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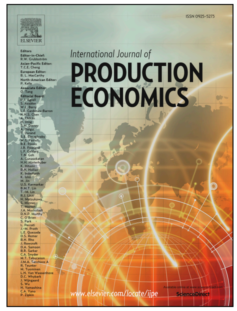

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Anna Ledwoch, Hakan Yasarcan, Alexandra Brintrup

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Authors:

Anna Ledwoch
Institute for Manufacturing,
Cambridge University,
17 Charles Babbage Rd, Cambridge,
CB3 0FS, United Kingdom
aml79@cam.ac.uk

Hakan Yasarcan
Department of Industrial Engineering,
Bogazici University,
34342, Bebek,
Istanbul, Turkey
hakan.yasarcan@boun.edu.tr

Alexandra Brintrup
Institute for Manufacturing,
Cambridge University,
17 Charles Babbage Rd, Cambridge,
CB3 0FS, United Kingdom
ab702@cam.ac.uk

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Abstract

While supply chain risk management offers a rich toolset for dealing with risk at the dyadic level, less attention has been given to the effectiveness of risk management in complex supply networks. We bridge this gap by building an agent based model to explore the relationship between topological characteristics of complex supply networks and their ability to recover through inventory mitigation and contingent rerouting. We simulate upstream supply networks, where each agent represents a supplier. Suppliers' connectivity patterns are generated through random and preferential attachment models. Each supplier manages its inventory using an anchor-and-adjust ordering policy. We then randomly disrupt suppliers and observe how different topologies recover when risk management strategies are applied. Our results show that topology has a moderating effect on the effectiveness of risk management strategies. Scale-free supply networks generate lower costs, have higher fill-rates, and need less inventory to recover when exposed to random disruptions than random networks. Random networks need significantly more inventory distributed across the network to achieve the same fill rates as scale-free networks. Inventory mitigation improves fill-rate more than contingent rerouting regardless of network topology. Contingent rerouting is not effective for scale-free networks due to the low number of alternative suppliers, particularly for short-lasting disruptions. We also find that applying inventory mitigation to the most disrupted suppliers is only effective when the network is exposed to frequent disruptions; and not cost effective otherwise. Our work contributes to the emerging field of research on the relationship between complex supply network topology and resilience.

Keywords: supply chain risk management, complex supply networks, random networks, scale-free networks, inventory mitigation, contingent rerouting, agent-based modelling

1. Introduction

Over the past decades, supply chains have grown longer and became interconnected as a result of globalisation and rising cost pressures (Christopher and Holweg, 2011). Interconnectedness implies that a failure in one supply chain entity can potentially cascade across the whole network (Schmitt and Singh, 2012), making risk monitoring and mitigation challenging.

Suppliers of multiple tiers are tied together creating emergent, yet predictable connection patterns, described as "supply network topology" (Thadakamalla et al., 2014). Studies on network topology, conducted under the framework of network science aim to unveil the behavioural phenomena of interconnected systems, which cannot be well understood from the perspective of a single entity. Understanding how the decision-making of multiple interconnected entities influence overall network resilience is necessary to cope with disruptions effectively because failures are more likely to propagate in certain topologies (Watts, 2002).

Supply Chain Risk Management (SCRM) methods rarely consider the impact of disruptions on the extended supply network, where the term *extended* refers to ties beyond a firm's direct suppliers and customers. The relationship between supply network topology and the effectiveness of recovery from disruptions using risk management strategies has not yet been explored.

We aim to address this gap as follows. After reviewing previous work done in the field of SCRM and complex supply networks, we employ a modelling approach, where several theoretical network topologies based on the extant empirical literature are generated. The generated topologies are used to configure a supply network, after which the networks are subjected to random disruptions. Two SCRM strategies, namely inventory mitigation and contingent rerouting, are applied and the extent to which these strategies are able to enhance network recovery is observed.

Our results sound a cautionary note. We find that the effectiveness of the two SCRM strategies is moderated by the topology of the supply network and that an increased understanding of supply network topology is necessary to underpin the choice of an effective strategy. First, it is shown that inventory mitigation outperforms contingent rerouting in a complex supply network setting regardless of topology. A key lesson is that random topologies need significantly higher inventory levels to recover from disruptions than scale-free networks. It is also observed that contingent rerouting is not effective for scale-free networks due to low numbers of alternative suppliers, particularly for short-term disruptions.

We then explore targeted risk management, where only suppliers which suffered the most from disruptions apply a risk management strategy. Targeting suppliers does not always result in cost reduction. On the contrary, targeted inventory mitigation might significantly increase costs when the network is exposed to rare disruptions due to excessive inventory being kept for long periods of time. Targeted contingent rerouting creates inventory oscillations when network is exposed to short-lasting disruptions, resulting in decreased fill-rates and increased costs. Our work motivates further studies on the relationship between the functionality and performance of supply networks and their topology.

2. Literature review

2.1. Supply Chain Risk Management

Supply networks are exposed to numerous risks such as natural catastrophes, epidemics, economic crises (Tang, 2006), IT failures, and many others. There are a multitude of risk management techniques aiming at reducing risk exposure in supply chains, gathered under collective term Supply Chain Risk Management (SCRM). SCRM literature refers to those strategies mainly as risk mitigation; however in this work *risk mitigation* is restricted to those proactive strategies performed before the occurrence of a disruption. Reactive strategies, which are performed after the occurrence of the disruption, are referred in this paper as *contingency strategies* (Tomlin 2006). Examples of risk management strategies are presented in Table 1, 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 Meindl, 2004; Talluri et al., 2013; Yang and Yang, 2010).

Table 1: Supply chain risk management strategies according to various sources

Reference	**Risk management strategies**
Juttner et al. (2003)	avoidance; control; cooperation; flexibility
Chopra and Meindl (2004)	additional capacity, additional inventory, redundant suppliers; increase responsiveness; increase flexibility; aggregate or pool demand; increase capability; multiple customers
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 (2008)	avoidance; postponement; speculation; hedging; control; transferring/sharing risk; security

Oke and Gopalakrishnan (2009)	multiple sourcing; managing demand; supplier collaboration; planning and coordination of supply demand
Giannakis and Louis (2011)	Intercoordination with software agents / information systems

There is no one-fits-all solution and each strategy aims at reducing certain risk type(s) (Chopra and Meindl, 2004). In this study, particular attention will be given to inventory mitigation and contingent rerouting as these are identified as effective strategies in reducing the impact of supply network disruptions (Chopra and Meindl, 2004), which is the main scope of the paper. *Inventory mitigation* is considered as a redundancy based strategy, where additional amounts of inventory is kept to prevent the focal company from stocking-out in the case of a disruption. Kurano et al. (2014) noted that the amount of additional inventory needed is dependent on the risk profile. 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 would not balance the risk, although it ensures production continuity in case of disruption (Kamalahmadi and Parast, 2017) and absorbs shocks (Mishra et al., 2016).

Contingent rerouting is considered as a flexibility based approach, where the company reorganises its ordering volumes after the disruption so as to minimise a disruption's impact. Literature highlights the dominance of flexibility based strategies over redundancy based ones (Talluri et al., 2013). For example, Carvalho et al. (2012) found that flexible transportation capacity performs better than inventory mitigation and Dong and Tomlin (2012) advocated that contingent rerouting is more effective in cost reduction than inventory mitigation for rare and long disruptions.

The performance of inventory mitigation and contingent rerouting have been broadly investigated in the literature. Tomlin (2006) and Qi and Lee (2015) investigated performance of inventory mitigation and contingent sourcing in a two echelon setting with reliable and unreliable manufacturers. Qi (2013) evaluated different sourcing strategies under disruptions at the primary supplier. Chen et al. (2012) evaluated the performance of contingent rerouting strategy with a backup supplier. Lakovou et al. (2015) determined the optimal capacity level while using emergency sourcing. However, SCRM studies focus on the local or dyadic perspectives giving little attention to how effectiveness of these strategies can be influenced by the supply chain members' connectivity patterns; namely *supply network topology*.

