700.0	16100.0	0.0	24
0.0	0.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
0.0	0.0	700.0	700.0	700.0	700.0	17500.0	0.0	26

0.0	0.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
0.0	0.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
0.0	0.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
0.0	0.0	700.0	700.0	700.0	700.0	20300.0	0.0	30

C.1.4 Supplier 3

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	350.0	350.0	350.0	350.0	0.0	0.0	1
0.0	0.0	350.0	350.0	350.0	350.0	350.0	0.0	2
0.0	0.0	350.0	350.0	350.0	350.0	700.0	0.0	3
0.0	0.0	350.0	350.0	350.0	350.0	1050.0	0.0	4
0.0	0.0	350.0	350.0	350.0	350.0	1400.0	0.0	5
0.0	0.0	350.0	350.0	350.0	350.0	1750.0	0.0	6
0.0	0.0	350.0	350.0	350.0	350.0	2100.0	0.0	7
0.0	0.0	350.0	350.0	350.0	350.0	2450.0	0.0	8
0.0	0.0	350.0	350.0	350.0	350.0	2800.0	0.0	9
0.0	0.0	350.0	350.0	350.0	350.0	3150.0	0.0	10
0.0	0.0	350.0	350.0	350.0	350.0	3500.0	0.0	11
0.0	0.0	350.0	350.0	350.0	350.0	3850.0	0.0	12
0.0	0.0	350.0	350.0	350.0	350.0	4200.0	0.0	13
0.0	0.0	350.0	350.0	350.0	350.0	4550.0	0.0	14
0.0	0.0	350.0	350.0	350.0	350.0	4900.0	0.0	15
0.0	0.0	350.0	350.0	350.0	350.0	5250.0	0.0	16
0.0	0.0	350.0	350.0	350.0	350.0	5600.0	0.0	17
0.0	0.0	350.0	350.0	350.0	350.0	5950.0	0.0	18
0.0	0.0	350.0	350.0	350.0	350.0	6300.0	0.0	19
0.0	0.0	350.0	350.0	350.0	350.0	6650.0	0.0	20
0.0	0.0	350.0	350.0	350.0	350.0	7000.0	0.0	21
0.0	0.0	350.0	350.0	350.0	350.0	7350.0	0.0	22
0.0	0.0	350.0	350.0	350.0	350.0	7700.0	0.0	23
0.0	0.0	350.0	350.0	350.0	350.0	8050.0	0.0	24
0.0	0.0	350.0	350.0	350.0	350.0	8400.0	0.0	25
0.0	0.0	350.0	350.0	350.0	350.0	8750.0	0.0	26
0.0	0.0	350.0	350.0	350.0	350.0	9100.0	0.0	27
0.0	0.0	350.0	350.0	350.0	350.0	9450.0	0.0	28
0.0	0.0	350.0	350.0	350.0	350.0	9800.0	0.0	29
0.0	0.0	350.0	350.0	350.0	350.0	10150.0	0.0	30

C.1.5 Supplier 4

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	350.0	350.0	350.0	350.0	0.0	0.0	1
0.0	0.0	350.0	350.0	350.0	350.0	350.0	0.0	2
0.0	0.0	350.0	350.0	350.0	350.0	700.0	0.0	3
0.0	0.0	350.0	350.0	350.0	350.0	1050.0	0.0	4
0.0	0.0	350.0	350.0	350.0	350.0	1400.0	0.0	5
0.0	0.0	350.0	350.0	350.0	350.0	1750.0	0.0	6
0.0	0.0	350.0	350.0	350.0	350.0	2100.0	0.0	7
0.0	0.0	350.0	350.0	350.0	350.0	2450.0	0.0	8
0.0	0.0	350.0	350.0	350.0	350.0	2800.0	0.0	9
0.0	0.0	350.0	350.0	350.0	350.0	3150.0	0.0	10
0.0	0.0	350.0	350.0	350.0	350.0	3500.0	0.0	11
0.0	0.0	350.0	350.0	350.0	350.0	3850.0	0.0	12
0.0	0.0	350.0	350.0	350.0	350.0	4200.0	0.0	13
0.0	0.0	350.0	350.0	350.0	350.0	4550.0	0.0	14
0.0	0.0	350.0	350.0	350.0	350.0	4900.0	0.0	15
0.0	0.0	350.0	350.0	350.0	350.0	5250.0	0.0	16
0.0	0.0	350.0	350.0	350.0	350.0	5600.0	0.0	17
0.0	0.0	350.0	350.0	350.0	350.0	5950.0	0.0	18
0.0	0.0	350.0	350.0	350.0	350.0	6300.0	0.0	19
0.0	0.0	350.0	350.0	350.0	350.0	6650.0	0.0	20
0.0	0.0	350.0	350.0	350.0	350.0	7000.0	0.0	21
0.0	0.0	350.0	350.0	350.0	350.0	7350.0	0.0	22
0.0	0.0	350.0	350.0	350.0	350.0	7700.0	0.0	23
0.0	0.0	350.0	350.0	350.0	350.0	8050.0	0.0	24
0.0	0.0	350.0	350.0	350.0	350.0	8400.0	0.0	25
0.0	0.0	350.0	350.0	350.0	350.0	8750.0	0.0	26
0.0	0.0	350.0	350.0	350.0	350.0	9100.0	0.0	27
0.0	0.0	350.0	350.0	350.0	350.0	9450.0	0.0	28
0.0	0.0	350.0	350.0	350.0	350.0	9800.0	0.0	29
0.0	0.0	350.0	350.0	350.0	350.0	10150.0	0.0	30

C.1.6 Supplier 5

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	700.0	700.0	700.0	700.0	0.0	0.0	1
0.0	0.0	700.0	700.0	700.0	700.0	700.0	0.0	2
0.0	0.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
0.0	0.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
0.0	0.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
0.0	0.0	700.0	700.0	700.0	700.0	3500.0	0.0	6