2.2 Supply Network Topology

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). 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). Two most characteristically distinct network topologies based on degree distribution are:

1. *random networks*, which are networks with Poisson degree distribution, where links between nodes are placed at random. There are two popular random network generation models: $G(n,m)$ and $G(n,p)$. $G(n,m)$ model assumes that m links are placed amongst n nodes at random; whereas $G(n,p)$ model assumes that connections between n nodes are chosen according to the probability p (Newman, 2010). Random networks are often used for benchmarking to verify whether the topology in question exhibits certain features.

2. *scale-free networks,* which are networks with a power-law degree distribution. They consist of large *hub* nodes that have very large number of links, 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 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).

Some of the first studies that challenged the perception of supply chains being linear and hierarchical include (Choi et al., 2001; Borgatti and Li, 2009; Lomi and Pattison, 2006, Basole and Bellamy, 2012). These authors replaced the linear chain idea by the notion of complex supply networks, which are intricately interconnected systems emerging without a single entity controlling them.

Empirical studies included: Kim et al. (2011) who mapped Honda supply network with 70 firms**;** Lomi and Pattison (2006) who analyzed Italian automotive supply network with 106 firms; and Keqiang et al. (2008) who mapped the Guangzhou automotive supply network with 84 firms. More recently, large-scale empirical studies have been conducted by Brintrup et al (2011), Kito et al., (2014); and Brintrup et al (2015).

Gafiychuk (2000), Thadakamalla et al. (2004), Nair and Vidal (2011), and Hearnshaw and Wilson (2013) suggested that supply networks exhibit scale-free topologies. Nair and Vidal (2011) created an agent based model that simulated production in random and scale-free supply network topologies showing that a scale-free network is more robust than a random network. Building on the scale-free network discussion, Mari et al (2015) designed a resilient network generation algorithm using a heterogeneous preferential attachment rule, differentiating between retailer, manufacturer and supplier nodes. Brintrup et al (2015) created a framework on how disruptions can be modelled in complex supply networks, showing that product distribution on the nodes need to be considered when evaluating possible failure propagation on the network topology. Kim et al (2015) highlighted the need to differentiate between node and link and network level failures on network topology.

Although the existence of a scale-free property has been widely discussed in literature, studies by Brintrup et al. (2011), and Kito et al. (2014) showed that Toyota network's in-degree and out-degree follow log-normal and stretched exponential distributions, respectively. This means that the networks have hubs but those hubs are not as big, as they would be in a scale-free network. Brintrup et al. (2015) further showed that Airbus supply network topology exhibits a hub structure, with majority of firms connecting only to these hubs. Yet, the Airbus sample was too small to determine the patterns in scale; therefore the authors did not refute nor reinforce the hypothesis of supply networks following scale-free patterns.

Following these studies, we use random and scale-free networks to characterise our supply networks because: (1) We concur with theoretical studies that point out the existence of hubs in supply networks; (2) multiple sources use these to model supply networks, including Thadakamalla et al. (2004), Nair and Vidal (2011), and Zhao et al. (2011); and (3) these models are well documented in the literature to have various strengths and weaknesses to different disruption types.

Supply network topology is important because it has been shown that different topologies exhibit certain robustness properties depending on how the network is disrupted. Network theory literature distinguishes two main types of disruptions: random and targeted. Random disruptions impact all network members with equal probability while in targeted disruptions nodes that fail are chosen based on some parameter such as its number of connections or position in the network. Random networks show vulnerability against random disruptions and robustness against targeted disruptions. Conversely, scale-free networks are vulnerable against targeted disruptions when a hub node is the target, and robust against random disruptions (Barabasi and Albert, 1999; Cohen et al., 2000). Simulation models built by Thadakamalla et al., (2004); and Nair and Vidal, (2011) have proved the same effect taking place in the context of supply networks. .

2.3. Knowledge Gap

SCRM literature focuses mostly on a given focal company and its direct business partners rather than the extended supply network. Nonetheless, there are exceptions where study has been extended to multi-tiered supply network. Benaicha and Hadj-Alouane (2013) assessed how adding a backup supply location in a network increases the performance in light of disruptions. Silbermayr and Minner (2014) evaluated performance of single and dual-sourcing strategies in a supply network subject to disruptions. Talluri et al. (2013) investigated the efficiency of different risk mitigation strategies in a multi-echelon supply network. Wang et al. (2010) assessed 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. Although these studies consider multi-tiered topologies, they have an underlying assumption on linear chain structures that do not account for complex topologies that empirical studies highlighted.

Regardless of the strategy applied, SCR managers often need to decide on the trade-offs between robustness and efficiency (Christopher and Peck, 2004). Schmitt and Singh (2012) highlighted that in order to strengthen the whole system, the performance of the weakest link needs to be improved. This assumption brings to life the considerations about targeted mitigation and contingency, where applying these strategies in the worst performing suppliers might substantially improve performance of the overall system.

While the extant literature studies the effectiveness of risk management strategies for a focal company, the effectiveness of mitigation and contingency in supply networks with distinct topological features has not been explored yet. In addition, there is a lack of understanding of whether and how strengthening the weakest supplier can benefit supply network performance. In what follows, we address this gap by applying risk management strategies in complex supply networks with distinct topological features.

3. Research design

This section discusses four main components of the research design: (a) an agent based model of the supply network; (b) a stock-management model; (c) performance metrics; and (d) the design of experiments used to extract the relationship between the network topology, risk profile, and effectiveness of risk management strategies.

3.1. Agent-based model

Literature advocates the use of multi-agent systems to model supply networks since it enables us to represent supply chain members as autonomous, interdependent, adaptive, and self-organising entities (Swaminathan et al., 1998). Agent based modelling methods are especially valuable since they capture complex phenomena at network-level (Pathak et al., 2007), which could not be obtained by traditional analytical approaches (Chatfield et al., 2013). Previous authors have also modelled complex supply networks with agent based approaches (Nair and Vidal 2011, Thadakamalla et al 2004).

In our work, an agent-based model is an upstream supply network comprised of interconnected agents. The model comprises of four types of agents: the Original Equipment Manufacturer (OEM) agent, supplier agents, logistics provider agents and dummy agents (Figure 1).

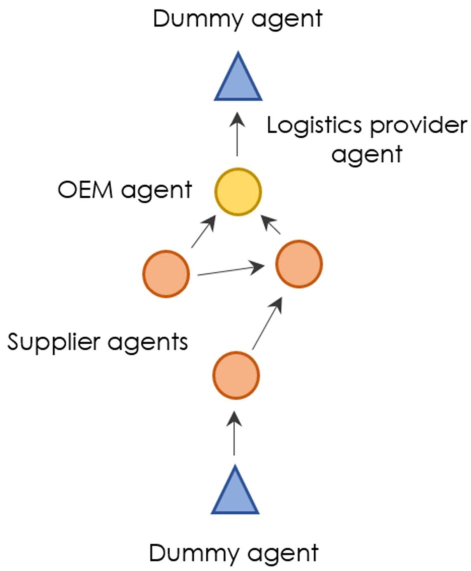
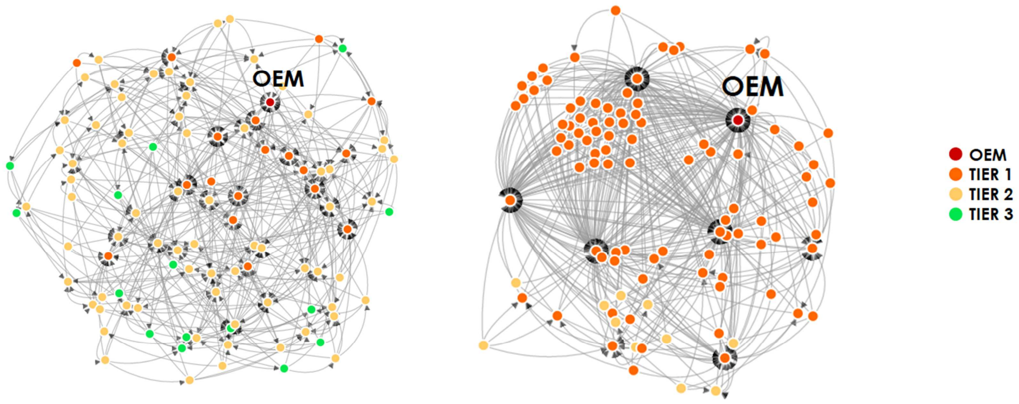


Figure 1. Illustration of agent types

- *The OEM agent* resides in the downstream part of the upstream supply network, and follows a simplified version of the anchor-and-adjust policy as given in Sterman (1989) and Edali and Yasarcan (2014) to manage its inventory.
- *Supplier agents* constitute the extended supply network of the OEM, being OEM's suppliers of the first, second, third, and further tiers. Similarly to the OEM, they follow a simplified version of the anchor-and-adjust policy as given in Sterman (1989) and Edali and Yasarcan (2014). A supplier agent can be a supplier of one company and a customer of another at the same time.
- *Logistics provider agents* form the links between nodes, delivering goods from a supplier to a customer. Each supplier-customer pair has a unique logistics provider assigned.
- The upstream and downstream ends of the network are represented by *dummy agents*, whose purpose is to pull the demand and provide an infinite supply of raw material.

The functionality scope of the OEM and supplier agents includes: order receipt, demand forecasting, shipping, and supply ordering. Agents order from their suppliers and accept orders from their customers communicating via messages. Simulation runs in a discrete manner, where agents simultaneously perform ordering decisions each week. Agents can have multiple customers and suppliers, responding to their requests on a first-come-first-served basis. We assume that all suppliers of an agent have perfectly substitutable goods. Agent-based model design is presented in Figures 2 and 3. Figure 2 shows two exemplary supply networks with random and scale-free topologies and Figure 3 shows the interactions between agents and logistics providers.



a) Random network b) scale-free network

Figure 2: Exemplary supply networks with random and scale free topologies. Arrows indicate material flow from the supplier to the customer.

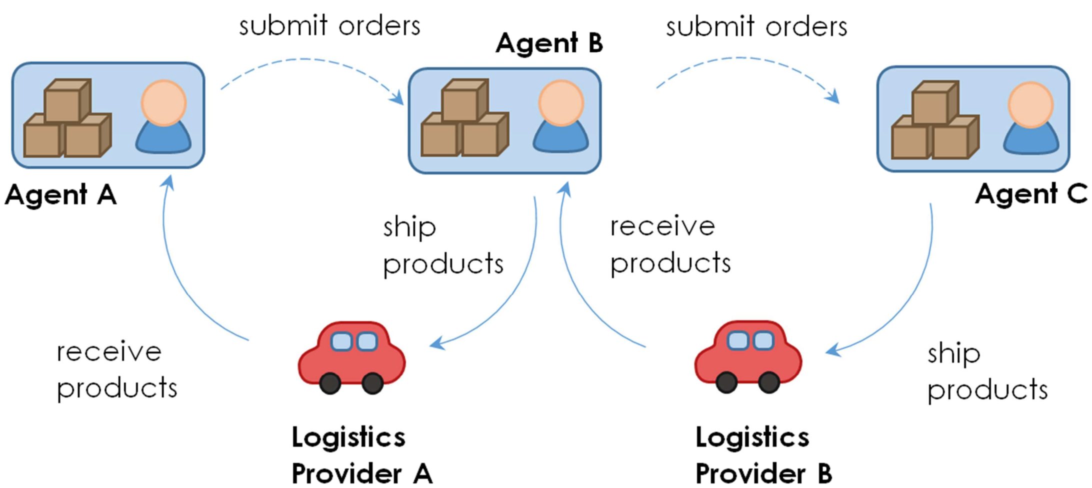


Figure 3: Interaction between supplier agents and logistics providers. Solid arrows indicate material flow from the supplier to the customer, and dashed arrows indicate information flow

3.2. Upstream supply network generation

Each topology consists of 103 nodes and 472 links, where number of nodes and links were chosen based on the size of an existing supply network topology, which could not be reported in this paper due to confidentiality issues. Nodes represent the OEM and supplier agents, and links represent material flow. Each link is assigned a logistics provider agent to carry out deliveries but these are not part of the topology. Dummy agents exist only for computational purposes, to provide raw materials and pull the demand, and hence are not part of the topology. Random and scale-free topologies are generated five times creating unique supply network instances. In order to create network topologies, two generation models are used: random attachment and preferential attachment. The *random attachment model* places m links between n nodes at random, generating random networks. The *preferential attachment model* places m links between n nodes, choosing a node to form a link with a probability proportional to the number of neighbours a node has, generating scale-free networks (Newman, 2010).

While our network generation algorithm follows the same underlying principles of random and preferential attachment, the generation process has been slightly modified as the original algorithms generate undirected networks with no constraints on the number of links. In order to address these shortcomings, and to make sure that the algorithm is applicable, the following set of rules is applied:

(1) The first node created is the OEM; (2) the direction of the link is always from the new node that is created to the existing node. Hence the next node generated is the first supplier of the OEM; (3) the rest of the nodes are created and attached using the random attachment and preferential attachment rules respectively (see Newman 2010); (4) The network is fully connected, and acyclic; (5) After generation, all nodes with zero in-degree have a dummy agent attached, which provides infinite amount of raw material; (6) There is only one dummy customer with only one incoming link which is the OEM; and (7) Each link is represented by a logistics provider agent, whose goal it is to deliver goods between suppliers and customers. The pseudo code for network generation is given on Figure 4.

```
Initialize:
n= number of nodes
m= number of links
k =(round)M/N, where k is average number of links yet to be allocated
Create OEM node
Create supplier node
Add incoming link from supplier node to OEM
m = m – 1
n = n - 2

While n > 0 do
   k = (round)m/n
   Create supplier node
   Add k outgoing links from a new node to existing nodes according to attachment rules (random or preferential)
   m = m – k
   n = n – 1
End while
```

Figure 4: Network generation process

3.3. The stock management model

Supplier agents and the OEM control their own inventory, which we modelled using a stock management structure (see Figure 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).

Each agent makes ordering decisions as described in the stock management model presented in Edali and Yasarcan (2014). The main differences between the work of Edali and Yasarcan (2014), and our work are:

(1) in Edali and Yasarcan (2014), the supply chain members are connected as a chain, whereas we simulate complex network structures;

(2) their model describes only four agents, whereas our model includes more than a hundred;

(3) in their paper, the end-customer demand is around eight units per week, but in this paper, it is assumed to be equal to 1400 units per week.

The model was reconstructed in the Java Agent Development Framework (JADE). The code was validated through comparison of output across different parameter settings. A further check included replication of optimum costs reported by Sterman (1989).