0.0	0.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
0.0	0.0	700.0	700.0	700.0	700.0	4900.0	0.0	8
0.0	0.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
0.0	0.0	700.0	700.0	700.0	700.0	6300.0	0.0	10
0.0	0.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
0.0	0.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
0.0	0.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
0.0	0.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
0.0	0.0	700.0	700.0	700.0	700.0	9800.0	0.0	15
0.0	0.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
0.0	0.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
0.0	0.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
0.0	0.0	700.0	700.0	700.0	700.0	12600.0	0.0	19
0.0	0.0	700.0	700.0	700.0	700.0	13300.0	0.0	20
0.0	0.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
0.0	0.0	700.0	700.0	700.0	700.0	14700.0	0.0	22
0.0	0.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
0.0	0.0	700.0	700.0	700.0	700.0	16100.0	0.0	24
0.0	0.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
0.0	0.0	700.0	700.0	700.0	700.0	17500.0	0.0	26
0.0	0.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
0.0	0.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
0.0	0.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
0.0	0.0	700.0	700.0	700.0	700.0	20300.0	0.0	30

C.2 Scenario (b)

C.2.1 OEM

I_t	S_t	D_t	O_t	A_t	EL_t	**sum**(O)	**sum**(UD)	t
0.0	0.0	1400.0	1400.0	1400.0	1400.0	0.0	0.0	1
0.0	0.0	1400.0	1400.0	1400.0	1400.0	1400.0	0.0	2
0.0	0.0	1400.0	1400.0	1400.0	1400.0	2800.0	0.0	3
0.0	0.0	1400.0	1400.0	1400.0	1400.0	4200.0	0.0	4
0.0	0.0	1400.0	1400.0	1400.0	1400.0	5600.0	0.0	5
0.0	0.0	1400.0	1400.0	1400.0	1400.0	7000.0	0.0	6
0.0	0.0	1400.0	1400.0	1400.0	1400.0	8400.0	0.0	7
0.0	0.0	1400.0	1400.0	1400.0	1400.0	9800.0	0.0	8
0.0	0.0	1400.0	1400.0	1400.0	1400.0	11200.0	0.0	9
0.0	−350.0	1400.0	1400.0	1050.0	1400.0	12600.0	350.0	10

0.0	−350.0	1400.0	1400.0	1400.0	1400.0	14000.0	700.0	11
0.0	−175.0	1400.0	1400.0	1575.0	1400.0	15400.0	875.0	12
0.0	−350.0	1400.0	1400.0	1225.0	1400.0	16800.0	1225.0	13
0.0	−350.0	1400.0	1400.0	1400.0	1400.0	18200.0	1575.0	14
0.0	−350.0	1400.0	1400.0	1400.0	1400.0	19600.0	1925.0	15
0.0	0.0	1400.0	1400.0	1750.0	1400.0	21000.0	1925.0	16
0.0	0.0	1400.0	1400.0	1400.0	1400.0	22400.0	1925.0	17
0.0	0.0	1400.0	1400.0	1400.0	1400.0	23800.0	1925.0	18
0.0	0.0	1400.0	1400.0	1400.0	1400.0	25200.0	1925.0	19
0.0	0.0	1400.0	1400.0	1400.0	1400.0	26600.0	1925.0	20
0.0	0.0	1400.0	1400.0	1400.0	1400.0	28000.0	1925.0	21
0.0	0.0	1400.0	1400.0	1400.0	1400.0	29400.0	1925.0	22
0.0	0.0	1400.0	1400.0	1400.0	1400.0	30800.0	1925.0	23
0.0	0.0	1400.0	1400.0	1400.0	1400.0	32200.0	1925.0	24
0.0	0.0	1400.0	1400.0	1400.0	1400.0	33600.0	1925.0	25
0.0	0.0	1400.0	1400.0	1400.0	1400.0	35000.0	1925.0	26
0.0	0.0	1400.0	1400.0	1400.0	1400.0	36400.0	1925.0	27
0.0	0.0	1400.0	1400.0	1400.0	1400.0	37800.0	1925.0	28
0.0	0.0	1400.0	1400.0	1400.0	1400.0	39200.0	1925.0	29
0.0	0.0	1400.0	1400.0	1400.0	1400.0	40600.0	1925.0	30

C.2.2 Supplier 1

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	700.0	700.0	700.0	700.0	0.0	0.0	1
0.0	0.0	700.0	700.0	700.0	700.0	700.0	0.0	2
0.0	0.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
0.0	0.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
0.0	0.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
0.0	0.0	700.0	1050.0	700.0	700.0	3500.0	0.0	6
0.0	0.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
0.0	−350.0	700.0	700.0	350.0	700.0	4900.0	350.0	8
0.0	−350.0	700.0	700.0	700.0	700.0	5600.0	700.0	9
0.0	−175.0	700.0	700.0	875.0	700.0	6300.0	875.0	10
0.0	−350.0	700.0	700.0	525.0	700.0	7000.0	1225.0	11
0.0	−350.0	700.0	700.0	700.0	700.0	7700.0	1575.0	12
0.0	−350.0	700.0	700.0	700.0	700.0	8400.0	1925.0	13
0.0	0.0	700.0	700.0	1050.0	700.0	9100.0	1925.0	14
0.0	0.0	700.0	700.0	700.0	700.0	9800.0	1925.0	15
0.0	0.0	700.0	700.0	700.0	700.0	10500.0	1925.0	16
0.0	0.0	700.0	700.0	700.0	700.0	11200.0	1925.0	17