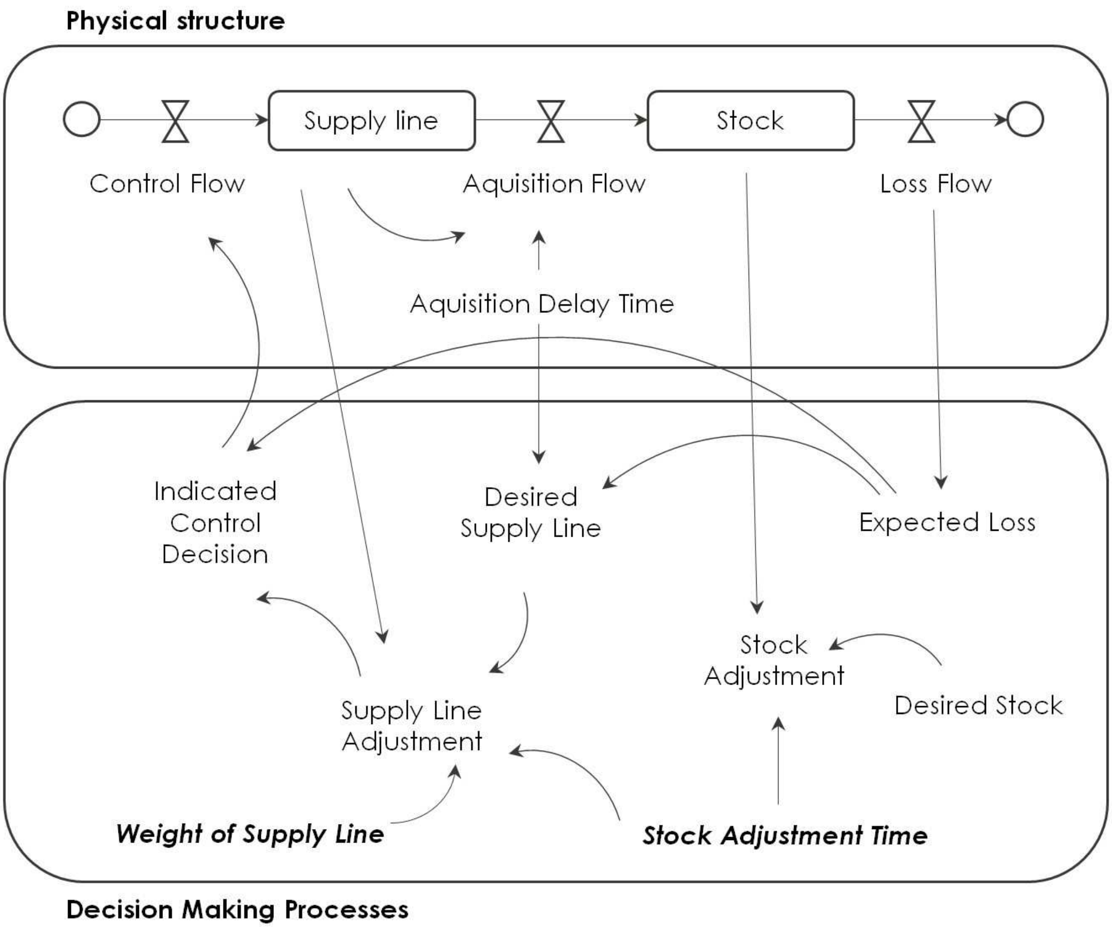


Figure 5 – Stock management model

3.3.1. Physical sub-structure

The inventory of an agent is updated weekly, where subscript *i,t* represents the variable associated with an agent *i* in week *t*. The acquisition flow (*af*) is the rate of receiving orders. Net inventory (*NI*) increases via *(af)*, and decreases via sales (*s*). Supply line (*SL*) represents orders that are placed and have not yet arrived to the ordering agent's inventory. Supply line increases via orders (*o*) and decreases via the acquisition flow (Equations 1 and 2).

$$NI_{i,t+1} = NI_{i,t} + af_{i,t} - s_{i,t} \tag{1}$$

$$SL_{i,t+1} = SL_{i,t} + o_{i,t} - af_{i,t} \tag{2}$$

On-hand inventory (I) and backlog (B) are obtained from net inventory using Equations 3 and 4; when net inventory is positive, we have on-hand inventory, and when it is negative, we have backlog.

$$I_{i,t} = MAX(0, NI_{i,t}) \tag{3}$$

$$B_{i,t} = MAX(0, -1 \cdot NI_{i,t}) \tag{4}$$

We assume that negative orders cannot be placed (i.e., once placed, orders cannot be cancelled). Thus, orders are formulated to be equal to indicated orders if indicated orders (*io*) are positive. Otherwise, orders are equal to zero (Equation 5).

$$o_{i,t} = MAX(0, io_{i,t}) \tag{5}$$

Orders that are placed enter supply line and remain there for a time period that is defined as the acquisition delay time (*adt*), which is also known as the lead time. The acquisition delay time can be expressed as the sum of mailing delay time (mdt) and shipment time (st), where mailing delay time is the time it takes for the order to be received by the supplier, and shipment time is the time it takes for goods to be delivered to the customer (Equation 6).

$$adt = mdt + st \tag{6}$$

Accordingly, acquisition flow is the delayed version of orders (Equation 7).

$$af_{i,t} = o_{i,t-adt} \tag{7}$$

3.3.2. Decision-making sub-structure

Indicated orders are formed using a simplified version of the anchor-and-adjust ordering policy (Sterman 1989). We present the equations of the simplified version below (see Sterman (1989) and Edali and Yasarcan (2016) for an extended version).

In our model, indicated orders is equal to the arithmetic sum of expected sales (*ES*), inventory adjustment (*ia*), and supply line adjustment (*sla*) terms (Equation 8).

$$io_{i,t} = ES_{i,t} + ia_{i,t} + sla_{i,t} \tag{8}$$

Expected sales *(ES)* is obtained by using simple exponential smoothing forecasting method (Equations 9 and 10). Expectation adjustment fraction (α) is a parameter, which was set to 0.2 in the agent-based simulation.

$$ES_{i,t+1} = ES_{i,t} + ear_{i,t} = ES_{i,t} + \alpha \cdot (s_{i,t} - ES_{i,t}) \tag{9}$$

$$ES_{i,t+1} = (1 - \alpha) \cdot ES_{i,t} + \alpha \cdot s_{i,t} \tag{10}$$

Where *ear* stands for expectation adjustment rate. Inventory adjustment (ia) is the discrepancy between desired inventory (I*) and net inventory (Equation 11).

$$ia_{i,t} = I_i^* - NI_{i,t} \tag{11}$$

Supply line adjustment (*sla*) is the discrepancy between desired supply line ($SL*$) and Supply line (Equation 12).

$$sla_{i,t} = SL^*_{i,t} - SL_{i,t} \tag{12}$$

Desired supply line is calculated by multiplying expected sales with acquisition delay time (Equation 13). This aims to keep supply line at a level that satisfies the lead time demand (Sterman, 1989; Yasarcan, 2011).

$$SL^*_{i,t} = adt \cdot ES_{i,t} \tag{13}$$

3.4. Experimental setup for the stock management structures in the network

The agent-based model allows for supplier agents and the OEM to have more suppliers than in original Sterman (1989) model. Therefore, we have updated the ordering decision rules. The agent performs the same ordering decisions as specified by the anchor-and-adjust policy, although when it has more than one supplier it splits the order volume equally between its suppliers as specified in Equation 14, where $o_{i,t}$ is the ordering decision of an agent i in week t; $o_{ij,t}$ is the order submitted by an agent i to an agent j in week t; A is the adjacency matrix of the network, where A_{ij} is equal to 1 when an agent j supplies to an agent i; and k^{in}_i is the number of suppliers of an agent i.

$$o_{ij,t} = \frac{A_{ij} o_{i,t}}{k_i^{in}} \tag{14}$$

The initial set up for the agent-based simulation is as follows:

- The dummy agent at the end of the supply-chain generates a constant demand of 1400 units per week.
- Each agent's desired inventory is equated to zero which corresponds to aiming to minimize the net inventory (Equation 15).

$$I_i^* = 0 \tag{15}$$

- The initial net inventory is equated to zero (Equation 16).

$$NI_{i,t0} = 0 \tag{16}$$

- In order to ensure that the simulation is in an equilibrium, the initial order of each agent is equal to the sum of initial orders of this agent's customers (Equation 17), where A is the adjacency matrix with A_{ji} equal to 1 when an agent j is a customer of an agent i, and $o_{ji,t0}$ is the initial order placed by an agent j to an agent i. The estimation of the initial order starts from the OEM, whose initial order is known and is equal to 1400 units per week.

$$o_{i,t0} = \sum_{j=0,j\neq i}^{N}(A_{ji}o_{ji,t0}) \tag{17}$$

- The initial supply line ($SL_{i,t0}$) of each agent is equal to initial demand of that agent multiplied by the acquisition delay time (Equation 18).

$$SL_{i,t0} = (adt) \cdot o_{i,t0} \tag{18}$$

- The timeframe of the simulation is extended to 500 weeks to prevent the effect of the short-term transient dynamics from dominating overall results.

If no disruptions are introduced, the model produces zero backlog and inventory costs, since the inventory that is acquired is immediately sold. When there are disruptions, the agent's inventory level can oscillate. In this case one of the following scenarios occur: 1) The agent ships to customers all of its inventory and also the newly arrived items to satisfy its demand. Thus, in that simulated week, no inventory or backlog cost is created for that agent; 2) The sum of newly arrived items and items in the inventory is greater than the demand. Thus, the agent must store the amount that is not shipped creating inventory holding costs for that week; 3) The agent receives demand more than it can satisfy. All unsatisfied demand is backordered, and backlog cost is created. We use first-come-first-serve rule for orders that arrive in different weeks. However, if an agent receives multiple orders within the same week, it randomly prioritizes the orders to be satisfied for that week.

When an agent applies inventory mitigation, the desired inventory level is equated to the initial order of that agent ($I_i^* = o_{i,t0}$). Contingent rerouting is 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.

3.5. Performance metrics

Supply network performance has been evaluated using: total costs incurred by all agents in the network (C_{NET}); costs incurred by the OEM (C_{MAN}); average unit fill-rate of agents in the network (FR_{NET}); and unit fill-rate of the OEM (FR_{MAN}). These four metrics enable us to evaluate trade-offs between maintaining low costs and keeping high customer service at the OEM and at the system level. C_{MAN} and FR_{MAN} are calculated as C_i and FR_i, respectively, where i corresponds to the OEM.

The total cost incurred by agent i is represented given by Equation 19:

$$C_i = \sum_{t=1}^{T} \left(0.5 \cdot I_{i,t} + 1 \cdot B_{i,t}\right) \tag{19}$$

$I_{i,t}$ is the on-hand inventory and $B_{i,t}$ indicates the backlog of an agent i in week t, *T* is the duration of a single simulation run that is 500 weeks. These values are multiplied by the inventory holding cost and backlog cost, which are 0.5$ and 1$ per unit per week, respectively (Sterman, 1989; Edali and Yasarcan, 2014). Inventory holding costs and backlog costs generated in each week are summed and show the total cost that agent i generated during 500 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 20).

$$C_{NET} = \sum_{i=1}^{N} C_i \tag{20}$$

Where *N* is the total number of agents in the network excluding dummy agents. 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). We refer later to this measure as fill-rate. Fill-rate of agent i (FR_i) is a percentage of net demand in 500 simulated weeks (Equation 21).

$$FR_i = \frac{\sum_{t=1}^{T} D_{i,t} - \sum_{t=1}^{T} UD_{i,t}}{\sum_{t=1}^{T} D_{i,t}} \tag{21}$$

$D_{i,t}$ and $UD_{i,t}$ are the demand and unmet demand of agent i in week t, respectively. FR_{NET} , , is the average of fill-rates of individual supplier agents (Equation 22).

$$FR_{NET} = \frac{\sum_{i=1}^{N} FR_i}{N} \tag{22}$$

3.6. Design of experiments

We opt out of modelling specific root causes of disruptions in our simulation and instead generalize disruptions under the collective characteristics of disruption frequency and duration by generating risk profiles (Table 2).

A risk profile is composed of risk frequency and duration, where frequency is categorised into rare and frequent disruptions, and duration into short and long. The probability of a disruption to occur is given by the risk frequency while the duration of the disruption is given by risk duration. An example of a rare and long disruption might be a fire; while an example of short and frequent disruption might be a logistics issue such as a truck arriving late.

A rare disruption is defined as one having 0.5% chance of occurrence per week, meaning that disruption happens approximately once per four years per agent. 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. Thus all supplier agents or a subset of them might be disrupted simultaneously in a single simulation run. Disruptions cause the agent to become unresponsive which halts their delivery to customers and demand to its own suppliers. We focus on random disruptions because literature shows numerous examples that highlight how disruptions in small, peripheral firms cascade in the network impacting hubs.

Table 2: Experimental set-up for performance assessment of mitigation and contingency

Experiments	(A) Topologies	(B) Risk profile	(C) Strategy	(D) Mit./Cont. level
14400*	5 Random 5 Scale-free	rare, short rare, long frequent, short frequent, long	Inventory mitigation Contingent rerouting	0%, 5% 25%, 50% 75%, 100%

* conducted using permutation of values in (A)-(D); includes 30 repetitions of each scenario

Table 3: Experimental set-up for targeted mitigation and contingency

Experiments	(A) Topologies	(B) Risk profile	(C) Strategy	(E) Targeting strategy
240*	5 Random 5 Scale-free	rare, short rare, long frequent, short frequent, long	Inventory mitigation Contingent rerouting	5% random 5% highest costs 5% lowest fill-rate

* conducted using permutation of values in (A)-(C) and (E)

The final experimental variable consists of two 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 apply the strategy. 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 the given strategy.

Thus, a single experimental run consists of a given topology, risk profile, strategy, and the level at which that strategy is pursued. Each experimental run is repeated 30 times, giving a total of 14400 experiments. Scenarios are summarized in Table 2.

The next set of experiments focuses on targeted risk management so as to investigate whether strengthening the worst performing agents influences overall network performance. The weakest agents are chosen based on their performances obtained in the scenarios with neither inventory mitigation nor contingent rerouting (0% mitigation/contingency level scenarios shown in Table 2). Then, for every topology and each risk profile, 5% of agents that obtained the highest cost C_i and 5% of agents that obtained the lowest fill-rate FR_i are chosen. The improvements in targeted and random risk management performances are then compared with each other. There are 240 experiments summarized in Table 3.

4. Results and discussion

In this section, we assess the performance of supply networks using costs and fill-rates at individual and system levels. The individual level corresponds to OEM's performance whereas the system level corresponds to overall network performance. We first expose the networks to random disruptions without applying either inventory mitigation or contingent rerouting to investigate how topology affects failure propagation in random and scale-free networks. Then, we apply mitigation and contingency strategies in randomly chosen firms to assess effectiveness of these strategies in networks with different topologies; we compare the effectiveness of strategies to conclude which one enables better recovery. Finally, we target the weakest firms to apply risk management strategies and compare the outcome with random selection.

4.1. Disruption impact

In a perfect just-in-time system, when demand is constant and there are no disruptions, C_{NET} is equal to 0 and FR_{NET} is equal to 100% for all scale-free and random topologies. This is because there are no inventory oscillations; everything that is ordered is immediately sold.

When the 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 4).

We found that random networks generate higher costs than scale-free for all risk profiles. For example, for low risk profile, costs are $1,180,476 and $82,835 for random and scale-free networks, respectively; for high risk profiles, costs are $13,615,534 and $2,469,877. The higher the risk profile is, the higher is the cost difference. Random networks incur on average 14 times higher costs than scale-free networks for low risk profiles and more than 50 times higher for high risk profiles.

Random networks have lower fill-rates than scale-free, which are 75.40% and 95.99% in random and scale-free networks, respectively, for low risk. When risk is high, random network fill-rates drop to 25.81%, which is half of the fill-rate obtained for scale-free networks under the same conditions.

Our work further validates conclusions of Nair and Vidal, (2011); and Thadakamalla et al., (2004) who posed that scale-free supply networks are more robust to random disruptions. Beyond this, our work shows that when Sterman (1989)'s model is extended to complex supply network topologies, scale-free supply networks generate lower costs and have higher fill-rates..

Table 4: Performance of supply networks exposed to disruptions, where inventory mitigation and contingent rerouting are not applied. σFR_{NET} and σC_{NET} are standard deviations of fill-rates and costs respectively.

Topology	Risk profile	FR_{NET} *	σFR_{NET}	C_{NET} *	σC_{NET}
Random	rare, short	75.40%	4.36%	1,180,476$	292,447$
	rare, long	46.39%	4.43%	3,479,350$	538,256$
	frequent, short	38.38%	2.17%	4,947,205$	370,403$
	frequent, long	25.81%	1.14%	13,615,534$	817,470$
Scale-free	rare, short	95.99%	1.15%	82,835$	24,860$
	rare, long	89.83%	2.67%	281,940$	86,666$
	frequent, short	75.96%	1.67%	707,977$	44,638$
	frequent, long	55.00%	1.85%	2,469,877$	130,704$

* average over 5 topologies and 30 trials

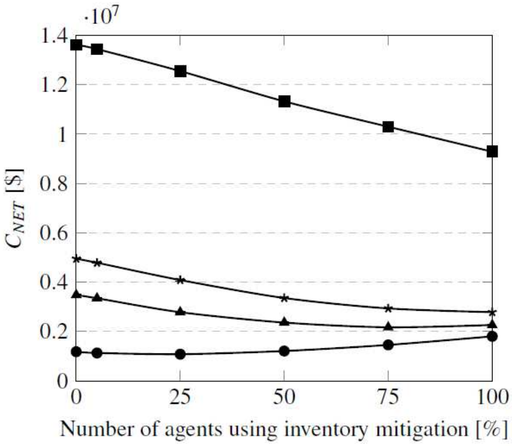
4.2. Effectiveness of inventory mitigation

The inventory mitigation strategy proves to be effective for scale-free and random topologies because it always increases fill-rates and might decrease costs. However, the amount of cost reduction depends on the network's risk profile and topology. Results are presented in Figures 6 and 7. For frequent and long disruptions, C_{NET} was decreased by 31.81% and 32.66%, and C_{MAN} by 53.78% and 64.31% for random and scale-free topologies, respectively. Cost reductions are caused by the fact that the increase in inventory holding costs resulting from the additional inventory is less than the decrease in the backlog costs.