0.0	0.0	700.0	700.0	700.0	700.0	11900.0	1925.0	18
0.0	0.0	700.0	700.0	700.0	700.0	12600.0	1925.0	19
0.0	0.0	700.0	700.0	700.0	700.0	13300.0	1925.0	20
0.0	0.0	700.0	700.0	700.0	700.0	14000.0	1925.0	21
0.0	0.0	700.0	700.0	700.0	700.0	14700.0	1925.0	22
0.0	0.0	700.0	700.0	700.0	700.0	15400.0	1925.0	23
0.0	0.0	700.0	700.0	700.0	700.0	16100.0	1925.0	24
0.0	0.0	700.0	700.0	700.0	700.0	16800.0	1925.0	25
0.0	0.0	700.0	700.0	700.0	700.0	17500.0	1925.0	26
0.0	0.0	700.0	700.0	700.0	700.0	18200.0	1925.0	27
0.0	0.0	700.0	700.0	700.0	700.0	18900.0	1925.0	28
0.0	0.0	700.0	700.0	700.0	700.0	19600.0	1925.0	29
0.0	0.0	700.0	700.0	700.0	700.0	20300.0	1925.0	30

C.2.3 Supplier 2

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	700.0	700.0	700.0	700.0	0.0	0.0	1
0.0	0.0	700.0	700.0	700.0	700.0	700.0	0.0	2
0.0	0.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
0.0	0.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
0.0	0.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
0.0	0.0	700.0	700.0	700.0	700.0	3500.0	0.0	6
0.0	0.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
0.0	0.0	700.0	700.0	700.0	700.0	4900.0	0.0	8
0.0	0.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
0.0	0.0	700.0	700.0	700.0	700.0	6300.0	0.0	10
0.0	0.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
0.0	0.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
0.0	0.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
0.0	0.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
0.0	0.0	700.0	700.0	700.0	700.0	9800.0	0.0	15
0.0	0.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
0.0	0.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
0.0	0.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
0.0	0.0	700.0	700.0	700.0	700.0	12600.0	0.0	19
0.0	0.0	700.0	700.0	700.0	700.0	13300.0	0.0	20
0.0	0.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
0.0	0.0	700.0	700.0	700.0	700.0	14700.0	0.0	22
0.0	0.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
0.0	0.0	700.0	700.0	700.0	700.0	16100.0	0.0	24

0.0	0.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
0.0	0.0	700.0	700.0	700.0	700.0	17500.0	0.0	26
0.0	0.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
0.0	0.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
0.0	0.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
0.0	0.0	700.0	700.0	700.0	700.0	20300.0	0.0	30

C.2.4 Supplier 3

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	350.0	350.0	350.0	350.0	0.0	0.0	1
0.0	0.0	350.0	350.0	350.0	350.0	350.0	0.0	2
0.0	0.0	350.0	350.0	350.0	350.0	700.0	0.0	3
0.0	0.0	350.0	350.0	350.0	350.0	1050.0	0.0	4
0.0	0.0	350.0	350.0	350.0	350.0	1400.0	0.0	5
0.0	0.0	0.0	0.0	0.0	0.0	1400.0	0.0	6
350.0	350.0	350.0	350.0	700.0	350.0	1750.0	0.0	7
175.0	175.0	525.0	665.0	350.0	385.0	2275.0	0.0	8
0.0	−175.0	350.0	322.0	0.0	378.0	2625.0	175.0	9
0.0	−175.0	350.0	327.6	350.0	372.4	2975.0	350.0	10
0.0	−175.0	350.0	332.1	350.0	367.9	3325.0	525.0	11
140.0	140.0	350.0	335.7	665.0	364.3	3675.0	525.0	12
112.0	112.0	350.0	338.5	322.0	361.5	4025.0	525.0	13
89.6	89.6	350.0	340.8	327.6	359.2	4375.0	525.0	14
71.7	71.7	350.0	342.7	332.1	357.3	4725.0	525.0	15
57.3	57.3	350.0	344.1	335.7	355.9	5075.0	525.0	16
45.9	45.9	350.0	345.3	338.5	354.7	5425.0	525.0	17
36.7	36.7	350.0	346.2	340.8	353.8	5775.0	525.0	18
29.4	29.4	350.0	347.0	342.7	353.0	6125.0	525.0	19
23.5	23.5	350.0	347.6	344.1	352.4	6475.0	525.0	20
18.8	18.8	350.0	348.1	345.3	351.9	6825.0	525.0	21
15.0	15.0	350.0	348.5	346.2	351.5	7175.0	525.0	22
12.0	12.0	350.0	348.8	347.0	351.2	7525.0	525.0	23
9.6	9.6	350.0	349.0	347.6	351.0	7875.0	525.0	24
7.7	7.7	350.0	349.2	348.1	350.8	8225.0	525.0	25
6.2	6.2	350.0	349.4	348.5	350.6	8575.0	525.0	26
4.9	4.9	350.0	349.5	348.8	350.5	8925.0	525.0	27
3.9	3.9	350.0	349.6	349.0	350.4	9275.0	525.0	28
3.2	3.2	350.0	349.7	349.2	350.3	9625.0	525.0	29
2.5	2.5	350.0	349.7	349.4	350.3	9975.0	525.0	30