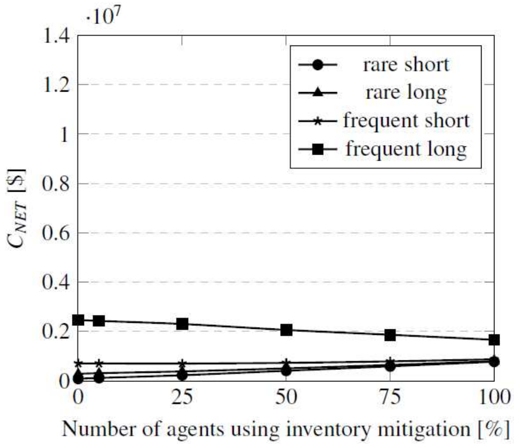
When disruptions are rare, topology has a strong impact on the effectiveness of the inventory mitigation strategy. A decrease in cost is observed only for random topologies, when 25% of firms keep additional inventory. Cost reduction does not occur for rare disruptions in scale-free topologies because they are robust by design, thus, they do not require as much inventory as random topologies. This is expressed by an increase in C_{NET} by 836.54% for rare and short disruptions, and by 182.64% for rare and long disruptions (Table 5).

The inventory mitigation strategy always improves fill-rates, regardless of topology (Figure 7). The FR_{NET} improvement for frequent and long disruptions is 13.43% and 17.44% for random and scale-free topologies, respectively. Scale-free topologies recover 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 topology, almost all agents need to keep additional inventory. For scale-free networks, the same result can be obtained with only 5% of agents applying inventory mitigation. It is also interesting that the OEM recovers better than the overall network for the majority of the risk profiles for both topology types. This is because additional inventory prevents failures to propagate across the network, stopping inventory oscillations from reaching the OEM. When risk is high, the amount of inventory is not enough to stop the failures and the impact of the disruption reaches the OEM.

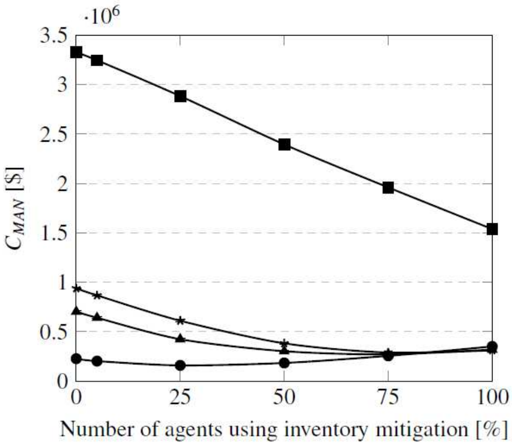
On average, scale-free networks are more robust to random disruptions, they recover better using inventory mitigation, generate lower C_{NET} and C_{MAN}, and have higher FR_{NET} and FR_{MAN}. They have higher disruption tolerance and need less inventory than random topologies for the same risk profile. 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.



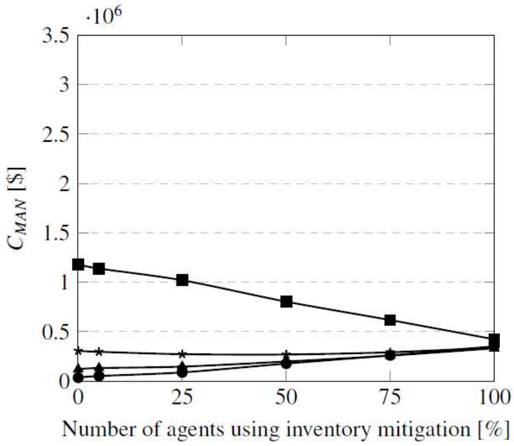
(a) C_{NET} for random topologies



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



(c) C_{MAN} for random topologies



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

Figure 6: (a, b) Network and (c, d) manufacturer's costs for inventory mitigation strategy for random and scale-free topologies