C.2.5 Supplier 4

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	350.0	350.0	350.0	350.0	0.0	0.0	1
0.0	0.0	350.0	350.0	350.0	350.0	350.0	0.0	2
0.0	0.0	350.0	350.0	350.0	350.0	700.0	0.0	3
0.0	0.0	350.0	350.0	350.0	350.0	1050.0	0.0	4
0.0	0.0	350.0	350.0	350.0	350.0	1400.0	0.0	5
0.0	0.0	350.0	350.0	350.0	350.0	1750.0	0.0	6
0.0	0.0	350.0	350.0	350.0	350.0	2100.0	0.0	7
0.0	−175.0	525.0	665.0	350.0	385.0	2625.0	175.0	8
0.0	−175.0	350.0	322.0	350.0	378.0	2975.0	350.0	9
0.0	−175.0	350.0	327.6	350.0	372.4	3325.0	525.0	10
0.0	−175.0	350.0	332.1	350.0	367.9	3675.0	700.0	11
140.0	140.0	350.0	335.7	665.0	364.3	4025.0	700.0	12
112.0	112.0	350.0	338.5	322.0	361.5	4375.0	700.0	13
89.6	89.6	350.0	340.8	327.6	359.2	4725.0	700.0	14
71.7	71.7	350.0	342.7	332.1	357.3	5075.0	700.0	15
57.3	57.3	350.0	344.1	335.7	355.9	5425.0	700.0	16
45.9	45.9	350.0	345.3	338.5	354.7	5775.0	700.0	17
36.7	36.7	350.0	346.2	340.8	353.8	6125.0	700.0	18
29.4	29.4	350.0	347.0	342.7	353.0	6475.0	700.0	19
23.5	23.5	350.0	347.6	344.1	352.4	6825.0	700.0	20
18.8	18.8	350.0	348.1	345.3	351.9	7175.0	700.0	21
15.0	15.0	350.0	348.5	346.2	351.5	7525.0	700.0	22
12.0	12.0	350.0	348.8	347.0	351.2	7875.0	700.0	23
9.6	9.6	350.0	349.0	347.6	351.0	8225.0	700.0	24
7.7	7.7	350.0	349.2	348.1	350.8	8575.0	700.0	25
6.2	6.2	350.0	349.4	348.5	350.6	8925.0	700.0	26
4.9	4.9	350.0	349.5	348.8	350.5	9275.0	700.0	27
3.9	3.9	350.0	349.6	349.0	350.4	9625.0	700.0	28
3.2	3.2	350.0	349.7	349.2	350.3	9975.0	700.0	29
2.5	2.5	350.0	349.7	349.4	350.3	10325.0	700.0	30

C.2.6 Supplier 5

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	700.0	700.0	700.0	700.0	0.0	0.0	1
0.0	0.0	700.0	700.0	700.0	700.0	700.0	0.0	2
0.0	0.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
0.0	0.0	700.0	700.0	700.0	700.0	2100.0	0.0	4

0.0	0.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
0.0	0.0	700.0	700.0	700.0	700.0	3500.0	0.0	6
0.0	0.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
0.0	0.0	700.0	700.0	700.0	700.0	4900.0	0.0	8
0.0	0.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
0.0	0.0	700.0	700.0	700.0	700.0	6300.0	0.0	10
0.0	0.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
0.0	0.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
0.0	0.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
0.0	0.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
0.0	0.0	700.0	700.0	700.0	700.0	9800.0	0.0	15
0.0	0.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
0.0	0.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
0.0	0.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
0.0	0.0	700.0	700.0	700.0	700.0	12600.0	0.0	19
0.0	0.0	700.0	700.0	700.0	700.0	13300.0	0.0	20
0.0	0.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
0.0	0.0	700.0	700.0	700.0	700.0	14700.0	0.0	22
0.0	0.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
0.0	0.0	700.0	700.0	700.0	700.0	16100.0	0.0	24
0.0	0.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
0.0	0.0	700.0	700.0	700.0	700.0	17500.0	0.0	26
0.0	0.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
0.0	0.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
0.0	0.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
0.0	0.0	700.0	700.0	700.0	700.0	20300.0	0.0	30

C.3 Scenario (c)

C.3.1 OEM

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	0.0	0.0	1
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	0.0	2
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	2800.0	0.0	3
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	4200.0	0.0	4
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	5600.0	0.0	5
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	7000.0	0.0	6
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	8400.0	0.0	7
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	9800.0	0.0	8

1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	11200.0	0.0	9
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	12600.0	0.0	10
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	14000.0	0.0	11
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	15400.0	0.0	12
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	16800.0	0.0	13
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	18200.0	0.0	14
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	19600.0	0.0	15
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	21000.0	0.0	16
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	22400.0	0.0	17
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	23800.0	0.0	18
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	25200.0	0.0	19
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	26600.0	0.0	20
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	28000.0	0.0	21
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	29400.0	0.0	22
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	30800.0	0.0	23
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	32200.0	0.0	24
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	33600.0	0.0	25
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	35000.0	0.0	26
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	36400.0	0.0	27
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	37800.0	0.0	28
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	39200.0	0.0	29
1400.0	1400.0	1400.0	1400.0	1400.0	1400.0	40600.0	0.0	30

C.3.2 Supplier 1

I_t	S_t	D_t	O_t	A_t	EL_t	**sum**(O)	**sum**(UD)	t
700.0	700.0	700.0	700.0	700.0	700.0	0.0	0.0	1
700.0	700.0	700.0	700.0	700.0	700.0	700.0	0.0	2
700.0	700.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
700.0	700.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
700.0	700.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
700.0	700.0	700.0	1050.0	700.0	700.0	3500.0	0.0	6
700.0	700.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
350.0	350.0	700.0	700.0	350.0	700.0	4900.0	0.0	8
350.0	350.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
700.0	700.0	700.0	700.0	1050.0	700.0	6300.0	0.0	10
700.0	700.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
700.0	700.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
700.0	700.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
700.0	700.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
700.0	700.0	700.0	700.0	700.0	700.0	9800.0	0.0	15

700.0	700.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
700.0	700.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
700.0	700.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
700.0	700.0	700.0	700.0	700.0	700.0	12600.0	0.0	19
700.0	700.0	700.0	700.0	700.0	700.0	13300.0	0.0	20
700.0	700.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
700.0	700.0	700.0	700.0	700.0	700.0	14700.0	0.0	22
700.0	700.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
700.0	700.0	700.0	700.0	700.0	700.0	16100.0	0.0	24
700.0	700.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
700.0	700.0	700.0	700.0	700.0	700.0	17500.0	0.0	26
700.0	700.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
700.0	700.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
700.0	700.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
700.0	700.0	700.0	700.0	700.0	700.0	20300.0	0.0	30