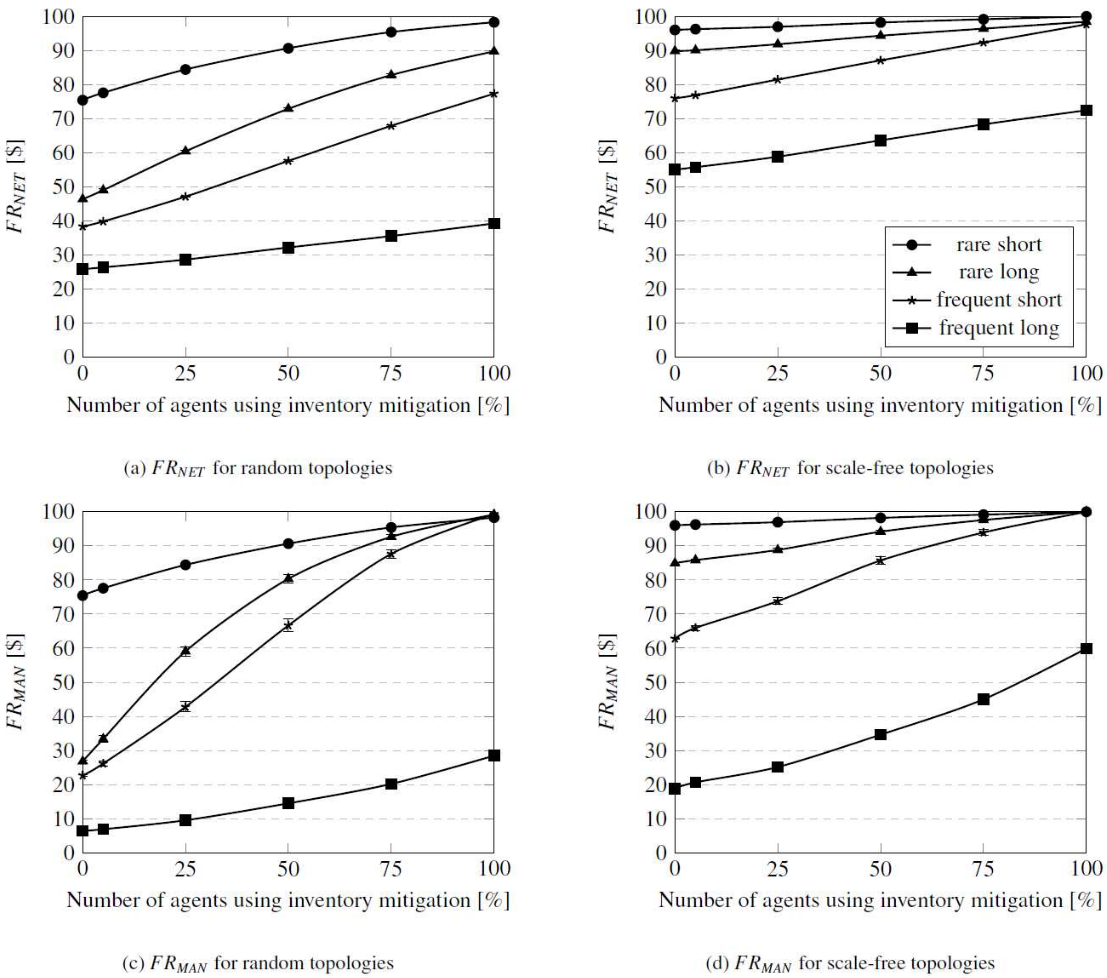
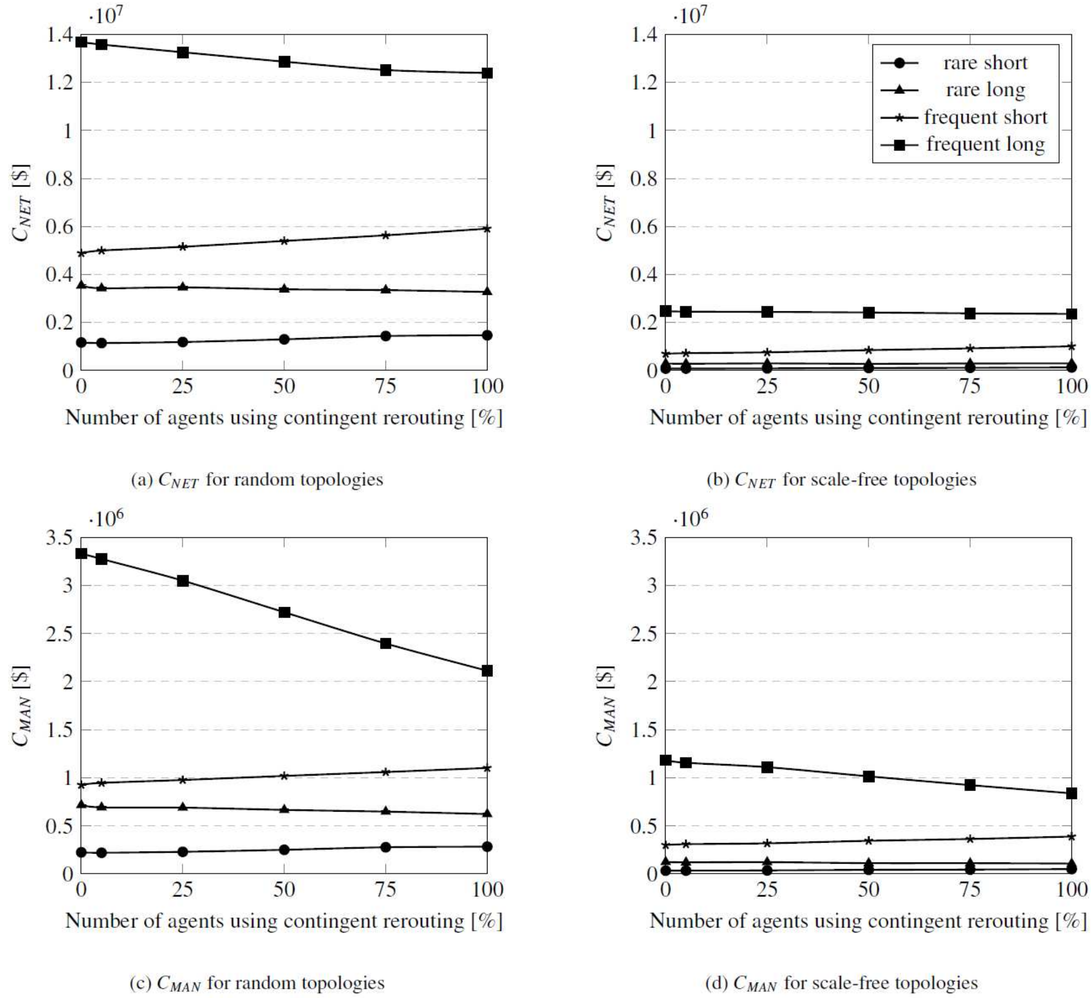


Figure 7: (a, b) Network and (c, d) manufacturer's fill-rates for inventory mitigation strategy for random and scale-free topologies

4.3. Effectiveness of contingent rerouting

Contingent rerouting is not effective for short disruptions because of order processing time (effectively acting as the mailing delay time parameter in Sterman, 1989). If the disruption duration is short, the disrupted supplier is back to business before its customer applies contingent rerouting. Delay in the application of contingency strategy causes unnecessary inventory oscillations and results in increased costs and decreased fill-rates for both the OEM and the whole network (Figures 8 and 9).

Contingent rerouting is effective for long disruptions, but not in all cases. It improves random network performance, with an increase in FR_{NET} and FR_{MAN}, and with a decrease in C_{NET} and C_{MAN}. For scale-free networks, the strategy works only for the OEM 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). This happens because the majority of firms within the scale-free network do not have many alternative sourcing options.



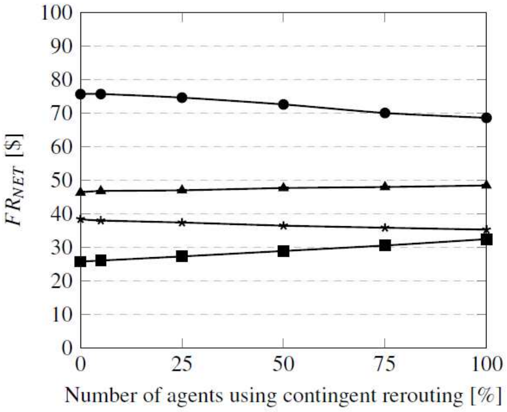
(a) C_{NET} for random topologies

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

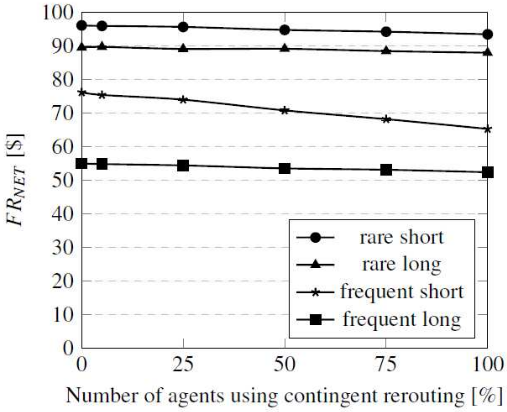
(c) C_{MAN} for random topologies

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

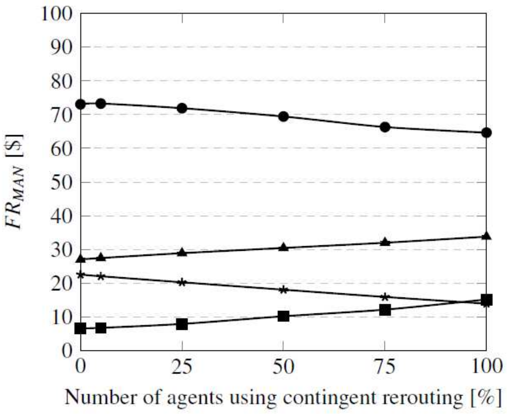
Figure 8: (a, b) Network and (c, d) manufacturer's costs for contingent rerouting strategy for random and scale-free topologies



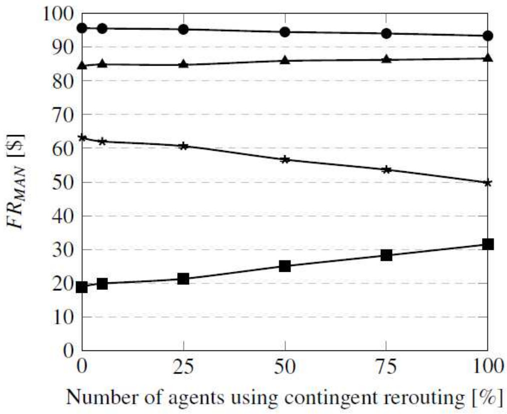
(a) FR_{NET} for random topologies



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



(c) FR_{MAN} for random topologies



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

Figure 9: (a, b) Network and (c, d) manufacturer's fill-rates for contingent rerouting strategy for random and scale-free topologies

4.4. Differences between inventory mitigation and contingent rerouting

The inventory mitigation strategy clearly outperforms contingent rerouting for both topology types and the majority of the risk profiles. The more additional inventory is kept in the network the lower the cost of disruptions is. However, network topology plays an important role in effectiveness of inventory mitigation because it influences the threshold value beyond which the cost of inventory exceeds the benefits obtained from it. Scale-free topologies have lower threshold than random, which implies that they need less inventory.