C.3.3 Supplier 2

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
700.0	700.0	700.0	700.0	700.0	700.0	0.0	0.0	1
700.0	700.0	700.0	700.0	700.0	700.0	700.0	0.0	2
700.0	700.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
700.0	700.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
700.0	700.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
700.0	700.0	700.0	700.0	700.0	700.0	3500.0	0.0	6
700.0	700.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
700.0	700.0	700.0	700.0	700.0	700.0	4900.0	0.0	8
700.0	700.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
700.0	700.0	700.0	700.0	700.0	700.0	6300.0	0.0	10
700.0	700.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
700.0	700.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
700.0	700.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
700.0	700.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
700.0	700.0	700.0	700.0	700.0	700.0	9800.0	0.0	15
700.0	700.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
700.0	700.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
700.0	700.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
700.0	700.0	700.0	700.0	700.0	700.0	12600.0	0.0	19
700.0	700.0	700.0	700.0	700.0	700.0	13300.0	0.0	20
700.0	700.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
700.0	700.0	700.0	700.0	700.0	700.0	14700.0	0.0	22

700.0	700.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
700.0	700.0	700.0	700.0	700.0	700.0	16100.0	0.0	24
700.0	700.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
700.0	700.0	700.0	700.0	700.0	700.0	17500.0	0.0	26
700.0	700.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
700.0	700.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
700.0	700.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
700.0	700.0	700.0	700.0	700.0	700.0	20300.0	0.0	30

C.3.4 Supplier 3

I_t	S_t	D_t	O_t	A_t	EL_t	**sum**(O)	**sum**(UD)	t
350.0	350.0	350.0	350.0	350.0	350.0	0.0	0.0	1
350.0	350.0	350.0	350.0	350.0	350.0	350.0	0.0	2
350.0	350.0	350.0	350.0	350.0	350.0	700.0	0.0	3
350.0	350.0	350.0	350.0	350.0	350.0	1050.0	0.0	4
350.0	350.0	350.0	350.0	350.0	350.0	1400.0	0.0	5
350.0	350.0	0.0	0.0	0.0	0.0	1400.0	0.0	6
700.0	700.0	350.0	350.0	700.0	350.0	1750.0	0.0	7
525.0	525.0	525.0	665.0	350.0	385.0	2275.0	0.0	8
175.0	175.0	350.0	322.0	0.0	378.0	2625.0	0.0	9
175.0	175.0	350.0	327.6	350.0	372.4	2975.0	0.0	10
175.0	175.0	350.0	332.1	350.0	367.9	3325.0	0.0	11
490.0	490.0	350.0	335.7	665.0	364.3	3675.0	0.0	12
462.0	462.0	350.0	338.5	322.0	361.5	4025.0	0.0	13
439.6	439.6	350.0	340.8	327.6	359.2	4375.0	0.0	14
421.7	421.7	350.0	342.7	332.1	357.3	4725.0	0.0	15
407.3	407.3	350.0	344.1	335.7	355.9	5075.0	0.0	16
395.9	395.9	350.0	345.3	338.5	354.7	5425.0	0.0	17
386.7	386.7	350.0	346.2	340.8	353.8	5775.0	0.0	18
379.4	379.4	350.0	347.0	342.7	353.0	6125.0	0.0	19
373.5	373.5	350.0	347.6	344.1	352.4	6475.0	0.0	20
368.8	368.8	350.0	348.1	345.3	351.9	6825.0	0.0	21
365.0	365.0	350.0	348.5	346.2	351.5	7175.0	0.0	22
362.0	362.0	350.0	348.8	347.0	351.2	7525.0	0.0	23
359.6	359.6	350.0	349.0	347.6	351.0	7875.0	0.0	24
357.7	357.7	350.0	349.2	348.1	350.8	8225.0	0.0	25
356.2	356.2	350.0	349.4	348.5	350.6	8575.0	0.0	26
354.9	354.9	350.0	349.5	348.8	350.5	8925.0	0.0	27
353.9	353.9	350.0	349.6	349.0	350.4	9275.0	0.0	28
353.2	353.2	350.0	349.7	349.2	350.3	9625.0	0.0	29

352.5	352.5	350.0	349.7	349.4	350.3	9975.0	0.0	30

C.3.5 Supplier 4

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
350.0	350.0	350.0	350.0	350.0	350.0	0.0	0.0	1
350.0	350.0	350.0	350.0	350.0	350.0	350.0	0.0	2
350.0	350.0	350.0	350.0	350.0	350.0	700.0	0.0	3
350.0	350.0	350.0	350.0	350.0	350.0	1050.0	0.0	4
350.0	350.0	350.0	350.0	350.0	350.0	1400.0	0.0	5
350.0	350.0	350.0	350.0	350.0	350.0	1750.0	0.0	6
350.0	350.0	350.0	350.0	350.0	350.0	2100.0	0.0	7
175.0	175.0	525.0	665.0	350.0	385.0	2625.0	0.0	8
175.0	175.0	350.0	322.0	350.0	378.0	2975.0	0.0	9
175.0	175.0	350.0	327.6	350.0	372.4	3325.0	0.0	10
175.0	175.0	350.0	332.1	350.0	367.9	3675.0	0.0	11
490.0	490.0	350.0	335.7	665.0	364.3	4025.0	0.0	12
462.0	462.0	350.0	338.5	322.0	361.5	4375.0	0.0	13
439.6	439.6	350.0	340.8	327.6	359.2	4725.0	0.0	14
421.7	421.7	350.0	342.7	332.1	357.3	5075.0	0.0	15
407.3	407.3	350.0	344.1	335.7	355.9	5425.0	0.0	16
395.9	395.9	350.0	345.3	338.5	354.7	5775.0	0.0	17
386.7	386.7	350.0	346.2	340.8	353.8	6125.0	0.0	18
379.4	379.4	350.0	347.0	342.7	353.0	6475.0	0.0	19
373.5	373.5	350.0	347.6	344.1	352.4	6825.0	0.0	20
368.8	368.8	350.0	348.1	345.3	351.9	7175.0	0.0	21
365.0	365.0	350.0	348.5	346.2	351.5	7525.0	0.0	22
362.0	362.0	350.0	348.8	347.0	351.2	7875.0	0.0	23
359.6	359.6	350.0	349.0	347.6	351.0	8225.0	0.0	24
357.7	357.7	350.0	349.2	348.1	350.8	8575.0	0.0	25
356.2	356.2	350.0	349.4	348.5	350.6	8925.0	0.0	26
354.9	354.9	350.0	349.5	348.8	350.5	9275.0	0.0	27
353.9	353.9	350.0	349.6	349.0	350.4	9625.0	0.0	28
353.2	353.2	350.0	349.7	349.2	350.3	9975.0	0.0	29
352.5	352.5	350.0	349.7	349.4	350.3	10325.0	0.0	30

C.3.6 Supplier 5

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
700.0	700.0	700.0	700.0	700.0	700.0	0.0	0.0	1
700.0	700.0	700.0	700.0	700.0	700.0	700.0	0.0	2

700.0	700.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
700.0	700.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
700.0	700.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
700.0	700.0	700.0	700.0	700.0	700.0	3500.0	0.0	6
700.0	700.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
700.0	700.0	700.0	700.0	700.0	700.0	4900.0	0.0	8
700.0	700.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
700.0	700.0	700.0	700.0	700.0	700.0	6300.0	0.0	10
700.0	700.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
700.0	700.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
700.0	700.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
700.0	700.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
700.0	700.0	700.0	700.0	700.0	700.0	9800.0	0.0	15
700.0	700.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
700.0	700.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
700.0	700.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
700.0	700.0	700.0	700.0	700.0	700.0	12600.0	0.0	19
700.0	700.0	700.0	700.0	700.0	700.0	13300.0	0.0	20
700.0	700.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
700.0	700.0	700.0	700.0	700.0	700.0	14700.0	0.0	22
700.0	700.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
700.0	700.0	700.0	700.0	700.0	700.0	16100.0	0.0	24
700.0	700.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
700.0	700.0	700.0	700.0	700.0	700.0	17500.0	0.0	26
700.0	700.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
700.0	700.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
700.0	700.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
700.0	700.0	700.0	700.0	700.0	700.0	20300.0	0.0	30

C.4 Scenario (d)

C.4.1 OEM

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	1400.0	1400.0	1400.0	1400.0	0.0	0.0	1
0.0	0.0	1400.0	1400.0	1400.0	1400.0	1400.0	0.0	2
0.0	0.0	1400.0	1400.0	1400.0	1400.0	2800.0	0.0	3
0.0	0.0	1400.0	1400.0	1400.0	1400.0	4200.0	0.0	4
0.0	0.0	1400.0	1400.0	1400.0	1400.0	5600.0	0.0	5
0.0	0.0	1400.0	1400.0	1400.0	1400.0	7000.0	0.0	6

0.0	0.0	1400.0	1400.0	1400.0	1400.0	8400.0	0.0	7
0.0	0.0	1400.0	1400.0	1400.0	1400.0	9800.0	0.0	8
0.0	0.0	1400.0	1400.0	1400.0	1400.0	11200.0	0.0	9
0.0	−350.0	1400.0	1400.0	1050.0	1400.0	12600.0	350.0	10
0.0	−350.0	1400.0	1400.0	1400.0	1400.0	14000.0	700.0	11
0.0	−700.0	1400.0	1400.0	1050.0	1400.0	15400.0	1400.0	12
0.0	−525.0	1400.0	1400.0	1575.0	1400.0	16800.0	1925.0	13
0.0	−525.0	1400.0	1400.0	1400.0	1400.0	18200.0	2450.0	14
0.0	−525.0	1400.0	1400.0	1400.0	1400.0	19600.0	2975.0	15
0.0	−175.0	1400.0	1400.0	1750.0	1400.0	21000.0	3150.0	16
0.0	−84.0	1400.0	1400.0	1491.0	1400.0	22400.0	3234.0	17
0.0	−67.2	1400.0	1400.0	1416.8	1400.0	23800.0	3301.2	18
0.0	−53.8	1400.0	1400.0	1413.4	1400.0	25200.0	3355.0	19
0.0	−43.0	1400.0	1400.0	1410.8	1400.0	26600.0	3398.0	20
0.0	−34.4	1400.0	1400.0	1408.6	1400.0	28000.0	3432.4	21
0.0	−27.5	1400.0	1400.0	1406.9	1400.0	29400.0	3459.9	22
0.0	−22.0	1400.0	1400.0	1405.5	1400.0	30800.0	3481.9	23
0.0	−17.6	1400.0	1400.0	1404.4	1400.0	32200.0	3499.5	24
0.0	−14.1	1400.0	1400.0	1403.5	1400.0	33600.0	3513.6	25
0.0	−11.3	1400.0	1400.0	1402.8	1400.0	35000.0	3524.9	26
0.0	−9.0	1400.0	1400.0	1402.3	1400.0	36400.0	3533.9	27
0.0	−7.2	1400.0	1400.0	1401.8	1400.0	37800.0	3541.1	28
0.0	−5.8	1400.0	1400.0	1401.4	1400.0	39200.0	3546.9	29
0.0	−4.6	1400.0	1400.0	1401.2	1400.0	40600.0	3551.5	30