Contingent rerouting decreases the costs for long disruptions and increases costs for short disruptions. However, even for long disruptions, effectiveness of inventory mitigation is still better than contingent rerouting (Table 5).

Inventory mitigation always improves the fill-rate, whereas contingent rerouting decreases it for the majority of the cases.

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 is not an attractive strategy (Dong and Tomlin, 2012; Tomlin, 2006; Talluri et al., 2013), whereas our results 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. High effectiveness of inventory mitigation results from the absorption of inventory oscillations across the network (Mishra et al., 2016). Low performance of contingent rerouting results from high interconnectedness of the supply network; in which the alternative supplier that receives demand has other supply obligations to meet. This short-term increase in demand at the alternative supplier causes inventory oscillations that travel through the network creating a bullwhip effect and generating higher backlogs.

Table 5: Effectiveness of mitigation and contingency when all agents apply IM or CR strategies. % change from when no IM/CR strategy is applied.

Topology	Risk profile	FR_{NET}		C_{NET}	
		IM*	CR*	IM*	CR*
Random	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%
Scale-free	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%

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

4.5. Effectiveness of targeted mitigation and contingency

Next, we investigate how strengthening the weakest firms influences overall network performance. To do so, we choose 5% of companies which showed lowest unit fill-rates and highest costs during the analysis. These firms then apply inventory mitigation and contingent rerouting (Tables 6 and 7). We then compare results of targeted mitigation with results obtained from runs with risk management strategies chosen at random.

For the majority of the cases, when 5% of firms with highest costs and lowest fill-rate are targeted for inventory mitigation the performance of the overall network is higher than when these 5% of firms were chosen at random. The observation does not hold for rare disruptions in scale-free networks. In those cases, targeting companies that generate highest costs significantly increases costs incurred - by 383.36% for rare and short disruptions and by 72.74% for rare and long disruptions compared to when the selection was random. This is because firms that generate highest costs also have the highest demand and inventory oscillations, which imply that the amount of additional inventory kept would be high and incur high inventory holding costs.

Targeted contingent rerouting proves to be effective only for long disruptions; for other cases, the performance is even worse than what it would be if the firms were chosen at random. Although a previous study advocated that strengthening the weakest link improves overall system performance (Schmitt and Singh, 2012), this did not hold true for some of our experiments. For some cases, scale-free topologies recovered better with random risk management strategies compared to the cases with the targeted ones.

Table 6: The change in C_{NET} and 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}				C_{NET}			
			RS*	RL*	FS*	FL*	RS*	RL*	FS*	FL*
Random	Random		2.86%	5.65%	3.80%	2.16%	-4.27%	-3.82%	-3.27%	-1.29%
	Targeted	Highest cost	4.90%	9.90%	5.20%	2.89%	0.60%	-21.21%	-14.75%	-9.25%
		Lowest fill-rate	6.46%	11.18%	5.38%	0.56%	-26.44%	-10.13%	-8.36%	-1.76%
Scale-free	Random		0.25%	0.24%	1.20%	1.35%	41.31%	10.27%	-0.33%	-1.72%
	Targeted	Highest cost	1.28%	1.53%	2.99%	1.17%	382.36%	72.74%	-5.09%	-22.68%
		Lowest fill-rate	0.21%	3.14%	2.00%	1.33%	30.99%	-15.60%	-2.17%	-23.43%

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

Table 7: The change in C_{NET} and 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}				C_{NET}			
			RS*	RL*	FS*	FL*	RS*	RL*	FS*	FL*
Random	Random		0.05%	0.97%	-1.07%	1.12%	-2.01%	-3.25%	2.25%	-0.76%
	Targeted	Highest cost	-5.59%	5.53%	-3.01%	3.65%	25.39%	-9.26%	8.28%	-3.76%
		Lowest fill-rate	0.06%	3.14%	-0.86%	3.10%	-0.76%	-0.69%	3.48%	-0.01%
Scale-free	Random		-0.16%	0.20%	-1.03%	-0.31%	2.88%	-2.93%	3.56%	-0.66%
	Targeted	Highest cost	-1.71%	0.79%	-12.10%	-5.37%	47.25%	-15.27%	40.84%	-4.97%
		Lowest fill-rate	-0.71%	1.01%	0.26%	-6.74%	34.08%	-0.94%	2.38%	-2.73%

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

5. Conclusions

SCRM approaches involve practices that are well understood at the local and dyadic levels. However, the relationship between the effectiveness of SCRM strategies and supply network topology has thus far not been investigated, despite recent studies highlighting complex network topologies that underpin supply chains. In this paper we bridged this gap by exploring effectiveness of inventory mitigation and contingent rerouting in supply networks with different topological characteristics.

After a review of literature, we focussed on two widely practiced SCRM strategies: inventory based risk mitigation and contingent routing; and two supply network topologies: a randomly organised supply network and a scale-free supply network. This was then followed by a simulation approach to test which strategy, at what level, in which topology results in a better performance for the OEM and for the overall network. Performance criteria included both network and the OEM's fill-rate and associated costs.

We came to the following conclusions about inventory mitigation strategy: (1) Additional inventory always increases fill-rate regardless of topology; (2) Additional inventory might decrease or increase costs depending on risk profile and network topology. Application of inventory mitigation for rare and long disruptions decreases costs in random networks and increases costs in scale-free networks, while the opposite is true for scale-free networks; (3) Scale-free networks have higher disruption tolerance and need less inventory to recover than random topologies for the same risk profiles.

We have come to the following conclusions about contingent rerouting strategy: (1) Contingent rerouting decreases costs and increases fill-rates only when disruption duration is long. For short disruptions, there is an increase in costs and decrease in fill-rates due to inventory oscillations caused by order processing time; (2) Contingent rerouting does not allow fill-rate increase and cost reduction for scale-free networks because most companies in the network have a small number of alternative suppliers.

Following on these findings, further experiments were conducted to explore whether the targeting of SCRM strategies in the network would affect the outcome differently. This involved selecting suppliers that had the highest costs and lowest fill-rates during disruptions in previous simulation runs. Interestingly, we found that targeting the worst performing companies did not always increase performance.

The following managerial implications may be deduced from our work: (1) Literature has often underestimated inventory mitigation as a risk treatment strategy. This research shows that it serves well in majority of cases as an effective shock absorption mechanism; (2) Scale-free supply network topologies need less inventory than random topologies to both withstand and recover from disruptions, therefore it is important to identify the topology under which an OEM's network operates when considering risk management strategies; (3) Contingent rerouting has proven to be less efficient than inventory mitigation in a complex supply network setting. In order for contingent rerouting to work well, specific conditions need to be met: (a) majority of supply chain members need to have multiple alternative suppliers, which might not be practical in real-world scenarios; (b) the response time has to be less than the disruption duration. If these conditions are not met, contingent rerouting results in increased inventory oscillations and drops in effectiveness; (4) Since supply network topologies show robustness to different risk types, theoretically it is possible to design supply network in a way that it is robust to specific types of risk; (5) Targeted risk management can be an effective tool to remedy the impact of disruptions, however it needs to be carefully designed. If misaligned, the strategy that initially was aimed at decreasing risk might end up significantly hurting the performance of the overall system.

In conclusion, this work shows that network topology plays a crucial role when exposed to random disruptions. There are a few limitations of this study that provide directions for the future research. We considered only two strategies as examples of redundancy and flexibility based approaches. In the future, more diverse mitigation and contingency strategies could be explored. Moreover, hybrid strategies that combine inventory mitigation and contingent rerouting could be applied. It should also be noted that strategies considered in our work are not a one-fits-all solution and they might increase other types of risks such as inventory handling risks (Chopra and Meindl, 2004). Future extensions could incorporate different types of targeted disruption scenarios.

The model presented in our paper is a single-product supply network, which assumes that all suppliers deliver perfectly substitutable goods. Multi-product considerations could bring more in-depth analysis on how a company's product portfolio influences the effectiveness of mitigation and contingency. Finally, while in this work we focus on the upstream part of the supply network, future extensions could incorporate the downstream network including distributors, wholesalers and retailers.

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