C.4.2 Supplier 1

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	700.0	700.0	700.0	700.0	0.0	0.0	1
0.0	0.0	700.0	700.0	700.0	700.0	700.0	0.0	2
0.0	0.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
0.0	0.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
0.0	0.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
0.0	0.0	700.0	700.0	700.0	700.0	3500.0	0.0	6
0.0	0.0	700.0	1050.0	700.0	700.0	4200.0	0.0	7
0.0	−350.0	700.0	700.0	350.0	700.0	4900.0	350.0	8
0.0	−350.0	700.0	700.0	700.0	700.0	5600.0	700.0	9
0.0	−700.0	700.0	700.0	350.0	700.0	6300.0	1400.0	10
0.0	−525.0	700.0	700.0	875.0	700.0	7000.0	1925.0	11
0.0	−525.0	700.0	700.0	700.0	700.0	7700.0	2450.0	12
0.0	−525.0	700.0	700.0	700.0	700.0	8400.0	2975.0	13

0.0	−175.0	700.0	700.0	1050.0	700.0	9100.0	3150.0	14
0.0	−84.0	700.0	700.0	791.0	700.0	9800.0	3234.0	15
0.0	−67.2	700.0	700.0	716.8	700.0	10500.0	3301.2	16
0.0	−53.8	700.0	700.0	713.4	700.0	11200.0	3355.0	17
0.0	−43.0	700.0	700.0	710.8	700.0	11900.0	3398.0	18
0.0	−34.4	700.0	700.0	708.6	700.0	12600.0	3432.4	19
0.0	−27.5	700.0	700.0	706.9	700.0	13300.0	3459.9	20
0.0	−22.0	700.0	700.0	705.5	700.0	14000.0	3481.9	21
0.0	−17.6	700.0	700.0	704.4	700.0	14700.0	3499.5	22
0.0	−14.1	700.0	700.0	703.5	700.0	15400.0	3513.6	23
0.0	−11.3	700.0	700.0	702.8	700.0	16100.0	3524.9	24
0.0	−9.0	700.0	700.0	702.3	700.0	16800.0	3533.9	25
0.0	−7.2	700.0	700.0	701.8	700.0	17500.0	3541.1	26
0.0	−5.8	700.0	700.0	701.4	700.0	18200.0	3546.9	27
0.0	−4.6	700.0	700.0	701.2	700.0	18900.0	3551.5	28
0.0	−3.7	700.0	700.0	700.9	700.0	19600.0	3555.2	29
0.0	−3.0	700.0	700.0	700.7	700.0	20300.0	3558.2	30

C.4.3 Supplier 2

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	700.0	700.0	700.0	700.0	0.0	0.0	1
0.0	0.0	700.0	700.0	700.0	700.0	700.0	0.0	2
0.0	0.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
0.0	0.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
0.0	0.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
0.0	0.0	700.0	700.0	700.0	700.0	3500.0	0.0	6
0.0	0.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
0.0	0.0	700.0	700.0	700.0	700.0	4900.0	0.0	8
0.0	0.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
0.0	0.0	700.0	700.0	700.0	700.0	6300.0	0.0	10
0.0	0.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
0.0	0.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
0.0	0.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
0.0	0.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
0.0	0.0	700.0	700.0	700.0	700.0	9800.0	0.0	15
0.0	0.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
0.0	0.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
0.0	0.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
0.0	0.0	700.0	700.0	700.0	700.0	12600.0	0.0	19
0.0	0.0	700.0	700.0	700.0	700.0	13300.0	0.0	20

0.0	0.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
0.0	0.0	700.0	700.0	700.0	700.0	14700.0	0.0	22
0.0	0.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
0.0	0.0	700.0	700.0	700.0	700.0	16100.0	0.0	24
0.0	0.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
0.0	0.0	700.0	700.0	700.0	700.0	17500.0	0.0	26
0.0	0.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
0.0	0.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
0.0	0.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
0.0	0.0	700.0	700.0	700.0	700.0	20300.0	0.0	30

C.4.4 Supplier 3

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	350.0	350.0	350.0	350.0	0.0	0.0	1
0.0	0.0	350.0	350.0	350.0	350.0	350.0	0.0	2
0.0	0.0	350.0	350.0	350.0	350.0	700.0	0.0	3
0.0	0.0	350.0	350.0	350.0	350.0	1050.0	0.0	4
0.0	0.0	350.0	350.0	350.0	350.0	1400.0	0.0	5
0.0	0.0	0.0	0.0	0.0	0.0	1400.0	0.0	6
350.0	350.0	350.0	350.0	700.0	350.0	1750.0	0.0	7
700.0	700.0	0.0	0.0	350.0	280.0	1750.0	0.0	8
175.0	175.0	525.0	441.0	0.0	329.0	2275.0	0.0	9
175.0	175.0	350.0	366.8	350.0	333.2	2625.0	0.0	10
175.0	175.0	350.0	363.4	350.0	336.6	2975.0	0.0	11
0.0	−175.0	350.0	360.8	0.0	339.2	3325.0	175.0	12
0.0	−84.0	350.0	358.6	441.0	341.4	3675.0	259.0	13
0.0	−67.2	350.0	356.9	366.8	343.1	4025.0	326.2	14
0.0	−53.8	350.0	355.5	363.4	344.5	4375.0	380.0	15
0.0	−43.0	350.0	354.4	360.8	345.6	4725.0	423.0	16
0.0	−34.4	350.0	353.5	358.6	346.5	5075.0	457.4	17
0.0	−27.5	350.0	352.8	356.9	347.2	5425.0	484.9	18
0.0	−22.0	350.0	352.3	355.5	347.7	5775.0	506.9	19
0.0	−17.6	350.0	351.8	354.4	348.2	6125.0	524.5	20
0.0	−14.1	350.0	351.4	353.5	348.6	6475.0	538.6	21
0.0	−11.3	350.0	351.2	352.8	348.8	6825.0	549.9	22
0.0	−9.0	350.0	350.9	352.3	349.1	7175.0	558.9	23
0.0	−7.2	350.0	350.7	351.8	349.3	7525.0	566.1	24
0.0	−5.8	350.0	350.6	351.4	349.4	7875.0	571.9	25
0.0	−4.6	350.0	350.5	351.2	349.5	8225.0	576.5	26
0.0	−3.7	350.0	350.4	350.9	349.6	8575.0	580.2	27

0.0	−3.0	350.0	350.3	350.7	349.7	8925.0	583.2	28
0.0	−2.4	350.0	350.2	350.6	349.8	9275.0	585.5	29
0.0	−1.9	350.0	350.2	350.5	349.8	9625.0	587.4	30

C.4.5 Supplier 4

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	350.0	350.0	350.0	350.0	0.0	0.0	1
0.0	0.0	350.0	350.0	350.0	350.0	350.0	0.0	2
0.0	0.0	350.0	350.0	350.0	350.0	700.0	0.0	3
0.0	0.0	350.0	350.0	350.0	350.0	1050.0	0.0	4
0.0	0.0	350.0	350.0	350.0	350.0	1400.0	0.0	5
0.0	0.0	350.0	350.0	350.0	350.0	1750.0	0.0	6
0.0	0.0	350.0	350.0	350.0	350.0	2100.0	0.0	7
0.0	−350.0	700.0	980.0	350.0	420.0	2800.0	350.0	8
0.0	−525.0	525.0	609.0	350.0	441.0	3325.0	875.0	9
0.0	−525.0	350.0	277.2	350.0	422.8	3675.0	1225.0	10
0.0	−525.0	350.0	291.8	350.0	408.2	4025.0	1575.0	11
105.0	105.0	350.0	303.4	980.0	396.6	4375.0	1575.0	12
364.0	364.0	350.0	312.7	609.0	387.3	4725.0	1575.0	13
291.2	291.2	350.0	320.2	277.2	379.8	5075.0	1575.0	14
233.0	233.0	350.0	326.1	291.8	373.9	5425.0	1575.0	15
186.4	186.4	350.0	330.9	303.4	369.1	5775.0	1575.0	16
149.1	149.1	350.0	334.7	312.7	365.3	6125.0	1575.0	17
119.3	119.3	350.0	337.8	320.2	362.2	6475.0	1575.0	18
95.4	95.4	350.0	340.2	326.1	359.8	6825.0	1575.0	19
76.3	76.3	350.0	342.2	330.9	357.8	7175.0	1575.0	20
61.1	61.1	350.0	343.7	334.7	356.3	7525.0	1575.0	21
48.9	48.9	350.0	345.0	337.8	355.0	7875.0	1575.0	22
39.1	39.1	350.0	346.0	340.2	354.0	8225.0	1575.0	23
31.3	31.3	350.0	346.8	342.2	353.2	8575.0	1575.0	24
25.0	25.0	350.0	347.4	343.7	352.6	8925.0	1575.0	25
20.0	20.0	350.0	348.0	345.0	352.0	9275.0	1575.0	26
16.0	16.0	350.0	348.4	346.0	351.6	9625.0	1575.0	27
12.8	12.8	350.0	348.7	346.8	351.3	9975.0	1575.0	28
10.2	10.2	350.0	349.0	347.4	351.0	10325.0	1575.0	29
8.2	8.2	350.0	349.2	348.0	350.8	10675.0	1575.0	30

C.4.6 Supplier 5

I_t	S_t	D_t	O_t	A_t	EL_t	sum(O)	sum(UD)	t
0.0	0.0	700.0	700.0	700.0	700.0	0.0	0.0	1
0.0	0.0	700.0	700.0	700.0	700.0	700.0	0.0	2
0.0	0.0	700.0	700.0	700.0	700.0	1400.0	0.0	3
0.0	0.0	700.0	700.0	700.0	700.0	2100.0	0.0	4
0.0	0.0	700.0	700.0	700.0	700.0	2800.0	0.0	5
0.0	0.0	700.0	700.0	700.0	700.0	3500.0	0.0	6
0.0	0.0	700.0	700.0	700.0	700.0	4200.0	0.0	7
0.0	0.0	700.0	700.0	700.0	700.0	4900.0	0.0	8
0.0	0.0	700.0	700.0	700.0	700.0	5600.0	0.0	9
0.0	0.0	700.0	700.0	700.0	700.0	6300.0	0.0	10
0.0	0.0	700.0	700.0	700.0	700.0	7000.0	0.0	11
0.0	0.0	700.0	700.0	700.0	700.0	7700.0	0.0	12
0.0	0.0	700.0	700.0	700.0	700.0	8400.0	0.0	13
0.0	0.0	700.0	700.0	700.0	700.0	9100.0	0.0	14
0.0	0.0	700.0	700.0	700.0	700.0	9800.0	0.0	15
0.0	0.0	700.0	700.0	700.0	700.0	10500.0	0.0	16
0.0	0.0	700.0	700.0	700.0	700.0	11200.0	0.0	17
0.0	0.0	700.0	700.0	700.0	700.0	11900.0	0.0	18
0.0	0.0	700.0	700.0	700.0	700.0	12600.0	0.0	19
0.0	0.0	700.0	700.0	700.0	700.0	13300.0	0.0	20
0.0	0.0	700.0	700.0	700.0	700.0	14000.0	0.0	21
0.0	0.0	700.0	700.0	700.0	700.0	14700.0	0.0	22
0.0	0.0	700.0	700.0	700.0	700.0	15400.0	0.0	23
0.0	0.0	700.0	700.0	700.0	700.0	16100.0	0.0	24
0.0	0.0	700.0	700.0	700.0	700.0	16800.0	0.0	25
0.0	0.0	700.0	700.0	700.0	700.0	17500.0	0.0	26
0.0	0.0	700.0	700.0	700.0	700.0	18200.0	0.0	27
0.0	0.0	700.0	700.0	700.0	700.0	18900.0	0.0	28
0.0	0.0	700.0	700.0	700.0	700.0	19600.0	0.0	29
0.0	0.0	700.0	700.0	700.0	700.0	20300.0	0.0	30